The real effects of household debt in the short and long run[1]

Marco Lombardi[2], Madhusudan Mohanty[3] and Ilhyock Shim[4]

19 October 2017

Abstract

Household debt levels relative to GDP have risen rapidly in many countries over the past decade. We investigate the macroeconomic impact of household debt by employing a novel estimation technique proposed by Chudik et al (2016), which tackles the problem of endogeneity in traditional panel regressions. Using data for 54 economies over 1990–2016, we show that household debt boosts GDP growth in the short run, mostly within one year. By contrast, a 1 percentage point increase in the household debt-to-GDP ratio tends to lower GDP growth in the long run by 0.1 percentage point. Moreover, the negative long-run effects on GDP growth intensifies as the household debt-to-GDP ratio exceeds 70%, suggesting that policy makers are likely to face non-trivial, real costs in stimulating the economy through credit expansion.

JEL classification: E21, E44, G21.

Keywords: household debt, consumption, cross-sectional autoregressive distributed lag model, output growth, threshold effect.

1 We thank participants in St Louis Fed Tipping Points Symposium on "Mapping and understanding the impact of debt on household financial well-being and economic growth", Korea Institute of Finance International Conference on "Policy responses to rising household debt: an international perspective", 2017 Asian Meeting of the Econometric Society, 2017 China Meeting of the Econometric Society, Annual Conference of the International Association for Applied Econometrics, and seminars at the BIS, the Bank of Japan and the Federal Reserve Bank of Dallas for their comments. We are grateful, in particular, to Ryan Banerjee, Claudio Borio, Andy Filardo, Enisse Kharroubi, Cathérine Koch, Luiz Pereira da Silva, Toshitaka Sekine and Hyun Song Shin for their helpful suggestions. We also acknowledge the excellent research assistance provided by Jimmy Shek and Agne Subelyte. All remaining errors are our own. The views expressed in this article are our own and do not necessarily represent those of the Bank for International Settlements.

2 Senior Economist, Bank for International Settlements, Centralbahnplatz 2, CH-4002 Basel, Switzerland. Tel. +41-61-280-9492. Fax +41-61-280-9100. E-mail: marco.lombardi@bis.org.

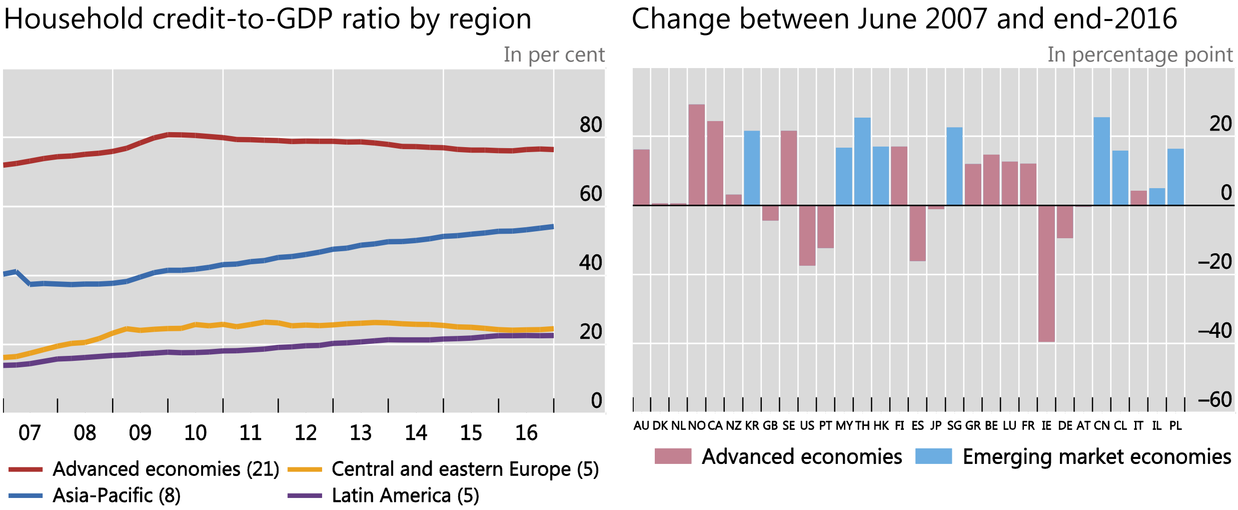
3 Head of Economics and Financial Markets for Asia-Pacific, Bank for International Settlements Representative Office for Asia and the Pacific, 78th floor, Two International Finance Centre, 8 Finance Street, Central, Hong Kong SAR. China. Tel. +852-2982-7171. Fax +852-2982-7123. E-mail: madhusudan.mohanty@bis.org.

4 Principal Economist, Bank for International Settlements Representative Office for Asia and the Pacific, 78th floor, Two International Finance Centre, 8 Finance Street, Central, Hong Kong SAR, China. Tel. +852-2982-7147. Fax +852-2982-7123. E-mail: ilhyock.shim@bis.org.

1. Introduction

Over the past decade, the global economy has been confronted with two seemingly interrelated problems. First, as Graph 1 shows, following the Great Financial Crisis (GFC) of 2007–2008, household debt levels relative to GDP have risen in many countries. Not only has deleveraging in the advanced economy (AE) household sector not proceeded as swiftly as expected but household indebtedness has also risen rapidly in many emerging market economies (EMEs) where they had remained modest in the previous decades. Second, despite record low interest rates, private spending has remained weak globally and recovery illusive, even a decade after the burst of the US housing bubble. The goal of this paper is to trace the link between these two developments, with a specific focus on how household debt influences private consumption and GDP growth.

Household debt across the world — Graph 1



In the left-hand panel, the 21 advanced economies include Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Luxembourg, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, the United Kingdom and the United States; the five central and eastern European economies include the Czech Republic, Hungary, Poland, Russia and Turkey; the eight Asia-Pacific emerging market economies include China, Hong Kong SAR, India, Indonesia, Korea, Malaysia, Singapore and Thailand; and the five Latin American economies include Argentina, Brazil, Chile, Colombia and Mexico. The economies shown in the right-hand panel are the top 30 economies in terms of the ratio of total credit to households and non-profit institutions serving households (NPISHs) to GDP at end-2014.

Sources: national data; BIS.

In standard macroeconomic models, household debt plays a limited role: although it affects households' ability to smooth out consumption, it is not by itself a major determinant of consumption. Yet household debt has been at the centre of many recent financial crises and recessions. Over the past decade, at least three strands of evidence have emerged about the relationship between household indebtedness and growth.

First, in a series of recent papers, Schularick and Taylor (2012) and Jordà et al (2013, 2015 and 2016) demonstrate that high debt levels are not only a good predictor of financial crisis but also a key determinant of the intensity of the ensuing recession. Complementing these findings is the recent early warnings literature, which suggests a key role of household debt servicing costs in predicting the future vulnerability of countries to banking system stresses and recession (Drehmann and Juselius (2014)). Going a step further, Mian et al (2015) refute the basic proposition underlying neoclassical models that debt accumulation is accompanied by expected future productivity growth. Their analysis suggests that an increase in the household debt-to-GDP ratio reduces consumption across countries with a lag of three years, and that even during normal times. In other words, the unconditional correlation between household debt and growth is negative after a certain lag.

A second source of evidence has come from micro-based studies focusing on the behaviour of US households following the US housing bubble's burst (Mian and Sufi (2010), Dynan (2012), and Mian et al (2013)).[5] Exploiting cross-sectional heterogeneity from US household surveys, these studies show that the financial exposures of households – hence the distribution of debt and assets – played a central role in depressing US consumption. For instance, Mian et al (2013) have argued that the recession was aggravated by the high marginal propensity to consume of heavily indebted US households who cut spending rapidly following the negative house price shock. Their estimates suggest that the marginal propensity to consume in US localities with a loan-to-value ratio of 90% was three times higher than that in localities with a LTV ratio of only 30%. Besides negative wealth effects, evidence also suggest that highly-leveraged US households may have deliberately withheld consumption in order to return to more manageable debt levels (Dynan (2012)).

