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EXPENDITURE CASCADES, LOW INTEREST RATES OR PROPERTY BOOMS? DETERMINANTS OF HOUSEHOLD DEBT IN OECD COUNTRIES

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Abstract

The past decades have witnessed a strong increase in household debt and high growth of private consumption expenditures in many countries. This paper empirically investigates four explanations: First, the expenditure cascades hypothesis argues that an increase in inequality induced lower income groups to copy the spending behaviour of richer peer groups and thereby drove them into debt ('keeping up with the Joneses'). Second, the housing boom hypothesis argues that increasing property prices encourage household spending and household borrowing due to wealth effects, eased credit constraints and the prospect of future capital gains. Third, the low interest hypothesis argues that low interest rates encouraged households to take on more debt. Fourth, the financial deregulation hypothesis argues that deregulation of the financial sector boosted credit supply. The paper tests these hypotheses by estimating the determinants of household borrowing using a panel of 11 OECD countries (1980-2011). Results indicate that real estate prices and low interest rates were the most important drivers of household debt. In contrast the data does not support the expenditure cascades hypothesis as a general explanation of debt accumulation across OECD countries. Our results are consistent with the financial deregulation hypothesis, but its explanatory power for the 1995-2007 period is low.

Keywords: household debt; income distribution; property prices

JEL codes: E12; E51; E70; D31

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1 Introduction

There is an increasing recognition of the critical role rising household debt plays as a cause of financial crises (Bezemer et al. 2016; Bezemer & Grydaki 2014; Schularick & Taylor 2012; Mian & Sufi 2009). However there is still relatively little systematic empirical research on the reasons for the spectacular rise of household debt in the last decades. In the nascent debate several factors have featured prominently.

First, as rising income inequality has been documented (Atkinson et al. 2011; Piketty 2014), inequality has gained prominence in explaining rising household debt. Kumhof et al. (2012) have proposed a two-class DSGE model where poor households are pushed into debt as they are trying to maintain their consumption levels. Several authors (Frank et al. 2014; Kapeller & Schütz 2014; Ryoo & Kim 2014; Behringer & Treeck 2013) have argued that rapidly growing top incomes lead to rising household debt if consumers follow social norms and imitate the lifestyle and expenses of richer peers. This latter argument is based on a behavioural economics approach, in particular other-regarding social norms for which there exists empirical support especially in the context of consumption and saving (Alvarez-Cuadrado & Japaridze 2017; Kim et al. 2015; Drechsel-Grau & Schmid 2014). We will refer to this as the expenditure cascades hypothesis (ECH) of household debt.

Second, rising real estate prices are another explanation for rising household debt. Most household debt is, in fact, mortgage debt. Jordà et al. (2016) document the rising importance of mortgage debt and highlight its link to real estate prices with historic macroeconomic data. Borio (2014), Goodhart and Hofmann (2008) and Leamer (2007) identify property prices as one of the key variables for financial and business cycles. Ryoo (2016) presents a formal Minsky model where household debt is driven by property prices. Bezemer et al. (2017) document in a new panel covering 74 countries that mortgages where the primary driver of household credit over their 1990-2011 sample period. However while there is an extensive literature on the effects of property prices or housing wealth on consumption expenditures, (see the surveys by Cooper and Dynan (2016) and Paiella (2009)), there is much less on their effects on household debt. This paper refers to this argument as the housing boom hypothesis (HBH): home buyers take out larger mortgages relative to their income in the face of rapidly rising house prices.

Third, the influence of monetary policy on household borrowing decisions works via interest rates. If central banks keep interest rates at very low levels, cheap (mortgage) rates will attract borrowers who may struggle with their repayments when interest rates increase. This explanation is called the

low interest rate hypothesis (LIH). Taylor (2009) has prominently argued that the failure of the US central bank to increase interest rates[1] in the early 2000s has been a main cause of the financial crisis and an over indebted household sector. Sinn and Valentinyi (2013) have made a similar argument for Europe and claim that European monetary unification has led to low interest rates in southern Europe, which resulted in a debt boom.

Fourth, financial deregulation and financial innovation may be behind the rise in household debt. If the financial sector becomes more risk seeking and its willingness to lend increases, households will be able to take on more debt. In particular for the USA, increasing securitization and the rise of the originate-to-distribute model of banking have been cited as causes of the crisis (Crotty 2009; Purnanandam 2011). More generally, if financial regulations are lifted this can boost credit supply and lead to increased household borrowing. We will refer to this explanation as the financial deregulation hypothesis (FDH) (Borio 2014; Borio & White 2004; Mian & Sufi 2009; Justiniano et al. 2015).

The contribution of this paper is to assess these hypotheses empirically. We are particularly interested in their ability to explain the increase in household debt prior to 2008.[2] In order to do so a household debt equation is estimated for a panel of 11 OECD countries for the period 1980-2011. The existing literature on the determinants of household debt is rather thin and typically only considers some of these hypotheses in isolation. Perugini et al. (2016) is an important exception as they control for three of the four hypotheses investigated in this paper. However their paper does not distinguish between household and business debt and it does not take property prices into account. Bordo and Meissner (2012), and, similar, if critical, Gu and Huang (2014) investigate the effect of inequality on debt over a long period (1920-2008), but do not control for real estate prices or financial regulation. Also none of these studies allows or tests for potential long run relationships. Thus the existing literature lacks a comprehensive empirical study. Assessing the explanatory power of these hypotheses is not only interesting from a theoretical perspective, but also for economic policy because they have very different policy implications.

The rest of the paper is organized as follows: Section 2 summarises the theoretical arguments involved and distils the key hypotheses. Section 3 reviews the relevant empirical literature on the

[1] In contrast Bernanke (2005) argues low interest rates are due to non-policy factors, in particular Chinese capital exports.

[2] The focus of this paper lies on the first three hypotheses. We have less confidence in the financial deregulation hypothesis because, firstly, due to data availability, we only account for financial regulation, but not for financial innovation and, secondly, financial regulation may work with longer time lags than the other variables in our model.

determinants of household debt. Section 4 discusses the data sources and the econometric method. Section 5 presents the empirical results and section 6 concludes.

2 Explanations of rising Household Debt

While the effects of household debt have recently attracted interest, there is comparatively less research on the determinants of household debt. In this paper we distinguish between approaches that derive debt from asset transactions, those that derive it from consumption decisions and those that highlight economic policy and regulations. Explanations of household debt accumulation, which emphasize asset transactions and real estate transactions in particular, are summarised under the label 'housing boom hypothesis' (HBH). Different authors propose different links between house prices and household indebtedness. First, New Keynesian[3] authors (Iacoviello 2005) argue that rising residential real estate prices can ease binding credit constraints and thus have the potential to boost household borrowing. If banks primarily consider collateral values when they grant loans, this can be an important channel through which rising real estate prices drive up household debt. In the New Keynesian framework binding credit constraints imply that even transitory increases in property prices will lead to increased household borrowing. Second, in Post Keynesian[4] stock flow consistent (SFC) models (Godley & Lavoie 2007; Zezza 2008; Nikolaidi 2015) household behaviour is anchored by so-called stock-flow norms. Assuming that consumption depends on disposable income and some measure of wealth, households will attempt to reach a target wealth-to-income ratio (Godley and Lavoie 2007, p.75). If property prices rise and household sector wealth increases beyond the target ratio, households will consume that 'excess wealth' by taking on debt if they cannot or do not want to sell their assets. Third, residential real estate prices increasing faster than disposable income, will lead to households taking out bigger mortgages relative to their income, if they are not willing to postpone their home purchases. This argument implicitly assumes that households are not perfectly foresighted, rational decision makers but are either myopic or follow rules of thumb. All three arguments imply that rising property prices encourage household borrowing and are summarised as the housing boom hypothesis.