More generally, models incorporating heterogeneous preferences are more sympathetic to the view that countries may face what is called a "debt limit" whereby, following a shock, certain frictions may cause debtors' consumption preferences to diverge significantly from those of creditors (King (1994), Guerrieri and Lorenzoni (2009), Curdia and Woodford (2010), Hall (2011), and Eggertsson and Krugman (2012)).[6] Those frictions arise not only because debtors are exposed to certain uninsurable income risks, such as uncertain payoffs from illiquid assets, but financial intermediaries may also incur losses, which can impair their capacity to intermediate. An excellent example of this class of models is Eggertsson and Krugman (2012). In their model, the debt limit becomes binding when the *impatient* households who borrow from the *patient* households are suddenly forced to cut spending and to deleverage.

A third of source of evidence has emerged from recent papers highlighting the supply-side effects of debt (Cecchetti and Kharroubi (2015), and Borio et al (2016)). Borio et al (2016), in particular, demonstrate that credit booms – particularly those in the construction sector – are accompanied by a severe misallocation of resources and a slowdown in productivity growth, with long-lasting adverse effects on the real economy. They argue that "when considering the macroeconomic implications of financial booms and busts, it is important to go beyond the current focus on aggregate demand effects".

While providing important insights into the importance of household debt to the economy, these studies are silent about the time path of the macroeconomic effects of debt and whether those effects are dependent on the level of debt itself. In this paper, we

[5] Among other studies, see Bhutta (2012), Cooper (2012), and Dynan and Edelberg (2013).

[6] For a recent review of the literature, see Sufi (2015).

therefore tackle two interrelated questions about household debt. The first question is what the short- and long-run effects of such debt are on the economy. It is often argued that debt has positive effects on growth because it facilitates spending by credit-constrained households, particularly following a financial crisis. However, those supposedly short-run positive effects should be temporary if debt adversely affects spending in the long run. Determining the impact of household debt on growth raises a first-order issue of understanding the trade-off it might pose to the economy. The second question we ask is whether the level of debt plays any role in determining its effects, consistent with the "debt limit" view discussed above. Put differently, is there a household debt level that can be considered safe for an economy? As in Cecchetti et al (2012) and Mian et al (2015), we take an empirical approach to answer these questions.

Given the objective of our paper, we follow a novel estimation strategy, i.e. the cross-sectional autoregressive distributed lag (CS-ARDL) approach developed by Chudik and Pesaran (2015) to estimate short- and long-run dynamics in panel data. This approach allows us to deal with two major empirical problems. First, since it is based on a cointegrating representation, it allows us to clearly distinguish the short-run effect of debt from its long-run impact. Second, the use of cross-sectional averages of the dependent and explanatory variables as well as their lags helps us account for cross-sectional dependence and induced feedback effects between the variables. This allows us to overcome the endogeneity bias in a straightforward and efficient way. Most researchers examining the relationship between debt and growth use instrumental variable regressions to deal with the endogeneity problem. However, as we show in the next section, the answers provided by these approaches are sensitive to the choice and availability of adequate instruments. We therefore believe that trying an alternative instrument, as built into the CS-ARDL model, can provide useful additional insights relative to the existing literature.

Our results suggest that debt boosts consumption and GDP growth in the short run, with the bulk of the impact of increased indebtedness passing through the real economy in the space of one year. However, the long-run negative effects of debt eventually outweigh their short-term positive effects, with household debt accumulation ultimately proving to be a drag on growth. Our estimates suggest that a 1 percentage point increase in the household debt-to-GDP ratio tends to lower output growth in the long run by around 0.1 percentage point, suggesting that policy makers face non-trivial, real costs in stimulating the economy through credit expansion. These findings are robust to alternative lag structures and control variables. Our analysis of the threshold effect suggests that the negative long-run impact of household debt on GDP growth tends to intensify as the household debt-to-GDP ratio exceeds a threshold of 70%. We also identify a positive impact of household debt on consumption growth, particularly when the ratio is low and growing above a threshold of 20%. Interestingly, our findings are roughly in line with those of several recent studies on public sector indebtedness, which have found similar thresholds for the public debt-to-GDP ratio (for example, Cecchetti et al (2012)).

The rest of the paper is organised as follows. Section 2 provides a brief factual overview of the recent build-up of household debt and its association with real variables such as consumption and GDP growth. Section 3 proposes a new empirical approach to study the relationship between debt and growth. Section 4 discusses the baseline empirical results. Section 5 investigates the potential nonlinear effects of household debt. Section 6 concludes.

2. Household debt and growth: facts and recent evidences

2.1 Data and stylised facts

Our analysis is based on quarterly household data for 54 economies (23 AEs and 31 EMEs) ranging from Q1 1990 (or from the earliest period of data availability) to Q4 2016. The household debt data collected from national sources measure loans extended by banks to households for the acquisition of housing and other assets (e.g. loans for vehicle purchase) as well as unsecured debt (including credit card and student debt). In our sample, most mortgage and consumer debt has been extended by banks. That said, our data would likely underestimate household debt for those economies where non-bank lenders account for a significant share of the mortgage credit market.[7] Following the standard practice of the cross-country debt literature, we scale debt by GDP to measure aggregate indebtedness of the household sector.[8] Table A1.2 in Appendix 1 provides the exact definitions and sources of data pertaining to debt as well as the period of data availability.

Graph 2 helps to demystify a number of beliefs relating to deleveraging in the AE household sector. As the left-hand panel of Graph 2 shows, median household debt in AEs as a percentage of GDP had risen strongly from 1990 to 2008, but decreased slightly over the period following the GFC. Among the 21 AEs shown in the right-hand panel of Graph 1, only Germany, Ireland, Portugal, Spain and the United States have seen any significant reductions in the household debt-to-GDP ratio since 2007. Household debt levels have been relatively constant in relation to GDP in Austria and Japan since the recent crisis, but they have grown rapidly in Australia, Canada and a few Nordic countries.

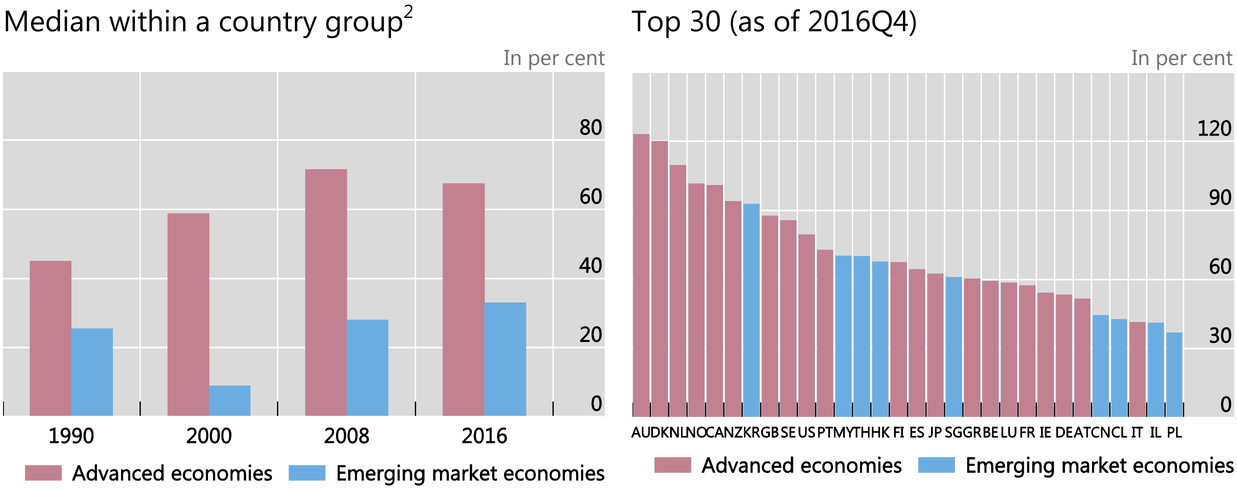
By the standards of AEs, it is true that the median household debt-to-GDP ratio in EMEs is still relatively small. But indebtedness is growing rapidly in this group of countries. And dispersion across regions remains high: the rise in household debt is much more widespread in emerging Asia than in Latin America, and central and eastern Europe. Within Asia, household indebtedness in Hong Kong SAR, Korea, Malaysia, Singapore and Thailand has now reached levels that are comparable to some of the most heavily indebted AEs (Graph 2, right-hand panel).

7 In Table A2.7 in Appendix 2, we also consider total credit to households and non-profit institutions serving households (NPISHs), which includes both bank and non-bank loans to the sector.

8 When considering a rise in aggregate household debt, it is important to differentiate between the intensive margin (i.e. the average amount of debt per borrower) and the extensive margin (i.e. the number of borrowers). The former is a more accurate measure of household indebtedness while the latter is a good indicator of access to credit, hence of the degree of financial deepening. In principle, such a distinction is very important in unravelling the true impact of household debt in EMEs, although the lack of detailed borrower-level data constrains its use in practice.

Household debt[1]

As a percentage of GDP — Graph 2



[1] Total credit to households and non-profit institutions serving households (NPISHs). [2] The 21 advanced economies include Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Luxembourg, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, the United Kingdom and the United States; and the 20 emerging market economies include Argentina, Brazil, Chile, China, Colombia, the Czech Republic, Hong Kong SAR, Hungary, India, Indonesia, Israel, Korea, Malaysia, Mexico, Poland, Russia, Singapore, South Africa, Thailand and Turkey.

Sources: national data; BIS.

How is the recent rise in household debt related to economic growth? To shed light on the most recent evidence, in Graph 3 we show two distinct aspects of the relationship between cross-country debt and growth since 2007. The left-hand panel of the graph shows the cross-country contemporaneous correlations between the average annual change in the household debt-to-GDP ratio and average annual consumption growth over the 2007–2016 period, which includes one episode of severe recession and one of modest expansion. What is clear from the graph is that the unconditional correlation of household debt with consumption growth is positive. This is consistent with cross-country evidence reported elsewhere (IMF (2012)) that an expansion of household credit is often associated with stronger private consumption and GDP growth.

The right-hand panel of Graph 3 presents the same correlation from a slightly different perspective. Instead of focusing on the contemporaneous relationship, the panel relates past changes in household debt to consumption growth in subsequent periods. More formally, we look at the past 3-year change in the debt level ($d_t = \Delta_3 D_t$) and relate it to year-on-year consumption growth ($c_t = \Delta \ln C_t$) by computing, for each country, the correlations

$$\rho_h^{dc} = \frac{\frac{1}{T-1}\sum_{t=1}^{T}(d_{t-1}-\bar{d})(c_{t+h}-\bar{c})}{\sqrt{\frac{\sum_{t=1}^{T}(d_{t-1}-\bar{d})^2\sum_{t=1}^{T}(c_{t-h}-\bar{c})^2}{T-1}}}$$

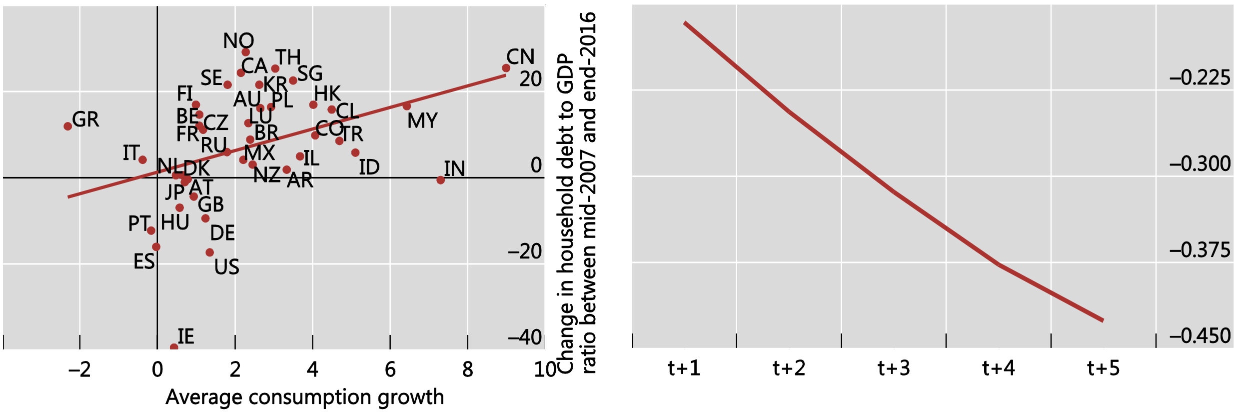
at horizons h=1, … , 5. We then average country-specific correlations, so that each point on the red line shows the average correlation across all countries in our sample.

Instantaneous and subsequent effects of debt accumulation on consumption growth

Graph 3

Scatter plot of the change in the household debt-to-GDP ratio[1] and the average growth rate of consumption[2]

Correlation between the three-year change in household debt up to year t-1 and subsequent consumption growth[3]



[1] In percentage points. [2] In per cent. [3] The growth rate is measured as the logarithmic difference of real consumption in year *t* and that in year *t+h*, where *h* = 1, 2, 3, 4, 5.

Sources: IMF, *World Economic Outlook*; authors' estimates.

The basic hypothesis is that if the neoclassical consumption hypothesis is correct, the correlation between past increases in debt and subsequent consumption growth should be positive because additional borrowing may well have been motivated by higher expected permanent income. On the other hand, if past increases in debt expose households to potential future borrowing constraints and greater risks of bankruptcy, they are likely to be associated with lower, not higher, consumption growth. Following Mian et al (2015), we choose three-year changes in household debt as a proxy for the income shock.

The right-hand panel of Graph 3 makes two points very clear. First, past increases in household debt are not a good predictor of positive growth but appear to be associated with weaker consumption and higher risks of recession. Second, the downward-sloping line suggests that the negative correlation between household debt and consumption actually strengthens over time, following a surge in household borrowing. What is striking is that the negative correlation coefficient nearly triples between the first and the fifth year following the increase in household debt.

As is well known, simple correlation does not suggest anything about the causal effects. That said, the preliminary evidence in Graph 3 appears to support the view that credit expansions may have very different effects on the short- and medium-run economic prospects of countries. It also confirms the findings of King (1994) that large increases in private debt in the 1980s made many OECD countries vulnerable to problems of weak growth and "debt deflation". He shows that the most severe recessions since the 1930s have occurred in countries that have seen the largest increases in private debt in the preceding five years.

2.2 Estimating the debt and growth relationship

Yet, estimating precisely the relationship in Graph 3 is challenging because debt and consumption belong to the same structural equation system and are, therefore, jointly determined in equilibrium. Resolving this identification problem is not easy in a cross-country setting. A popular approach is the instrumental variable (IV) technique, which has made great strides in the literature on public debt and growth following the GFC (see, for instance, Panizza and Presbitero (2013) and the survey of the literature therein). Among the recent studies applying this approach to household debt data in a cross-country framework is that of Mian et al (2015).