Regarding household expenditures, behavioural economics stresses that household preferences may be interdependent. People's wellbeing and behaviour is influence by the behaviour of peers. Building on Veblen (1899) and Duesenberry (1949), Frank (1985) and Frank et al. (2014) emphasize that

[3] We use the term "New Keynesian" to refer to micro founded models which incorporate several market frictions such as sticky prices, credit constraints or information asymmetries.

[4] The label "Post Keynesian" refers to aggregated macroeconomic models which emphasize the role of effective demand and are not based on rational optimization as the decision making process.

households do not only spend in order to fulfil their needs but also to signal status. They argue that households' expenditures not only depend on own income but also on the expenditures of other households. In particular Frank et al. (2014) argue that households compare themselves with peers who are richer than themselves, i.e. people look up the distribution of income when assessing their status. In times of growing top incomes, those households in the bracket just below the top group will be trying to keep up with the richer top group and take on debt in order to finance their status comparison-induced expenditures. Households in the third income bracket will run into debt when they try to keep up with those in the second bracket etc.. The result is a cascade of debt-financed status expenditures flowing downwards from the top of the income distribution; thus we use the term expenditure cascades hypothesis (ECH). Several authors have incorporated these assumptions in Post Keynesian macroeconomic models (Belabed et al. 2013; Kapeller & Schütz 2014; Ryoo & Kim 2014; Cardaci 2014). A similar explanation of increased household borrowing posits that households (building on prospect theory) do not want to reduce consumption below levels reached in the past or below a minimum level. Kumhof and Ranciere (2010) adopt the latter approach and show that a decline in bargaining power of workers leads to increased income inequality and results in a debt-financed attempt to maintain living standards. While similar to ECH in terms of the prediction that higher inequality may lead to higher consumption Kumhof and Ranciere (2010) is based on self-regarding (rather than upward-looking) preferences and stagnant income for the lower group.

There are several authors who regard the changes to the regulatory framework of the financial industry over the last two decades as the key factor in explaining rising household debt levels (Crotty 2009; Mian & Sufi 2009; Rajan 2010).[5] We refer to this as the financial deregulation hypothesis (FDH). In particular the shift from a traditional originate and hold to an originate and distribute model of banking, where banks sell off their loans in the form of asset backed mortgage securities is blamed for over accumulation of debt in the household sector (Mian & Sufi 2009). This switch has led to declining lending standards because the risks associated with issuing mortgages to low quality borrowers could be quickly removed from the issuing institution's balance sheets. This gave low quality debtors who were previously excluded access to the mortgage market. In addition, households which already had a mortgage, were able to take out larger ones relative to their disposable income. Both effects led to higher aggregate debt levels. Another policy-related argument is that low interest rates, especially after the dot-com bubble in the US, encouraged households to take on unsustainable debt loads. We will refer to this explanation as the low interest rate hypothesis

[5] It is important to point out that for Rajan (2010) financial deregulation and easing of credit constraints is the result of political pressure due to increased income inequality.

(LIH). Taylor (2009) is a prominent proponent of the LIH for the US case. He argues that central banks and the Fed in particular kept interest rates too low for too long and effectively failed to follow a rule-based policy approach which he proposes. For Europe Sinn (2014) argues that common monetary policy resulted in low interest rates for southern European countries which encouraged debt-fuelled bubbles. Interest rate discrepancies were exacerbated by private investors' disregard for country-specific default risk. The LIH is at its core a theory of government failure, unlike ECH and HBH, which are about private sector mechanisms.

To investigate these arguments the paper estimates a debt accumulation function which models the stock of household sector debt as a function of disposable income (Y^D), property price indices (PP), a measure of income inequality (Q), a real interest rate (R), the population share older than 65 (OLD) and a credit regulation index ($CRED$):

$$D = d(Y^D, PP, Q, R, CRED, OLD) \tag{1}$$

According to the ECH households engage in debt-financed spending in an attempt to emulate the social status of richer peers. Thus household borrowing increases with income inequality: $\frac{\partial D}{\partial Q} > 0$. According to the HBH, changes in debt are driven by asset transactions and collateral-backed borrowing due to wealth-effects. Here the key driving variable are property prices: $\frac{\partial D}{\partial PP} > 0$. The FDH argues that credit market deregulation allowed financial institutions to increase lending, which enabled households to take out larger mortgages relative to their disposable income and also gave previously excluded households access to the mortgage market. Thus credit market deregulation drives up household borrowing: $\frac{\partial D}{\partial CRED} > 0$. Finally, according to the LIH low real interest rates have encouraged households to take on debt at unsustainable rates: $\frac{\partial D}{\partial R} < 0$. Table 1 summarises these hypotheses.

Table 1. Hypotheses on debt determinants

	Hypothesis	Theoretical Argument	Predicted signs
1	expenditure cascades hypothesis (ECH)	Households make consumption decisions with respect to richer peers. Consumption decisions drive debt	$\frac{\partial D}{\partial Q} > 0$
2	housing boom hypothesis (HBH)	Debt is driven by asset transactions and wealth effects. Rising asset prices lead to higher debt and higher spending.	$\frac{\partial D}{\partial PP} > 0$
3	financial deregulation hypothesis (FDH)	Deregulation of the financial industry lifts lending restrictions and allows households to take on more debt.	$\frac{\partial D}{\partial CRED} > 0$
4	low interest rate hypothesis (LIH)	Loose monetary policy in the form of low interest rates encourages	$\frac{\partial D}{\partial R} < 0$

		household borrowing.	

D is household debt, Q is a measure of income inequality, C is a measure of aggregate consumption, $CRED$ stands for credit regulation, R is a real interest rate and PP indicates property prices.

The way we have specified the partial effects implicitly assumes that they work in the upswing as well as in the downswing of the business cycle. However there are reasons why this symmetry may not hold in practice. Most importantly, it is easier for households to accumulate debt during a boom than to deleverage in particular in a recession with falling incomes. We will thus also investigate whether there is evidence for asymmetric adjustment.

3 The Empirical Literature

The Financial Crisis triggered by the collapse of the US mortgage market has motivated a wave of empirical studies which look at the relationship between the trend of rising income inequality and household indebtedness (Klein 2015; Perugini et al. 2016; Gu & Huang 2014; Malinen 2014; Behringer & Treeck 2013; Bordo & Meissner 2012; Kumhof et al. 2012). Most of these studies are motivated by the theoretical work of Rajan (2010) and Kumhof and Rancière (2010) and do not estimate theory-derived structural models but rely on ad hoc specifications instead. For example Perugini et al. (2016) apply a dynamic system GMM estimator to a panel of 18 OECD countries from 1970 and 2007. They find a positive impact of top income shares on private sector debt. Gu and Huang (2014) and Bordo and Meissner (2012) in contrast use long data series going back to the 1920s and the logarithmized difference of real private sector debt as their dependent variable. The latter do not find a positive impact of top income shares whereas the former do claim to find such a relationship but it hinges on interacting the inequality measure with GDP growth.