A key issue confronting researchers is finding an instrument that is, on the one hand, theoretically consistent and strongly correlated with the potentially endogenous debt variable and, on the other hand, weakly correlated with the growth variable. As pointed out by Stock et al (2002), the weak instrument problem remains a pervasive issue in economics. This reduces the reliability of the standard IV and generalised method of moments (GMM) estimates. Bound et al (1995) show that the weak instrument problem leads to significant inconsistency in IV estimates, even when the correlation of the instrument with the errors generated by the original equation is small. Similarly, Guggenberger (2012) shows that the small-sample properties of IV estimators can be poor when instruments that are not strictly exogenous are used. Moreover, instruments strongly supported by theory may not work well in practice.

IV estimates of household debt and GDP growth relationship — Table 1

Quarters ahead	1	4	8	12
		Local currency bond spread		
Coefficient	0.036	–0.070*	0.053*	–0.057*
	(*0.026*)	(*0.028*)	(*0.025*)	(*0.026*)
N	3429	3284	3090	2897
Weak instruments test	69.200	66.606	63.692	60.877
		Foreign currency bond spread		
Coefficient	–5.054	–1.533	–0.805	–0.143
	(*16.722*)	(*6.080*)	(*2.452*)	(*0.591*)
N	2099	1997	1856	1712
Weak instruments test	0.092	0.064	0.114	0.125
		Home ownership		
Coefficient	–0.017	–0.347	0.323	–0. 300
	(*0.175*)	(*0.259*)	(*0.211*)	(*0.225*)
N	2645	2576	2445	2298
Weak instruments test	4.088	4.139	4.517	3.922
Stock-Yogo (2005) weak ID test critical values:			*10% max IV size*	*16.38*
			15% max IV size	*8.96*
			20% max IV size	*6.66*
			25% max IV size	*5.53*

+, *, and ** denote statistical significance at the 10 percent, 5 percent and 1 percent level, respectively. Standard errors are in parentheses.

To illustrate the issue, in Table 1 we present the IV estimates of the household debt and GDP growth relationship using three different instruments. The first is the local currency bond spread as used by Mian et al (2015), measured as the difference between the local currency government bond yield and the US Treasury yield. Since a large part of the local currency bond spread reflects anticipated changes in the exchange rate, which is likely to be correlated with growth, we also tried the foreign currency bond spread, defined as the yield on US dollar-denominated government bonds over the US Treasury yield, as our second instrument. The foreign currency bond spread is not only a cleaner measure of risk premium paid by sovereign borrowers on their debt but it is also closely associated with global investors' risk appetite. As a third instrument, we use the home ownership ratio. In the past decades, policy factors played a major role in boosting mortgage credit growth and the home ownership ratio in many countries (Jordà et al (2016)). Because of its weak correlation with consumption, home ownership could be an ideal instrument for the regression.

The estimates reported in Table 1 suggest that the choice of instrument has a strong influence on the results. For instance, when household debt is instrumented by local currency sovereign spreads, the relationship between debt and GDP growth appears to be negative at lags above one year (first block), which is in line with the findings of Mian et al (2015). The null hypothesis of weak instrument is rejected by the Stock and Yogo (2005) test. However, the results using alternative instruments clearly suggest caution. When one uses the foreign currency bond spread as instrument, which might arguably be more appropriate for EMEs with high level of US dollar borrowing, statistical significance is lost. Similarly, insignificant results are found if one uses home ownership as instrument. In both cases, anyway, the Stock and Yogo (2005) test fails to reject the null hypothesis of weak instrumentation.

3. Empirical approaches

3.1 Autoregressive distributed lag (ARDL) model

In this section, we propose an alternative approach that can help overcome these inconsistencies. Our approach relies on a standard method to estimate a long-run relationship in data, which not only tackles the problems of endogeneity but also provides a useful tool to disentangle the short- and long-run role of household debt.

The most popular econometric instrument for assessing long-run relationships is cointegration (Engle and Granger (1987)). One approach to cointegration that lends itself particularly well to the analysis of panel data is the autoregressive distributed lag (ARDL) model, first proposed by Pesaran and Smith (1995). Let us illustrate it with an example that closely follows the approach of Chudik et al (2016). Suppose we are interested in examining the long-run relationship between GDP growth (y_t) and household indebtedness (x_t), and assume that their joint dynamics is determined by the following VAR(1) model:

$$\begin{bmatrix} y_t \\ x_t \end{bmatrix} = \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ x_{t-1} \end{bmatrix} + \begin{bmatrix} e_t^y \\ e_t^x \end{bmatrix}. \tag{1}$$

The innovations e_t^y and e_t^x would in general be correlated, which leads to a contemporaneous correlation between y_t and x_t. This means that if one were to perform a simple OLS regression of y_t on x_t, endogeneity would be a major issue. However, the innovations can be decomposed and their orthogonal component can be spelled out in the following way:

$$e_t^y = E\left(e_t^y \mid e_t^x\right) + u_t = \omega e_t^x + u_t \,, \tag{2}$$

where $\omega = \text{cov}(e_t^y, e_t^x)/\text{var}(e_t^x)$. Now, the innovation to the equation for y_t can be decomposed into two elements, one of which (u_t) is orthogonal to the innovation to x_t. By substituting equation (2) into the equation for y_t in (1), we obtain:

$$y_t = \phi_{11} y_{t-1} + \phi_{12} x_{t-1} + \omega e_t^x + u_t \,, \tag{3}$$

while from the equation for x_t in (1), we obtain:

$$e_t^x = x_t - \phi_{21} y_{t-1} - \phi_{22} x_{t-1} \,. \tag{4}$$

Substituting (4) into (3) yields:

$$y_t = \varphi y_{t-1} + \beta_0 x_t + \beta_1 x_{t-1} + u_t \,, \tag{5}$$

where $\varphi = \phi_{11} - \omega\phi_{21}, \beta_0 = \omega, \beta_1 = \phi_{12} - \omega\phi_{22}$.

Equation (5) is a simple ARDL specification. Since u_t is orthogonal to x_t and its lags by construction, it follows that equation (5) does not suffer from endogeneity and can be consistently estimated using OLS. In a sense, this can be seen as a consequence of the fact that the ARDL specification is derived from a VAR model for the joint dynamics of the variables. Furthermore, Pesaran and Shin (1999) also show that OLS estimates of equation (5) are consistent, irrespectively of whether those variables are I(1) or I(0).

The model can also be written in the following cointegrating form:

$$y_t = \theta x_t + \alpha\left(L\right)\Delta x_t + \tilde{u}_t \,, \tag{6}$$

where $\tilde{u}_t = \varphi\left(L\right)^{-1} u_t$. In equation (6), the long-run coefficient $\theta = (\beta_0 + \beta_1)/(1 - \varphi)$ is expressed explicitly. If the variables y_t and x_t are I(1), equation (6) is a cointegrating relationship with cointegrating vector $(1, -\theta)'$. However, if the variables are I(0), θ can still be interpreted as a long-run impact in the sense that it represents the impact on y_t of a permanent change in the mean of x_t (Chudik et al (2016)).

The easiest approach to estimate θ is to obtain estimates of the short-run coefficients of equation (5) and plug them in the expression $\theta = (\beta_0 + \beta_1)/(1 - \varphi)$. However, it has to be kept in mind that the uncertainty relating to the long-run coefficient can be large, since it is determined by cumulating the standard errors of all the short-run coefficients.

An alternative is to estimate equation (6) directly, by truncating the lag polynomial $\alpha(L)$ at a sufficiently high level. This is sometimes referred to as distributed-lag (DL) approach, and has the advantage that the estimate of θ will be subject to substantially lower uncertainty, especially when the sample size is relatively small. The disadvantage, however, is that the error term in equation (6) is no longer orthogonal to x_t, which will make the estimates inconsistent whenever the variables of interest are endogenously determined.

3.2 ARDL model in a cross-sectional framework

Equations (5) and (6) are easy to be cast in a panel framework. When we denote by i the country index, the expression for a generic ARDL(p,q) model is

$$y_{i,t} = \sum_{k=1}^{p} \varphi_{i,k} y_{i,t-k} + \sum_{l=0}^{q} \beta'_{i,l} x_{i,t-l} + u_{i,t} \,, \tag{7}$$

while its cointegrating form would be

$$y_{i,t} = \theta_i x_{i,t} + \alpha'_i \left(L\right) \Delta x_{it} + \tilde{u}_{i,t} \,. \tag{8}$$

One complication of the panel framework, though, is that the errors are likely to be correlated across countries, which makes pooled estimates of the θ parameter inconsistent. One solution to this problem is to postulate a common unobserved factor structure for the errors in the following way:

$$u_{i,t} = \gamma'_i F_t + \varepsilon_{i,t} \,. \tag{9}$$

Chudik and Pesaran (2015) show that a straightforward way to correct for this is to augment equation (7) with cross-sectional averages of the dependent and explanatory variables, as well as their lags, which are supposed to proxy for the unobserved common factors. They refer to this approach as the cross-section augmented ARDL (CS-ARDL) model. Similarly, Chudik et al (2016) demonstrate that the same approach of augmenting the regression with cross-sectional averages also works for the direct estimation of equation (8), and denote the approach by CS-DL.[9]

4. Empirical results for the household debt-growth nexus

In this section, we apply the econometric methods detailed above to analyse the long-run interaction of household debt and economic growth as well as to look for possible nonlinearity in these relationships. To check for the robustness of our results, we also consider additional elements in the long-run relationship, such as the long-term interest rate, inflation, terms of trade, house prices, debt service ratio and population growth.

4.1 Long-run effects

4.1.1 Baseline results

Our baseline specification simply relates GDP growth to (changes in) the ratio of household debt to GDP. In Table 2, we report the results for the plain ARDL model with no cross-sectional correction, as well as the CS-ARDL and CS-DL models. Here we report all results for the sake of completeness, but since endogeneity is a very likely issue, we focus in what follows on CS-ARDL estimates. We experimented with different choices of AR lag length. The number of lags for the cross-sectional correction was fixed to two, after having checked the

9 Chudik et al (2017) apply this approach to the study of the relationship between public debt and growth.

results of the Pesaran (2004) test for cross-sectional correlation of the residuals. The rows for the cross-sectional dependence (CSD) test report the test statistics of the test. They show that the adjustment is able to eliminate cross-sectional dependence at the 5% significance level.

Regression results from the baseline specification Table 2

	GDP growth			Consumption growth	
	ARDL	CS-ARDL	CS-DL	CS-ARDL	CS-DL
			1 lag		
Theta	–0.093**	–0.081**	–0.059**	0.062**	0.063**
	(*0.029*)	(*0.020*)	(*0.018*)	(*0.018*)	(*0.017*)
N	4104	4104	4104	4104	4104
CSD test	119.35**	1.01	0.59	–0.76	–0.29
			2 lags		
Theta	–0.113**	–0.112**	–0.063**	0.044*	0.066**
	(*0.033*)	(*0.023*)	(*0.020*)	(*0.022*)	(*0.019*)
N	4072	4072	4072	4072	4072
CSD test	117.15**	1.17	0.57	–0.58	–0.02
			3 lags		
Theta	–0.153**	–0.118**	–0.067**	0.033	0.065**
	(*0.047*)	(*0.023*)	(*0.021*)	(*0.026*)	(*0.020*)
N	4039	4039	4039	4039	4039
CSD test	113.49**	1.34	0.57	–0.26	0.29

ARDL stands for autoregressive distributed lag, and corresponds to equation (7), CS-ARDL for cross-section augmented ARDL and corresponds to equation (7) augmented by cross-sectional averages of the dependent and explanatory variables. CS-DL stands for cross-section augmented distributed lag and corresponds to equation (8) augmented by cross-sectional averages of the dependent and explanatory variables. Theta corresponds to the long-run coefficient θ in equation (8), and is estimated indirectly for the ARDL and CS-ARDL approach. $^{+}$, *, and ** denote statistical significance at the 10 percent, 5 percent and 1 percent level, respectively. Standard errors are in parentheses.

The first three columns report the estimates for GDP growth; the rows correspond to different lag length in the short-run dynamics. We note that all coefficients are statistically significant and negative, which suggests that in the long run, household indebtedness is a drag on GDP growth. Depending on the specification chosen, the long-run coefficients vary between –0.06 and –0.15 and cluster around –0.1. This means that a 1 percentage point increase in household indebtedness is associated, in the long run, with lower GDP growth of 0.1 percentage point. Note also that the long-run coefficients do not lose significance as more lags are allowed in the short-run dynamics. Mian et al (2015) report a somewhat higher impact of household indebtedness on GDP growth: 0.3 percentage point over a three-year horizon. In a somewhat different set-up, Jordà et al (2013) find that a recession preceded by strong credit expansion implies a loss of output in the region of 0.2 to 1 percentage point, compared with a standard recession.

For the sake of completeness, the last two columns show the estimates for consumption growth. The coefficients have positive signs, which seems to indicate that higher indebtedness is associated with higher consumption in the long run.[10] In this case, however, we note that the CS-ARDL estimates of the long-run coefficient progressively lose statistical significance as more lags in the short-run dynamics are added. As we show in the next subsection, this could be a sign that rising indebtedness promotes consumption in the short run rather than in the long run, and that failing to allow for sufficient short-run dynamics conceals this effect. Furthermore, as we discuss in section 5, the lack of statistical significance could also mask potential nonlinearities in the transmission mechanism, particularly if household debt has different macroeconomic effects at very low and very high levels.

4.1.2 Robustness under additional explanatory variables

To further verify the robustness of our results, we consider additional explanatory variables that could also play a role in explaining long-run GDP trends and their interaction with household indebtedness. More specifically, we include inflation, house price growth, long-term interest rates, terms of trade, debt service ratio and population growth.[11]

The results in Table 3 suggest that the long-run relationship between GDP growth and household debt is not undermined by the inclusion of the additional explanatory variables.[12] The coefficients, which remain negative and statistically significant, range from –0.08 to –0.17. The coefficients on the additional variables are broadly in line with expectations: rising inflation and interest rates depress growth while increasing house prices boost it. A higher burden of interest payments, as summarised by the debt service ratio (Dembiermont et al (2013)), also acts as a drag on growth, which is consistent with the findings of Juselius and Drehmann (2015). By contrast, the terms of trade do not seem to play a role in the long-run relationship. The tests for cross-sectional independence of the residuals succeed at the 5% significance level for all models except for the one with inflation (which succeeds at the 1% level, though), long-term interest rates and the debt service ratio.[13]

Consistent with what we find in Table 2, the results with consumption growth are less clear-cut. The coefficients are all positive but only remain significant and in the same order of magnitude when controlling for the long-term interest rate, the terms of trade, population growth. However, the significance level and the magnitude of impact decline when we control for the debt service ratio. In all cases except the long-term rate, however, the control variable appears to be non-significant. Interestingly, the controls for house and consumer price inflation are significant: the former seems to act as a drag on consumption whereas the

[10] We also ran regressions using the sum of total consumption and residential investment as a proxy for household consumption. Although the cross-sectional dimension was slightly smaller due to limited availability of such data, the regression results were virtually unchanged.