Table 2: Effects of income distribution on household debt

authors	specification	country	findings
Behringer and van Treeck 2013	CA=f(Top1/Gini, NFA, govB, rel. Y, old, n, PC,); also use HFB and S instead of CA	annual data, G7, 1972-2007	top income shares and Gini coefficients have negative effects on dep. vars.
Bordo and Meissner 2012	DBP=f(Top1, R, GDP, I, M)	annual data, 14 OECD countries, 1920-2008	no statistically significant effect of top 1% income shares on dep. var. and negative interest rate effect
Gu and Huang 2014	DBP=f(Top1,R,GDPc, Iy,M)	annual data, 14 OECD countries, 1920-2008	statistically significant positive effect of top 1% income shares on dep. var. if interacted with GDP growth and pos. interest rate effect
Klein 2015	CPH=f(Top1, Gini,	annual data, 9	statistically significant positive effect of

	wage share),	OECD countries, 1953-2008	top 1% income share, Gini coefficient, wage share
Kumhof et al. 2012	CA=f(Top1, youth, old, trade, PC, rel. Y, g, govB, NFA),	annual data, 18 OECD countries, 1968-2006	statistically significant negative effect of top income shares on current account,
Malinen 2014	DBP=f(Top1, GDPc, Iy, M, R),	annual data, 8 OECD countries, 1960-2008	statistically significant positive effect of top 1% income shares on dep. var.
Perugini et al. 2016	DCP=f(Top1, R, FD, My, GDPc, g, Iy, PI),	annual data, 18 OECD countries, 1970-2007	statistically significant positive effects of top 1% / 5% / 10% income shares on dep. var. and no interest rate effect, positive deregulation effect

CA stands for current account balance in % of GDP, **HFB** is the household sector financial balance in % of GDP, **S** is the household sector saving rate, **DBP** is real domestic bank loans to the private sector from the Schularick and Taylor (2012) data set., **CPH** is real credit to household sector per capita, **DCP** is domestic credit to the private sector in % of GDP, **Top1** is the top 1% income share, **R** stands for interest rates, **g** for real GDP growth, **GDP(c)** is real GDP (per capita), **I(y)** is investment (in % of GDP), **NFA** is stock of net foreign assets in % of GDP, **M(y)** is M2 (relative to GDP), **PI** is portfolio investment in % of GDP, **youth** and **old** are the shares of under 15 and over 65 year olds, **trade** is the sum of exports and imports of goods in % of GDP, **PC** is private credit in % of GDP, **rel. Y** is per capita income in PPPs relative to the US, **govB** is the general government fiscal balance and **FD** are financial deregulation proxies.

Only Perugini et al. (2016) make an attempt to control for credit supply conditions and find a positive effect of the credit market deregulation index supplied by the Fraser Institute. When it comes to the effects of interest rates, results are mixed. Perugini et al. (2016) find no statistically significant effect, Bordo and Meissner (2012) find a statistically significant negative effect and Gu and Huang (2014) report a statistically significant positive effect.

Klein (2015) and Malinen (2014) are motivated by previous empirical studies and the lack of cointegration tests therein. Both investigate bivariate cointegration relationships between household debt (Klein 2015) or bank credit to the private sector (Malinen 2014) and top income shares. They find that debt and income inequality are cointegrated. Klein (2015) estimates the cointegrating vector in a strictly bivariate model whereas Malinen (2014) controls for short run fluctuations in GDP, investment and the money stock M2. A key shortcoming of this approach is that it almost surely suffers from omitted variable bias since inequality is not the only factor driving household or private debt. We aim to address this problem in this paper by going beyond bivariate models.

Behringer and van Treeck (2013) and Kumhof et al. (2012) do not investigate the determinants of private sector or household debt but focus on the current account balance in % of GDP instead. They argue that if households engage in debt-financed expenditure cascades due to upward-looking status comparison, then household net-lending will decrease and given the corporate and public sector balance the current account will deteriorate. Thus they estimate a model with the current account as

dependent variable and top income shares as their preferred measure of income inequality. A negative effect of top income shares on the current account balance is interpreted as inequality induced spending and evidence in favour of the expenditure cascades hypothesis. Both studies report negative effects of top income shares but do not control for credit market supply shifts or interest rates. Table 2 summarizes the empirical literature investigating the effects of shifts in the distribution of income on household borrowing.

It is important to emphasize a common characteristic which all of the papers discussed so fare share: They do not include real estate prices in their analysis. This is interesting because there is a large time series literature which consistently finds a positive link between property prices and household sector borrowing[6]. However at the same time the property price literature ignores the swings in the distribution of income as a relevant factor. This paper is an attempt to bring these two branches of the literature on household debt together.

The number of studies using panel data for investigating the impact of property prices on household borrowing is small compared to the number of time series papers on the topic. Égert et al. (2006) estimate the determinants of credit to the private sector over GDP in order to assess whether debt levels in central and eastern European countries are in line with long run equilibrium estimates. They use simple fixed effects models as well as the mean group estimator (Pesaran et al. 1999) and dynamic OLS and find a significant and positive effect of house prices on private credit. They also include the spread between lending and deposit rates as a proxy for competition within the banking sector but it remains statistically insignificant as long as house prices are included in the regression. They find positive as well as negative interest rate effects varying across samples and estimation methods.

Goodhart and Hofmann (2008) estimate a panel VAR based on a sample of quarterly data from 1970-2006 of 17 OECD countries. The VAR includes nominal bank credit to the private sector, nominal house prices, real GDP, the CPI, nominal interest rates and the money aggregate M3. Based on Granger causality testing and a simple Cholesky decomposition (ordering: GDP, CPI, interest rate, property prices, money, private credit) they find multidirectional links between these variables. They that house prices positively influence private credit and money. They also find a lasting negative

[6] In the time series literature most authors (Oikarinen 2009; Anundsen & Jansen 2013; Meng et al. 2013) use broad measures of household sector borrowing and report a statistically significant, positive long-run impact of property prices on borrowing. In contrast Gimeno and Martinez-Carrascal (2010) restrict their analysis of property price effects in Spain to housing secured debt only and Chrystal and Mizen (2005) look at wealth effects on unsecured borrowing in the UK. Lastly, Arestis and Gonzalez (2014) and Hofman (2004) analyse the impact of property prices on private credit in OECD countries.

impact of higher interest rates. In order to account for shifts in the regulatory framework of credit markets they re-estimate the model on the shorter period 1986-2006 and find particularly strong effects of house prices.

Table 3: Effects of property prices on household debt

Authors	specification	Country	findings
Egert et al. 2006	PC=f(GDPc, BCgov, R, CPI, PP, FD, reg)	annual panel data 43 countries, 1975-2004	find a significant and positive effect of nominal house prices on private credit, no consistent finding with respect to interest rates
Goodhart and Hofmann 2008	panel VAR including: BCP, GDP, CPI, R, PP, M2)	17 OECD countries, 1970-2006, quarterly data	interdependency between nominal house prices and household borrowing, statistically significant negative interest rate effect
Rubaszek and Serwa 2014	HL=f(GDP, R, GDPc, u, PP, longU)	36 countries, 1995-2009	positive and highly statistical significant effect of real property prices on borrowing and positive interest rate effect

PC stands for private credit in % of GDP, **GDPc** is GDP per capita, **BCgov** is bank credit to the government sector in % of GDP, **R** stands for interest rates, **CPI** represents an inflation measures, **PP** is a property price index, **FD** stands for financial deregulation proxies, **reg** is an indicator variable for public and private land registries, **BCP** is bank credit to the private sector, **M2** is a money supply measure, **HL** is household credit in % of GDP, **u** is the unemployment rate and **longU** is the share of long term unemployed.

Rubaszek and Serwa (2014) build a theoretical model of household borrowing and compare it with single equation cointegration estimations based on a panel of 36 countries. They use household borrowing relative to GDP as their explanatory variable and find a positive long run impact of house prices on household borrowing as well as a positive real interest rate effect. The spread between lending and deposit rates is used as a measure of banking sector competition. Table 3 summarizes the literature investigating the nexus between real estate prices and household borrowing.

In addition to papers emphasizing distributional shifts and property prices as drivers of household debt, there is a literature which focuses on the impact of shifts in credit supply conditions and the deregulation of financial markets. However this literature hardly uses macroeconomic panel data and is therefore not directly comparable to this paper. Mian and Sufi (2009) for example use a ZIP code based panel data set of household borrowing information and argue that debt increased most in those areas where large proportions of the mortgage pool were securitized. They interpret this as evidence that in the US changes in the behaviour of financial institutions were key in enabling household debt accumulation. Jordà et al. (2015) use newly constructed long series of mortgage debt and assess the role of loose monetary conditions, measured by interest rates, for household

borrowing and house prices. Their conclusion is that especially in the post war era low interest rates strongly contributed to residential property booms and as a result mortgage debt booms.

Five general patterns emerge from the empirical literature on the determinants of household and private sector borrowing: First, most studies do not distinguish between the household and the corporate sector. In contrast we explicitly use a measure of household sector borrowing instead of credit to the private sector. This is important because the channels influencing household and corporate borrowing are quite different and this paper is only interested in the former group. Second, there is a lack of studies which investigate the impact of income inequality and property prices on household borrowing simultaneously, although there is very robust empirical evidence backing the theoretical prediction of wealth effects. Starting to fill this gap is one of the main contributions of this paper. Third, most papers do rely on short run analysis of differenced data. If cointegration analysis is applied a bivariate relationship is tested. This paper aims to go beyond bivariate cointegration testing and thus avoid potentially serious omitted variable bias. Fourth, little attention is paid to the role of shifts in credit supply conditions. The most important reason is the inherent difficulty for measuring such shifts besides very broad measures such as debt-to-GDP ratios. Fifth, findings with respect to interest rate effects vary and are not consistent across studies and sometimes not even within studies.

4 Data and Econometric Method

Our dataset is an unbalanced annual panel covering 11 countries from 1980 to 2011[7]. Definitions and data sources are provided in the Appendix (Table A1) as well as descriptive statistics (Table A2).

Real residential property price indices are used as proxies for housing wealth of the household sector, because wealth data are not available (for sufficiently long time periods) for most countries. This is common in the literature estimating wealth effects.[8] The drawback is that price indices capture quantity changes only indirectly. We use two different measures of the distribution of income. The share of total income which is received by the richest 1% of households ($TOP1$) captures the dynamics at the top of the distribution. Since the expenditure cascades hypothesis predicts debt-financed spending sprees to be triggered by concentration of income at the top this is our preferred measure for testing that hypothesis. In addition we use a Gini coefficient which is

[7] The countries included are: Australia, Belgium, Canada, Finland, France, Italy, Netherlands, Norway, Sweden, United Kingdom and the US.

[8] See Paiella (2009), Attanasio and Weber (2010) and Cooper and Dynan (2016) for recent surveys.

directly computed from income data ($GINI$). The Gini index is less sensitive to distributional changes at the top.

Although shifts in credit supply conditions are important determinants of household borrowing, measuring the state of credit supply and the willingness to lend by financial institutions is difficult. One approach in the literature focuses entirely on credit regulations and financial reforms and argues that a less regulated financial sector should be expected to enhance borrowing. Indices based on the existence of interest rate controls, the relation of public to private borrowing, entry barriers to the financial sector and the existence of capital account restrictions are derived and used in empirical analysis. A widely used index following such an approach is the Fraser Index on credit regulation. A different approach aims to capture shifts in banks' willingness to lend due to changes in the sector's risk appetite (Fernandez-Corugedo & Muellbauer 2006).[9] In this paper we will use the Fraser Index because credit supply indices in the spirit of Fernandez-Corugedo and Muellbauer (2006) are not available for the countries of our panel in a consistent form. A shortcoming of the Fraser index is that it does not capture shifts in the risk appetite of the financial sector. It also does not capture those changes to the regulatory framework which turned out to be key for the pre-crisis period: the use of off-balance sheet vehicles, increased proprietary trading and low capital requirements for assets in the trading book.

We specify our debt accumulation equation as an error correction (EC) model:

$$\Delta Z_{it} = \alpha_i + \sum_{p=0}^{1} \beta_{1t} \Delta X_{i,t-p}^{1} + \cdots + \sum_{p=0}^{1} \beta_{6t} \Delta X_{i,t-p}^{6} - \gamma_i \left(Z_{it-1} + \theta_1 X_{i,t}^{1} + \cdots + \theta_6 X_{i,t}^{6} \right) + \mu_{it} \quad (2)$$

The dependent variable Z is our measure of total household sector liabilities in billion of local currency ($\log(D_{it})$) and $(X^1, \dots, X^6)$ are vectors of real disposable household income in billion of local currency ($\log(Y_{it}^D)$), the income share of the richest 1% of households ($TOP1_{it}$), alternatively we also use a Gini coefficient ($GINI_{it}$) of income inequality. Furthermore we use real property price indices ($\log(PP_{it})$), the real long term interest rate (R_{it}), the ratio of people older than 65 in the population (OLD_{it}) and the credit market regulation index published by the Fraser Institute ($\log(CRED_{it})$) (subcategory 5A of the Economic Freedom of the World index). Monetary variables and the interest rate are deflated by the consumer price index.

The key advantage of EC or autoregressive distributed lag (ARDL) models is that they allow for I(0) as well as I(1) variables and require no prior knowledge of the order of integration (Pesaran & Shin

[9] Fernandez-Corugedo and Muellbauer (2006) estimate a common trend in the volume of mortgages and unsecured debt and in the fraction of high loan-to-value and loan-to-income borrowers in the UK. They interpret this common trend as a credit conditions index.

1999). This means we are able to take a potential long run relationship into account instead of only using differenced regressors. Estimation is based on dynamic fixed effects (DFE) and the Pooled Mean Group (PMG) estimator of Pesaran et al. (1999) as a robustness check. While the DFE restricts all coefficients to be identical across countries, the PMG approach allows the short term parameters and the adjustment speed to be heterogeneous across countries, while the long run equilibrium relationship is assumed to be homogeneous. Thus the PMG estimator represents a compromise between allowing for cross country parameter heterogeneity on the one hand and keeping the number of model parameters small on the other hand.[10] In order to determine the lag structure of the error correction model we apply a testing down procedure. First a fully specified model including contemporaneous as well as one-period lags of all short term effects is estimated. This corresponds to including 2 lags in level form. Starting from this general specification statistically insignificant short run effects are removed sequentially.

The estimated coefficients from equation (2) cannot be interpreted in a causal way, as we cannot fully rule out the possibility that an omitted third factor drives the dependent variable as well as some of the regressors. Also we cannot fully rule out the issue of reverse causation between household debt and property prices. Nevertheless we think estimating equation (2) is a fruitful exercise for two reasons. First, there is empirical evidence supporting the notion that higher residential property prices drive up household borrowing (Jordà et al. 2015; Mian & Sufi 2011). In addition, against the background of stagnant income growth in most countries of our sample over the last two decades, we are not convinced that households' optimistic expectations of future productivity and wage growth was the key driver of household debt accumulation omitted from our model. Second, any causal statement about the drivers of household debt needs to be consistent with the patterns we find in the data. Therefore the reduced from regressions we present in this paper can be used to rule out explanations of household borrowing which are not consistent with the results.