[11] Inflation is measured by the GDP deflator obtained from the IMF WEO database. House prices for 51 economies are obtained from the BIS property price database. Long-term interest rates are proxied by yields on 10-year local currency government bonds obtained from the Global Financial Database and Bloomberg for 51 economies (excluding Argentina, Estonia and Serbia). Data on the terms of trade are obtained from the IMF WEO database. Data on the debt service ratio are from the Bank for International Settlements. Finally, data on population growth are from the IMF WEO database.

[12] Although not shown in Table 3, the results using the CS-DL approach are virtually identical to those using the CS-ARDL approach reported in the table.

[13] However, it should be noted that in this case the sample size is much smaller due to missing data for some countries.

latter seems to boost it. In these two cases, the controls also mop up the explanatory power, and the coefficient on indebtedness becomes insignificant.

Results under CS-ARDL with additional explanatory variables — Table 3

	Baseline	Inflation	House price	LT rate	ToT	DSR	Population
GDP growth							
Theta	–0.081**	–0.120**	–0.167**	–0.113**	–0.077**	–0.106**	–0.095**
	(*0.020*)	(*0.025*)	(*0.033*)	(*0.022*)	(*0.020*)	(*0.032*)	(*0.024*)
Zeta		–0.226**	0.117**	–0.122**	0.012	–0.152^{+}	–0.413*
		(*0.054*)	(*0.021*)	(*0.031*)	(*0.048*)	(*0.080*)	(*0.210*)
N	4104	4104	2914	3158	4061	2095	4061
CSD test	1.17	2.36*	1.59	3.87**	0.80	5.33**	0.40
Consumption growth							
Theta	0.062**	0.008	0.025	0.052*	0.031*	0.043^{+}	0.053*
	(*0.018*)	(*0.016*)	(*0.026*)	(*0.025*)	(*0.016*)	(*0.025*)	(*0.020*)
Zeta		–0.427**	0.107**	–0.093*	–0.033	–0.058	–0.249
		(*0.072*)	(*0.020*	(*0.036*)	(*0.058*)	(*0.119*)	(*0.293*)
N	4104	4104	2914	3158	4061	2095	4061
CSD test	–0.58	1.02	–0.44	2.00*	1.63	1.60	–0.27

CS-ARDL stands for cross-section augmented autoregressive distributed lag and corresponds to equation (7) augmented by cross-sectional averages of the dependent and explanatory variables. Theta corresponds to the long-run coefficient θ in equation (8), and Zeta is the equivalent long-run coefficient associated with the additional explanatory variable. $^{+}$, *, ** denote statistical significance at the 10 percent, 5 percent and 1 percent level, respectively. Standard errors are in parentheses. LT is the long-term rate, ToT represents the terms of trade and DSR the debt service ratio.

4.2 Short-run effects

The models we estimated in Table 2 are based on the cointegrating form of equation (8), so in principle one could use the same specification to retrieve the short-run dynamics of the system. However, one important difference with a conventional cointegrating approach is that in the short-run equation the contemporaneous value of the explanatory variable is also included. This is needed to account for possible endogeneity: the contemporaneous value of x_t in equation (5) disappears only when ω is zero, i.e., the innovations in the VAR representation of equation (1) are orthogonal.

This has important implications for the estimates. Since the denominator of the explanatory variable is the level of the dependent variable itself, it is not surprising that the contemporaneous relationship between the two is negative. This, however, is of limited use if one wants to investigate the short-run dynamics of the system, i.e., how changes in indebtedness would spill over to GDP. To this end, we re-estimate the CS-ARDL specifications of Table 2 by explicitly dropping the contemporaneous value of the explanatory variable in the short-run equation.

The results reported in Table 4 suggest that debt boosts GDP and consumption in the short run. The coefficients on the first lag of the short-run part of the cointegrating equation are positive and significant in all three cases. The second and third lags also display positive coefficients, and are at times statistically significant at the 10% level, but they are anyway of smaller magnitude. The magnitude of the coefficients also suggests that the bulk of the pass-through of increased household indebtedness to GDP growth occurs in the space of one year. The estimated half-life for GDP growth is 4.2~4.6 quarters depending on the number of lags.

Results on the short-run impact of household debt Table 4

	GDP growth			Consumption growth		
	1 lag	2 lags	3 lags	1 lag	2 lags	3 lags
Theta	–0.156**	–0.166**	–0.147**	0.023	0.016	0.022
	(*0.027*)	(*0.029*)	(*0.033*)	(*0.022*)	(*0.023*)	(*0.032*)
Alpha$_1$	0.020**	0.028**	0.019**	0.023**	0.028**	0.028**
	(*0.007*)	(*0.007*)	(*0.008*)	(*0.005*)	(*0.006*)	(*0.007*)
Alpha$_2$		0.015**	0.007		0.007	0.017*
		(*0.005*)	(*0.007*)		(*0.006*)	(*0.008*)
Alpha$_3$			0.009			0.022**
			(*0.008*)			(*0.008*)
N	4083	4050	4014	4083	4050	4014
CSD test	0.96	1.01	1.10	–0.98	–0.76	0.41

Theta and Alpha$_i$ correspond, respectively, to the long-run coefficient θ and the short-run coefficients α_i in equation (8). $^+$, *, and ** denote statistical significance at the 10 percent, 5 percent and 1 percent level, respectively. Standard errors are in parentheses.

5. Threshold effects

In section 4, we examined the relationship between household debt and GDP growth in an inherently linear framework, finding that the accumulation of debt was a drag on long-run growth. However, there are hints that the relationship might be nonlinear: some household debt may be beneficial but excessive indebtedness can divert a growing share of households' income to debt repayments and make households more vulnerable to income and interest rate shocks, thus affecting consumption and growth (Juselius and Drehmann (2015)). In a similar spirit, several recent papers document a nonlinear relationship between public debt and growth (Cecchetti et al (2012), Eberhardt and Presbitero (2015) and Chudik et al (2017)).

In this section, we investigate possible nonlinearities in the relationship between household debt and GDP growth by means of simple dummy variables that take a value of 1 when the household debt-to-GDP ratio surpasses a certain threshold. We then employ such dummies in the CS-DL regressions to account for two possible types of nonlinearity: a change in the level and a change in the slope of the relationship. The former accounts for the fact that growth tends to be slower (or higher) after the debt-to-GDP ratio exceeds the threshold while the latter allows for the possibility that the impact of high debt on growth intensifies as the economy moves farther above the threshold. This set-up is similar to the one employed by Chudik et al (2017).

To evaluate possible thresholds, we follow a grid-search approach similar to that of Chudik et al (2017). We first specify a (finite) number of possible thresholds, ranging from 10% up to 90%, for the household debt-to-GDP ratio, and then select the one as "optimal" that maximises the sup-t statistic (alternatively, F when both types of nonlinearities are considered), as suggested by Andrews and Ploberger (1994). The sup-t/F is computed by comparing the sum of squared residuals of the model with thresholds (SSR_τ) and those of the baseline model (SSR_b).

More precisely, for a certain threshold τ,

$$t/F_\tau = [(SSR_b - SSR_\tau)/r]/[SSR_\tau/(N - q - r)], \qquad (10)$$

where N is the sample size, q the number of parameters of the baseline model, and r the number of restricted coefficients (ie, one when the threshold effect applies to only the intercept or the slope and two when it applies to both). The test has a non-standard distribution, but Hansen (1996) provides tabulated critical values.