5 Determinants of Household Debt

This section discusses the results from estimating equation (2), presented in Table 4. In columns (1) and (2) the top 1% income share is used as a measure of the income distribution while specifications (3) and (4) rely on a Gini coefficient. Furthermore columns (1) and (3) are based on DFE estimators

[10] For example estimating an unrestricted autoregressive distributed lag model $ARDL(p_0, p_1, \dots, p_k)$ which allows estimates to be country specific with common lag length p, k regressors and N countries, requires to estimate $2N + (p+1)kN$ parameters. In contrast estimating the PMG version of that model only requires $2N + k(pN + 1)$ parameters. With 11 countries, 5 regressors and 1 lag this amounts to 132 and 82 parameters, respectively.

while columns (2) and (4) are based on the PMG estimator as a robustness check. First, all four specifications exhibit a statistically significant adjustment towards the estimated long run trend. This indicates that there exists a cointegrating relationship. This result is further supported by carrying out panel unit root tests (Choi 2001) on the residuals (H_0: $r = I(1)$) from estimating equation (2) which lead to a rejection of the null hypothesis of unit roots in the residuals. The p-values from these unit root tests are provided at the bottom of Table 4. The long run trend is characterized by an income elasticity of 1 since the hypothesis of a unit elasticity (H_0: $\beta_{y^D} = 1$) is not rejected except in specification (4). This indicates that when holding the other explanatory variables constant, debt to income ratios remain stable. Conversely, rising debt to income ratios are explained by the remaining variables. Second, the long run residential property price elasticity is between 0.41 and 0.62 and is highly statistically significant in all specifications. Thus there is a strong direct link between real estate prices and household borrowing, which is in line with the HBH. Third, the estimated long-run income distribution semi-elasticities are not consistent across specifications and are statistically insignificant in most cases. While the positive coefficient on the Gini in specification (4) is consistent with the ECH, status-induced household borrowing should be closely related to rising top incomes as debt-financed expenditure cascades would be triggered at the top of the distribution. It is important to point out that also the short run income distribution coefficients are not statistically significant, which is why they were dropped. Fourth, the long-run real interest rate semi-elasticity is statistically significant and negative at the 5% level in the DFE specifications. This finding is in line with the LIH, which predicts lower real interest rates coinciding with higher household debt levels. Fifth, the old-rage ratio is not a statistically significant predictor of household debt in most specifications and therefore is not included in later specifications. Only column (4) of Table 1 exhibits a statistically significant positive semi-elasticity of the old age ratio, which however is not in line with a basic life-cycle interpretation. Finally the long run coefficient of the credit market regulation index is positive and highly statistically significant across all specifications. This latter finding is in line with the FDH which states that household debt expanded due to shifts in credit supply conditions as a result of a financial sector more willing to lend.

So overall Table 4 provides strong and robust support for the HBH as residential real estate price coefficients are highly statistical significant across all specifications. Equally robust is only the statistically positive elasticity of the credit market regulation index which supports the FDH. Finding negative interest rate coefficients is sensitive to the estimation method while positive coefficients of the income inequality measure are only found in 1 specification while they are statistically not significant in the others. This latter finding is not consistent with the ECH.

Table 4: Household debt, baseline specifications

	(1) DFE	(2) PMG	(3) DFE	(4) PMG
$\log(Y_t^D)$	0.984***	0.888***	0.954***	0.687***
	(0.22)	(0.11)	(0.23)	(0.07)
$\log(PP_t)$	0.414***	0.570***	0.426***	0.622***
	(0.14)	(0.07)	(0.15)	(0.04)
$TOP1_t$	-0.674	0.454		
	(1.89)	(0.75)		
$GINI_t$			-0.169	3.438***
			(1.07)	(0.49)
R_t	-3.712**	-0.601	-3.703**	-0.421
	(1.50)	(0.58)	(1.49)	(0.40)
OLD_t	0.34	0.977	0.27	5.996***
	(1.74)	(1.31)	(1.88)	(1.01)
$\log(CRED_t)$	0.790***	0.710***	0.780***	0.439***
	(0.28)	(0.16)	(0.28)	(0.08)
		short run		
$adjustment$	-0.061***	-0.066***	-0.059***	-0.075**
	(0.01)	(0.01)	(0.01)	(0.03)
$\Delta\log(Y_t^D)$	0.169***	0.156*	0.166***	0.209**
	(0.06)	(0.09)	(0.06)	(0.09)
$\Delta\log(Y_{t-1}^D)$	-0.131**		-0.125**	
	(0.06)		(0.06)	
$\Delta\log(PP_t)$	0.216***	0.189***	0.213***	0.166***
	(0.02)	(0.06)	(0.02)	(0.06)
$\Delta\log(PP_{t-1})$	-0.106***		-0.102***	
	(0.03)		(0.03)	
ΔR_t	0.182***	0.094	0.185***	0.115**
	(0.06)	(0.07)	(0.06)	(0.06)
$\Delta\log(CRED_t)$	-0.076***	-0.148***	-0.074***	-0.112***
	(0.03)	(0.02)	(0.03)	(0.02)
$\Delta\log(D_{it-1})$.	0.682***	0.522***	0.677***	0.507***
	(0.04)	(0.06)	(0.04)	(0.06)
$constant$	-0.086	-0.048***	-0.066	-0.087**
	(0.10)	(0.01)	(0.09)	(0.04)
N	362	374	371	374
H_0: $r = I(1)$	0.00	0.00	0.00	0.00
H_0: $\beta_{y^D} = 1$	0.94	0.32	0.84	0.00
H_0: $\beta_{PP} = 1$	0.00	0.00	0.00	0.00

Error correction models estimated with Pooled Mean Group (PMG) and Dynamic Fixed Effects (DFE) estimators. Dependent variable: $\Delta\log(D_{it})$. *Stars indicate statistical significance: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in brackets. The bottom three lines of the table report p-values of hypothesis tests.* H_0: $r = I(1)$ *is the hypothesis that the residuals contain a unit root and* H_0: $\beta_{y^D} = 1$ *and* H_0: $\beta_{PP} = 1$ *are the hypotheses that the long run elasticities for disposable income and property prices are equal to 1.*

The results of Table 4 are based on the assumption that household borrowing reacts to increases and decreases in property prices as well as top income shares in a symmetric way. However since the process of leveraging up, especially in an environment of general optimism, is easier than to deleverage, potentially in an economic downturn, such symmetric behaviour might not hold. Specifications (1) and (2) in Table 5 provide a test for that assumption. We re-estimate the baseline model with an additional indicator variable (I^{PP}) which is equal to one in periods of declining or stagnating residential property prices. This dummy is then interacted with the measure of real residential property prices itself. Table 5 shows the house price growth dummy itself as well as its interaction with property prices are not statistically significant. Thus we fail to find evidence supporting asymmetric responses of household borrowing to increasing and stagnant property prices.

Columns (3) and (4) of Table 5 introduce the same dummy variable into the baseline model but interact it with the income distribution measures. The rationale is that if households are credit constrained, it might be the case that inequality induced borrowing only happens in periods of house price growth because rising property prices will ease the households' credit constraints. However, neither the top income share specification in column (3) nor the Gini specification in column (4) supports this argument. In both cases the dummy for periods of house price growth and its interaction with the distribution measures are not statistically significant. Inequality induced household borrowing is not explicitly linked to periods of growing house prices.

Despite the pronounced increase in top income shares over the last three decades in many OECD countries (Atkinson et al. 2011), we did not find measures of the distribution of income to be statistically significant predictors of household borrowing, neither in the long nor short run. In specifications (5) and (6) in Table 5 we define a post-crisis dummy (I^{cris}) which is equal to one for the period 2009 to 2011 in order to test whether inequality induced debt accumulation was primarily a pre-crisis phenomenon. When interacting the post crisis dummy with the top income share and the Gini coefficient, neither the interaction nor the dummy nor the income distribution measures exhibit statistically significant semi-elasticities. The only exception is the interaction with the top income share in specification 5, which exhibits a negative coefficient, statistically different from 0 at the 10% level. Therefore, these interactions do not provide evidence for a positive link between higher income inequality and household borrowing and thus do not support the ECH.