The test statistics of equation (10), as well as their statistical significance, are reported in Table 5. They point to a threshold of 70% for both GDP and consumption growth; the effect is especially strong when the level dummy is included in the model. Looking at possible lower thresholds, however, reveals some bimodality in the behaviour of the test statistics. We clearly see two peaks: one at 35% when only the level dummy is employed, and the other at 20% when both level and slope dummies are included. The non-liner effects seem to be particularly strong for consumption growth compared to GDP growth. This is interesting in that a "low" threshold may have distinct features from a high one.[14]

Determining the optimal threshold – full sample — Table 5

	GDP growth			Consumption growth		
Threshold	Level	Interaction	Both	Level	Interaction	Both
10%	0.908	1.594	4.174**	0.372	3.547$^+$	4.906*
15%	0.594	1.016	2.085	1.114	3.886$^+$	3.804$^+$
20%	3.499*	0.445	**6.126****	1.240	**4.551***	**12.325****
25%	7.157**	0.011	4.720**	0.775	2.176	4.589*
30%	7.629**	0.025	2.238	5.060**	1.565	4.379*
35%	**9.354****	0.059	5.105**	**12.554****	0.673	8.808**
40%	4.021*	0.052	0.073	8.058**	1.336	0.438
45%	8.726**	0.574	5.870**	7.881 **	1.714	9.369**
50%	10.458**	2.080	6.719**	12.711**	2.442	13.755**
55%	5.487**	4.047*	6.253**	3.437$^+$	0.530	6.505**

14 We obtain similar but less strong results when we consider only EMEs. See the details in Table A.2.2 and the associated text in Appendix 2.

60%	6.676**	3.456+	7.957**	9.074**	4.459*	16.657**
65%	6.299**	2.219	6.245**	9.862**	2.930	12.460**
70%	**11.219****	**8.499****	**23.229****	**21.120****	2.837	**27.354****
75%	8.827**	1.049	8.095**	13.177**	1.506	19.006**
80%	1.852	1.034	3.015	3.641+	0.305	5.355**
85%	0.128	0.045	7.550**	0.344	0.039	0.724
90%	10.285**	4.174*	10.379**	0.121	0.004	0.308

+, *, and ** denote statistical significance at the 10 percent, 5 percent and 1 percent level, respectively.

To check if the effects of household debt are consistently different at thresholds, in Table 6 we report the estimates of the coefficients on the dummies for the two optimally-selected thresholds, i.e., the high 70% debt-to-GDP ratio and the low 20% and 35% ratios. The first hypothesis we test is whether the relationship between household debt and growth changes at very low level of household debt. Low debt ratio could the consequence of an underdeveloped financial system that is unable to sustain credit intermediation. The results reported in Table 6 lend some support to such a claim. Starting from GDP growth, we observe that the level dummies have negative signs and are statistically significant in most models; this results suggest that countries with debt-to-GDP ratios above 20% (or 35%) do indeed experience slower GDP growth. However, when the slope dummy is included in the specification, it comes with a positive sign; this means that, when debt starts growing above the low threshold, it actually provides a boost to long-term growth. To give a sense of the magnitudes involved, household debt growing by 3 percentage points above the 20% threshold is already able to offset the negative effects coming from the intercept, and eventually provide a boost to long-term growth. This result is even stronger for consumption: the intercept and the slope coefficient are of similar magnitude, so that a 1.5 percentage point increase in household indebtedness is sufficient to offset the negative intercept, and provide a long-term boost to growth.

The second hypothesis is that excessive household debt is a drag on growth. If this is the case, we should expect to see that the negative relationship identified in section 4 intensifies as household debt piles up above the 70% debt-to-GDP threshold. In terms of the dummy setup outlined above, a negative coefficient on the level dummy would signal that when the household debt-to-GDP ratio exceeds the threshold, GDP and consumption growth are on average lower, over and above the negative relationship identified in the previous section. A negative coefficient on the slope dummy would instead indicate that the negative relationship between household debt and growth intensifies as the debt grows beyond the threshold. The level coefficient is indeed negative and statistically significant across all specifications, including those accounting for cross-sectional dependence. In contrast with the results on the low thresholds outlined in the previous paragraph, here the slope coefficient is negative for both GDP growth and consumption, though it is not always statistically significant.[15]

[15] The results reported in Table 6 still hold when we consider additional explanatory variables as in Table 3. Table A.2.1 in Appendix 2 provide such results. In addition, we obtain similar results when we only consider EMEs (Table A.2.3).

Results from threshold regressions – Full sample

Table 6

Threshold		Pooled	Mean group	Cross-section (CS)		
			GDP growth			
20%	Level	–0.492**	–0.341**	-0.110^{+}	-0.147^{+}	
		(*0.042*)	(*0.082*)	(*0.059*)	(*0.078*)	
	Interaction				0.058*	0.021
					(*0.029*)	(*0.031*)
	t-/F-statistics			3.50	6.44	6.13
	N	4163	3355	3258	3258	3258
35%	Level	–0.420**	–0.365**	–0.202**	–0.203**	
		(*0.039*)	(*0.097*)	(*0.066*)	(*0.090*)	
	Interaction				0.026	–0.009
					(*0.042*)	(*0.038*)
	t-/F-statistics			14.26	0.08	0.81
	N	4163	2704	2639	2639	2639
70%	Level	–0.453**	–0.503**	–0.300**	–0.289*	
		(*0.048*)	(*0.169*)	(*0.089*)	(*0.139*)	
	Interaction				–0.060	–0.141**
					(*0.068*)	(*0.049*)
	t-/F-statistics			11.22	8.50	23.23
	N	4163	826	818	818	818
			Consumption growth			
20%	Level	–0.486**	–0.319**	–0.072	–0.171*	
		(*0.045*)	(*0.083*)	(*0.064*)	(*0.087*)	
	Interaction				0.120**	0.080*
					(*0.037*)	(*0.038*)
	t-/F-statistics			1.24	4.55	12.32
	N	4163	3355	3258	3258	3258
35%	Level	–0.425**	–0.362**	–0.241**	–0.241**	
		(*0.038*)	(*0.092*)	(*0.068*)	(*0.084*)	
	Interaction				0.068	0.034
					(*0.046*)	(*0.042*)
	t-/F-statistics			12.55	8.81	0.67
	N	4163	2704	2639	2639	2639
70%	Level	–0.359**	–0.305**	–0.239**	–0.234**	
		(*0.044*)	(*0.102*)	(*0.052*)	(*0.077*)	
	Interaction				–0.057	-0.126^{+}
					(*0.090*)	(*0.075*)
	t-/F-statistics			21.12	2.84	27.35
	N	4163	826	818	818	818

$^{+}$, *, and ** denote statistical significance at the 10 percent, 5 percent and 1 percent level, respectively. Standard errors are in parentheses.

6. Concluding remarks

This paper investigates the short-run and long-run effects of a rise in household indebtedness on output and consumption growth, using the CS-ARDL model proposed by Pesaran and Smith (1995) and Chudik et al (2016). It uses data on 54 AEs and EMEs over the period of 1990–2016, and shows that an increase in the household debt-to-GDP ratio boosts consumption and GDP growth in the short run but tends to lower GDP growth in the long run. The negative long-run effects on consumption and GDP growth tend to intensify as the household debt-to-GDP ratio exceeds a threshold of 70%. We also find some evidence of the positive effects of household debt on consumption growth as the household debt-to-GDP ratio surpasses a low threshold of 20% and increases.

Our results are related to the broader debate about the role of debt in the economy. The real and financial effects of high levels of household debt as well as the rapid growth of such debt have become a key concern for policymakers since the financial crisis of 2007–2008. At the centre of this debate is the question of whether rapid increases in household debt in a country are a reflection of a financial deepening process or a build-up of financial imbalances. Our results do not provide much direct evidence on the former, besides suggesting that growth performance is not significantly weaker in countries with very low levels of household debt (less than 20% of GDP) relative to those with moderate levels of debt.