Table 5: Household debt, housing boom and post crisis interactions

	dummy for periods of declining PP (I^{PP})	dummy for periods of declining PP (I^{PP}) inter.	post crisis dummy (2009-2011) (I^{cris}) interacted

	interacted with PP		with Top1 and Gini		with Top1 and Gini	
	(1)	(2)	(3)	(4)	(5)	(6)
	DFE	DFE	DFE	DFE	DFE	DFE
$\log(Y_t^D)$	0.930***	0.966***	0.934***	0.944***	0.956***	0.997***
	(0.21)	(0.23)	(0.22)	(0.23)	(0.22)	(0.24)
$\log(PP_t)$	0.374***	0.367**	0.413***	0.432***	0.408***	0.445***
	(0.12)	(0.15)	(0.12)	(0.15)	(0.13)	(0.15)
$\log(PP_t)$ x I^{PP}	0.142	0.154				
	(0.11)	(0.12)				
$TOP1_t$	0.428		0.471		1.64	
	(1.96)		(2.09)		(2.17)	
$TOP1_t$ x I^{PP}			0.161			
			(1.26)			
$Gini_t$		-0.317		-0.281		-0.255
		(1.01)		(1.04)		(1.07)
$Gini_t$ x I^{PP}				0.527		
				(0.92)		
$TOP1_t$ x I^{cris}					-3.118*	
					(1.77)	
$Gini_t$ x I^{cris}						-2.463
						(2.23)
I^{PP}	0.04	0.045	-0.008	-0.231		
	(0.06)	(0.06)	(0.13)	(0.43)		
I^{cris}					0.239	1.125
					(0.18)	(1.07)
R_t	-3.502**	-3.962***	-3.504**	-3.955***	-3.560**	-4.246***
	(1.38)	(1.39)	(1.42)	(1.42)	(1.46)	(1.53)
$\log(CRED_t)$	0.821***	0.818***	0.819***	0.794***	0.652***	0.710***
	(0.22)	(0.24)	(0.23)	(0.24)	(0.24)	(0.26)
			short run			
$adjustment$	-0.063***	-0.061***	-0.062***	-0.059***	-0.060***	-0.057***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	362	371	362	371	362	371
H_0: $r = I(1)$	0.00	0.00	0.00	0.00	0.00	0.00

Error correction models estimated with Dynamic Fixed Effects (DFE) estimators. Dependent variable: $\Delta \log(D_{it})$. Stars indicate statistical significance: * p<0.1, ** p<0.05, *** p<0.01. Standard errors in brackets.

Importantly all specifications in Table 5 remain consistent with the baseline results from Table 4: The long-run income elasticity of household debt is not statistically different from one, the long-run coefficients on real property prices and the credit regulation index are positive and statistically significant while the real interest rate coefficients are statistically significant and negative.

Table 6 presents three robustness checks. First, the ability of households to borrow might crucially depend on the development and state of the domestic financial sector. Countries with more developed financial sectors might exhibit higher levels of household sector indebtedness. In addition

it may also be the case that borrowing is more sensitive to collateral values in more developed systems because financial institutions are (seemingly) better able to handle the risk of higher loan to income ratios. In addition a more sophisticated financial sector could be better at channelling the risks associated with uncollateralized borrowing for status expenditures to risk seeking investors. Thus debt-financed expenditure cascades should be more likely to happen in financially developed countries. In order to test these arguments we divide the sample into a group of countries with highly developed financial markets and a group of countries with less developed financial markets. In line with the literature (Law & Singh 2014) we choose domestic credit to the private sector relative to GDP as a proxy for financial development. Ranking countries based on this financial development measure in 2005 yields a group of seven highly developed countries consisting of: Japan, United States, Canada, United Kingdom, Netherlands and Australia. The six less financially developed countries in our samples are: Germany, Sweden, France, Norway, Italy, Finland and Belgium. In Table 6, specifications (1) and (2) are based on the first group and specifications (3) and (4) are based on the second group. The regressions based on the sample of countries with highly developed financial sectors exhibit statistically significant residential property price elasticities of 0.81 and 0.97 respectively. In comparison the long-run property price elasticities of household borrowing in the sample of countries with less developed financial sectors are only 0.37. While the standard errors especially for the first set of results are large, this pattern is consistent with collateral playing a more important role in higher developed financial markets where it is easier to re-mortgage and benefit from increasing property prices. However the results in specifications (1) to (4) do not support the notion that status induced borrowing is more likely to occur with more developed financial markets. The latter group of countries with more developed financial markets does not report statistically significant coefficients of the income distribution measures. Overall this sample split shows important differences between the two groups but still supports the main findings from the previous specifications: there is a statistically highly significant link between household borrowing and residential property prices as well as credit deregulation and low interest rates. There is no evidence of a positive link between higher measures of income inequality and household borrowing.

Table 6: Robustness checks

	high financial development		low financial development		lagged PP	no PP
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(Y_t^D)$	1.150*	0.837	1.077***	1.092***	1.159***	1.448***
	(0.66)	(0.64)	(0.20)	(0.25)	(0.19)	(0.19)
$\log(PP_t)$	0.814**	0.968**	0.373***	0.372**		
	(0.37)	(0.43)	(0.14)	(0.16)		

$\log(PP_{t-1})$					0.292***	
					(0.11)	
$TOP1_t$	-0.59		-4.779**		-0.843	-1.845
	(4.32)		(2.43)		(1.66)	(2.00)
$GINI_t$		0.723		-1.575		
		(2.32)		(1.54)		
R_t	4.744	4.815	-4.640***	-3.297**	-4.904***	-4.952***
	(4.40)	(4.64)	(1.59)	(1.33)	(1.46)	(1.39)
$\log(CRED_t)$	1.487*	1.48	1.137***	1.035***	0.831***	0.854***
	(0.89)	(1.07)	(0.28)	(0.30)	(0.20)	(0.24)
			short run			
	-0.037**	-0.035*	-0.079***	-0.073***	-0.076***	-0.064***
$adjustment$	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
N	137	141	171	174	349	362

Error correction models estimated with Dynamic Fixed Effects (DFE) estimators. Dependent variable: $\Delta \log(D_{it})$. Stars indicate statistical significance: * p<0.1, ** p<0.05, *** p<0.01. Lower case letters indicate variables are transformed by taking natural logarithms. Standard errors in brackets.

A possible objection to our specification is that there may be an endogeneity problem due to inverse causation between property prices and household debt. While there is considerable evidence that higher property prices boost household borrowing (Rubaszek & Serwa 2014; Mian & Sufi 2011; Goodhart & Hofmann 2008), it might also be the case that additional household borrowing leads to higher demand for residential real estate and given that supply is inelastic, to higher property prices. Specification (5) of Table 6 presents a simple check whether such a reverse link distorts our results: only lagged values of property prices are used in the regression. Results are similar, but the estimated long-run property price elasticity of household debt is 0.29 (compared to 0.41 with contemporaneous property price effects, specification (1) in Table 4). This supports our argument that property prices are a key driver of household debt accumulation. Notably, all of the key results of the baseline specification are qualitatively similar: the top income share coefficient remains statistically insignificant, the real interest rate coefficients remain statistically significant and negative and the coefficient on the credit regulation index is significant and positive.

In a final robustness check we assess whether higher inequality might work through the real estate market. Several of our explanatory variables might also push up property prices. For example, if the residence were the main item for social status comparison, then increasing income inequality might be triggering a debt-financed cascade of house purchases which could lead to increasing property prices if supply is inelastic. In order to allow for such a mechanism we drop residential property prices from the regression in order to allow the distribution of income to vary independently of property prices. Specification (6) of Table 6 clearly does not support such an argument. The coefficient on the top income share remains statistically insignificant but the disposable income

coefficient increases to 1.45 which emphasizes the important role of the housing market: Without taking property prices into account the model predicts implausible, because unsustainable, long run income elasticities above unity.

Overall, the robustness checks support the main findings in the baseline specification. First, the long run income elasticity of household debt is statistically not different from one which indicates that holding factors such as property prices, interest rates and credit regulation constant, long run debt to income ratios remain stable. Second, real residential property prices exhibit a statistically highly significant positive long run coefficient. This finding is extremely robust across specifications and is consistent with the HBH. Third, top income shares and Gini coefficients do not exhibit statistically significant coefficients in most specifications. In particular the data does not support a positive link between the distribution of income and household borrowing as predicted by the ECH, neither in the group of countries with highly developed financial markets nor in a specification without property prices. Fourth, real interest rates and the credit regulation index exhibit statistically significant negative and positive elasticities, respectively. These findings are robust across specifications and are in line with the LIH and the FDH, respectively.

While the signs of the estimated long run elasticities allow us to draw some conclusions about the explanatory power of the different hypotheses, the economic significance is crucial when it comes to assessing the relative importance of competing explanations. We want to compare the contribution of the different independent variables to changes in household debt over the 1995-2007 period. This will allow us to determine which of the three hypotheses consistent with our results (HBH, LIH, FDH) is most relevant for predicting household debt in the pre-crisis period. For that purpose cross section averages are taken of all series, after transforming monetary series into chained purchasing power parity 2005 dollars. Then predicted changes in debt to income ratios are computed based on the long run estimates obtained from DFE and PMG estimators. The method is described in detail in Appendix B, results are presented in Table 7.

Table 7: Contributions to changes in household debt to income ratios between 1995 and 2007

	actual change in D/Y^D	predicted change in D/Y^D	Y^D	PP	$TOP1$	R	OLD	$CRED$
DFE	44%	33%	-2%	19%	-1%	11%	1%	3%
PMG	44%	33%	-4%	27%	2%	2%	2%	3%

The predicted change in debt is computed based on equation (5). Contributions of individual variables are computed equivalent to equation (7). Calculations used the estimated coefficients from columns 1 (DFE) and 2 (PMG) in Table 4. Results were obtained by taking GDP weighted averages across countries after transforming monetary series into constant 2005 purchasing parity dollars. The product of the individual change factors yields the predicted change in D/Y^D.

Five results emerge from Table 7: First, household debt grows almost directly in proportion to disposable income when all other factors are held constant. This result is reflected by the fact that the contribution of disposable income to changes in the debt to income ratio over the 1995-2007 period is very small and slightly negative at -2% and -4%, depending on the estimator. Second, real appreciations of residential property prices explain between 19% and 27% of the change in household debt to income ratios, ceteris paribus. This result supports the HBH which predicts that the main driver of debt to income ratios were strongly increasing real estate prices. The different contributions of 19% and 27% reflect differences in the DFE and PMG estimates. As can be seen in Table 4 the DFE specification exhibits a long run property price elasticity of 0.41 compared to 0.57 in the PMG specification. Third, the top income share is not very useful in predicting debt to income ratios. The ECH is not supported by the data. Fourth, real interest rates, explain about a third of the increase in debt to income ratios when using the DFE estimator. Fifth, demographic shifts and changes in credit market regulation played a negligible role for household borrowing outcomes according to the estimated model. Overall residential real estate prices stand out as the most important predictor of household debt to income ratios.

6 Conclusion

This paper investigates the explanatory power of rising income inequality, growing property prices, low interest rates and financial deregulation as causes of rising household debt by estimating a debt accumulation equation for a panel of 11 OECD countries spanning from 1980 to 2011. While we are not able to give a causal interpretation to our findings, any causal claim about the determining factors of household sector debt needs to be consistent with the patterns we find. It is in this spirit that we interpret our results. First, we find that real residential property prices are the single most important predictor of aggregate household debt to income ratios. Over the 1995 to 2007 period they explain between 19% and 27% out of the total 44% increase in the panel averaged debt to income ratio which is consistent with the prediction of the housing boom hypothesis. Since real estate is the most significant asset type for the vast majority of households in OECD countries, this is a highly plausible but often underappreciated result. Second, we fail to find a robust statistically significant relationship between income inequality measures and household debt. Using the top 1% income share as well as a Gini coefficient, we do neither find a robust positive nor negative relationship. This is not consistent with the expenditure cascades hypothesis. Third, the second most important predictor of household debt to income ratios are low interest rates which often show statistically significant coefficients, however are sensitive to estimator choice. For the 1995 to 2007 period real interest rates explain between 11% and 2% out of the total 44% increase in the panel

averaged debt to income ratio, consistent with the low interest rate hypothesis. Finally we find that financial deregulation is a robust predictor of household borrowing, however the size of this effect is limited with an explained increase of the aggregate debt to income ratio of 3% between 1995 and 2007. This low predictive power reflects the fact that our measure is a credit regulation index that does not capture changing practices in the financial industry which potentially played a more important role such as changes in risk appetite and lending practices.

Our results endorse a view that regards household debt as an outcome primarily of real estate transactions, supported by loose monetary policy and financial regulation while the distribution of income only plays a minor role in explaining household indebtedness. Thus macroeconomic models that aim at explaining household debt should explicitly model real estate prices. When it comes to developing models for studying the emergence of debt-fuelled bubbles, ignoring the housing market is strikingly inconsistent with macroeconomic stylized facts. This does imply a word of caution towards the enthusiasm with which macroeconomists (Frank et al. 2014; Kapeller & Schütz 2014; Belabed et al. 2013) have embraced upward-looking consumption norms.

With respect to the existing macroeconometric panel literature which investigates the drivers of private sector borrowing, we confirm the previous finding that real house prices are the most important predictor of household sector debt levels. In contrast we fail to find evidence for a positive link between an increasingly polarized distribution of income and household indebtedness as reported by several authors (Behringer & Treeck 2013; Gu & Huang 2014; Kumhof et al. 2012; Klein 2015; Malinen 2014; Perugini et al. 2016). We think our paper is different in three key aspects which explain the differences in the results. First, none of these papers controls for the impact of property prices and thus face a potentially sever omitted variable problem. Second, many of them analyse the determinants of private sector debt, including the non-financial corporate sector, instead of the household sector. Third, only Kumhof et al. (2012) estimate fully specified, in contrast to bivariate, cointegration relationships which suffer from omitted variable problems

This paper has taken a reduced-form approach, which allowed us to use panel data. Future research should distinguish between credit supply and credit demand. The difficulty of finding appropriate instruments for shifts in the credit supply for a broad set of countries, will make a time series approach attractive for such an exercise. Furthermore future analysis should address the endogenous nature of the involved variables, which lends itself to a systems approach. Disposable income, interest rates, house prices and credit all interact with each other and thus it might be worth to trade off degrees of freedom to model these interactions and to assess the robustness of the

results. Theoretically, our findings suggest the need to develop theoretical models that allow for boom bust cycles in real estate prices and household debt.

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Appendix A: Definitions, descriptive statistics and unit root tests

Table A1. Data definitions and sources

abbreviation	full variable name	unit	source
Y^D	Disposable real gross income, household sector (deflated using PC)	national currency, billion	AMECO
PC	Price deflator private final consumption expenditure (PCPH)	2005=1	AMECO
R	Real long-term interest rates, deflator GDP	%	AMECO and OECD (MEI)
OLD	Fraction of population aged 65 and older	%	AMECO
D	Total credit to the household sector (deflated using PC)	national currency, billion	BIS
TOP1	Top 1% income share of the SWIID	%	SWIID v4
GINI	Gini coefficient (pre tax and post transfer) of the Standardized World Income Inequality Database		SWIID v5
PP	Real property prices BIS (exact definitions vary across countries, deflated using PC)	2005=1	BIS
SP	Share price index (deflated using PC)	2005=1	IMF (International Financial Statistics) and OECD (MEI)
CRED	Fraser Index, Subcategory 5A Credit Regulation: percentage of privately held deposits (higher values higher percentage), interest rate controls (market rates and positive real rates result in higher values), private sector credit (higher values less gov borrowing)	index between [0,10]	Fraser Institute
FIN	Index of financial reforms measuring: credit controls, interest rate controls, entry barriers, state ownership in banking, capital account restrictions, supervision of the banking sector and securities market policy. Policies in each of these 7 areas are awarded a number of 0 to 3 where higher numbers represent liberal policies.	index between [1,21]	IMF (Abiad et al. 2008 - A New Database of Financial Reforms)

Table A2. Data summary statistics I

Variable		Mean	Std. Dev.	Min	Max	Observations	
DH/Y^D	overall	0.90	0.40	0.15	2.44	N	418
	between		0.33	0.33	1.61	n	13
	within		0.26	0.12	1.73	T-bar	32.2
PC	overall	0.86	0.20	0.23	1.26	N	418
	between		0.06	0.76	0.98	n	13
	within		0.20	0.33	1.28	T-bar	32.2
R	overall	0.04	0.02	-0.07	0.12	N	400
	between		0.00	0.03	0.04	n	13
	within		0.02	-0.07	0.13	T	30.8
OLD	overall	0.15	0.03	0.09	0.24	N	407
	between		0.02	0.12	0.17	n	13
	within		0.02	0.08	0.23	T	31.3
TOP1	overall	0.08	0.03	0.03	0.18	N	393
	between		0.03	0.05	0.14	n	13
	within		0.02	0.03	0.18	T	30.2
GINI	overall	0.45	0.05	0.29	0.55	N	406
	between		0.03	0.39	0.53	n	13
	within		0.03	0.35	0.53	T-bar	31.2
PP	overall	0.82	0.27	0.40	1.61	N	418
	between		0.15	0.62	1.19	n	13
	within		0.23	0.44	1.49	T-bar	32.2
CRED	overall	8.83	1.04	5.00	10.00	N	406
	between		0.73	7.17	9.61	n	13
	within		0.75	6.28	11.07	T	31.2

Table A3: Unit root tests, first differenced series

	P	L	Z	deterministic part
dh	0.70	0.61	0.61	trend and constant
yd	0.00	0.01	0.01	trend and constant
pp	0.00	0.00	0.00	trend and constant
TOP1	0.00	0.00	0.00	trend and constant
GINI	0.00	0.00	0.00	trend and constant
OLD	0.69	0.98	0.97	trend and constant
CRED	0.00	0.00	0.00	trend and constant
R	0.00	0.00	0.00	trend and constant
dh	0.07	0.05	0.05	constant
yd	0.25	0.17	0.15	constant
pp	0.00	0.00	0.00	constant
TOP1	0.00	0.00	0.00	constant
GINI	0.00	0.00	0.00	constant
OLD	0.26	0.89	0.86	constant
CRED	0.00	0.00	0.00	constant
R	0.00	0.00	0.00	constant

Panel unit root tests (H_0: all series contain unit roots) based on Choi (2001) who uses the following labels: inverse chi-square test (P), inverse normal test (Z) and logit test (L). P-values from ADF tests with 3 lags are combined. Lower case letters indicate variables are transformed by taking natural logarithms.

Appendix B: Deriving effect size computations

This appendix describes how the results for Table 7 are obtained. These effect size computations are based on the estimated long run elasticities. Taking the difference of the predicted dependent variable between 2007 and 1995 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:

$$\log\left(\frac{\widehat{D}_{2007}}{\widehat{D}_{1995}}\right) = \hat{\theta}_1 \log\left(\frac{Y^D_{2007}}{Y^D_{1995}}\right) + \hat{\theta}_2 \log\left(\frac{PP_{2007}}{PP_{1995}}\right) + \hat{\theta}_3(Q_{2007} - Q_{1995}) + \hat{\theta}_4(R_{2007} - R_{1995}) + \hat{\theta}_5(OLD_{2007} - OLD_{1995}) + \hat{\theta}_6 \log\left(\frac{CRED_{2007}}{CRED_{1995}}\right) \quad \text{(A1)}$$

For equation (A1) all series are aggregated by taking GDP weighted cross section averages after transforming monetary series into chained purchasing power parity 2005 Dollars. $\widehat{D}_{2007}$ and $\widehat{D}_{1995}$ represent the predicted long run debt levels in 2007 and 1995 based on these averaged series and the estimated long run coefficients. After some manipulation equation (A1) becomes:

$$\frac{\widehat{D}_{2007}}{\widehat{D}_{1995}} = \left(\frac{Y^D_{2007}}{Y^D_{1995}}\right)^{\widehat{\theta}_1} \left(\frac{PP_{2007}}{PP_{1995}}\right)^{\widehat{\theta}_2} e^{\widehat{\theta}_3(Q_{2007}-Q_{1995})} e^{\widehat{\theta}_4(R_{2007}-R_{1995})} e^{\widehat{\theta}_5(OLD_{2007}-OLD_{1995})} \left(\frac{CRED_{2007}}{CRED_{1995}}\right)^{\widehat{\theta}_6} \quad \text{(A2)}$$

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

$$\frac{\frac{\widehat{D}_{2007}}{Y^D_{2007}}}{\frac{\widehat{D}_{1995}}{Y^D_{1995}}} = \left(\frac{Y^D_{2007}}{Y^D_{1995}}\right)^{(\widehat{\theta}_1-1)} \left(\frac{PP_{2007}}{PP_{1995}}\right)^{\widehat{\theta}_2} e^{\widehat{\theta}_3(Q_{2007}-Q_{1995})} e^{\widehat{\theta}_4(R_{2007}-R_{1995})} e^{\widehat{\theta}_5(OLD_{2007}-OLD_{1995})} \left(\frac{CRED_{2007}}{CRED_{1995}}\right)^{\widehat{\theta}_6} \quad \text{(A3)}$$

From equation (A3) each variable's contribution to the predicted change in household debt to income ratios between 1995 and 2007 can be defined. For example in the case of disposable household income itself as well as property prices these contributions are:

$$\left.\frac{\frac{\widehat{D}_{2007}}{Y^D_{2007}}}{\frac{\widehat{D}_{1995}}{Y^D_{1995}}}\right/ = \left(\frac{Y^D_{2007}}{Y^D_{1995}}\right)^{(\widehat{\theta}_1-1)} \quad \text{(A4)}$$

$$\left.\frac{\frac{\widehat{D}_{2007}}{Y^D_{2007}}}{\frac{\widehat{D}_{1995}}{Y^D_{1995}}}\right/ = \left(\frac{PP_{2007}}{PP_{1995}}\right)^{\widehat{\theta}_2} \quad \text{(A5)}$$

The contributions to changes in household debt to income ratios between 2007 and 1995 for all variables are presented in Table 7. Results are presented based on DFE and PMG estimates, from columns 1 and 2 in Table 4, respectively.