An important question, on which this paper is largely silent, is the role of various factors in the accumulation of household debt.[16] One issue in the context of the risk-taking channel of monetary policy (Borio and Zhu (2012)) is the extent to which low short- and long-term rates over the past eight years may have played a role in the recent rapid rise in household debt in many countries and may even have constrained central banks in raising rates. Even though such a question remains beyond the purview of this paper, any assessment must consider the various short- and long-run effects associated with any strategy aimed at stimulating the economy through ever larger debt levels.

[16] A recent review can be found in Cecchetti et al (2012).

References

Andrews, D and W Ploberger (1994): "Optimal tests when a nuisance parameter is present only under the alternative", *Econometrica*, vol 62, no 6, pp 1383–1414.

Borio, C, E Kharroubi, C Upper and F Zampolli (2016): "Labour reallocation and productivity dynamics: financial causes, real consequences", *BIS Working Paper*, no 534.

Borio, C and H Zhu (2012): "Capital regulation, risk-taking and monetary policy: a missing link in the transmission mechanism?" *Journal of Financial Stability*, vol 8, no 4, pp 236–51.

Bhutta, N (2012): "Mortgage debt and household deleveraging: accounting for the decline in mortgage debt using consumer credit record data", Board of Governors of the Federal Reserve System, *Finance and Economics Discussion Series*, no 2012-14.

Bound, J, D Jaeger and R Baker (1995): "Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak", *Journal of the American Statistical Association*, vol 90, no 430, pp 443–450.

Cecchetti, S and E Kharroubi (2015): "Why does financial sector growth crowd out real economic growth?" *BIS Working Paper*, no 490.

Cecchetti, S, M Mohanty and F Zampolli (2012): "The real effects of debt", *Jackson Hole Economic Symposium Conference Proceedings*, pp 145–196.

Chudik, A, K Mohaddes, M Pesaran and M Raissi (2016): "Long-run effects in large heterogeneous panel data models with cross-sectionally correlated errors", in R Hill, G Gonzalez-Rivera, and T-H Lee (eds), *Advances in Econometrics (Volume 36): Essays in Honour of Aman Ullah*, pp 85–135, Emerald Publishing.

Chudik, A, K Mohaddes, M Pesaran and M Raissi (2017): "Is there a debt-threshold effect on output growth?" *Review of Economics and Statistics*, forthcoming.

Chudik, A and M Pesaran (2015): "Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors", *Journal of Econometrics*, vol 188, no 2, pp 393–420.

Cooper, D (2012): "US household deleveraging: what do aggregate and household level data tell us?", *Federal Reserve Bank of Boston Public Policy Brief*, no 12-2.

Curdia, V and M Woodford (2010): "Credit spreads and monetary policy", *Journal of Money, credit and Banking*, vol 42, no 6, pp 3–35.

Dembiermont, C, M Drehmann and S Muksakunratana (2013): "How much does the private sector really borrow? A new database for total credit to the private non-financial sector", *BIS Quarterly Review*, March, pp 65–81.

Drehmann, M and M Juselius (2014): "Evaluating early warning indicators of banking crises: satisfying policy requirements", *International Journal of Forecasting*, vol 30, no 3, pp 759–780.

Dynan, K (2012): "Is a household debt overhang holding back consumption?" *Brookings Paper on Economic Activity*, spring, pp 299–362.

Dynan, K and W Edelberg (2013): "The relationship between leverage and household spending behaviour: evidence from the 2007–2009 survey of consumer finance", *Federal Reserve Bank of St. Louise Review*, September/October, pp 425–448.

Eberhardt, M and A Presbitero (2015): "Public debt and growth: heterogeneity and non-linearity", *Journal of International Economics*, vol 97, 1, pp 45–58.

Eggertsson, G and P Krugman (2012): "Debt, deleveraging and the liquidity trap: a Fisher-Minsky-Koo approach", *Quarterly Journal of Economics*, vol 127, no 3, pp 1469–1513.

Engle, R and C Granger (1987): "Cointegration and error correction: representation, estimation and testing", *Econometrica*, vol 55, no 2, pp 251–276.

Guerrieri, V and G Lorenzoni (2011): "Credit crisis, precautionary savings and the liquidity trap", *NBER Working Paper*, no 17583.

Guggenberger, P (2012): "On the asymptotic size distortion of tests when instruments locally violate the exogeneity assumption", *Econometric Theory*, vol 28, no 2, pp 387–421.

Hall, R (2011): "The long slump" *American Economic Review*, vol 101, no 2, pp 431–469.

Hansen, B (1996): "Inference when a nuisance parameter is not identified under the null hypothesis", *Econometrica*, vol 64, no 2, pp 413–430.

IMF (2006): "Household credit growth in emerging market countries", *Global Financial Stability Report,* Chapter II, September, pp 46–73.

IMF (2012): "Dealing with household debt", *World Economic Outlook,* Chapter III, April, pp 89–124.

Jordà, Ò, M Schularick and A Taylor (2013): "When credit bites back", *Journal of Money, Credit and Banking*, vol 45, no S2, pp 3–28.

Jordà, Ò, M Schularick and A Taylor (2015): "Betting the house", *Journal of International Economics*, vol 96, no S1, pp S2–S18.

Jordà, Ò, M Schularick and A Taylor (2016): "The great mortgaging: housing finance, crises and business cycles", *Economic Policy*, vol 31, no 85, pp 107–152.

Juselius, M and M Drehmann (2015): "Leverage dynamics and the real burden of debt", *BIS Working Paper*, no 501.

King, M (1994): "Debt deflation: theory and evidence", Presidential Address, *European Economic Review*, vol 38, no 3–4, pp 419–445.

Laeven, L and F Valencia (2013): "Systemic banking crises database", *IMF Economic Review*, vol 61, no 2, pp 225–270.

Mian, A and A Sufi (2010): "Household leverage and the recession of 2007 to 2009", *IMF Economic Review*, vol 58, no 1, pp 74–117.

Mian, A, K Rao and A Sufi (2013): "Household balance sheets, consumption and the economic slump", *Quarterly Journal of Economics*, vol 128, no 4, pp 1687–1726.

Mian, A, A Sufi and E Verner (2015): "Household debt and business cycles worldwide", *NBER Working Paper*, no 21581.

Panizza, U and A Presbitero (2013): "Public debt and economic growth in advanced economies: a survey", *Swiss Journal of Economics and Statistics*, vol 149, no 2, pp 175–204.

Pesaran MH (2004): "General diagnostic tests for cross section dependence in panels", *IZA Discussion Paper*, no 1240.

Pesaran, MH and Y Shin (1999): "An autoregressive distributed lag modelling approach to cointegration analysis", in S Strom (ed), *Econometrics and economic theory in the 20th century: the Ragnar Frisch centennial symposium*, Cambridge University Press, chapter 11, pp 371–413.

Pesaran, MH and R Smith (1995): "Estimating long-run relationships from dynamic heterogeneous panels", *Journal of Econometrics*, vol 68, no 1, pp 79–113.

Schularick, M and A Taylor (2012): "Credit booms gone bust: monetary policy, leverage cycles and financial crises", *American Economic Review*, vol 102, no 2, pp 1029–1061.

Stock, J, J Wright and M Yogo (2002): "A survey of weak instruments and weak identification in generalized method of moments", *Journal of Business and Economic Statistics*, vol 20, no 4, pp 518–529.

Stock, J and M Yogo (2005): "Testing for weak instruments in linear IV regression", in D Andrews (ed), *Identification and Inference for Econometric Models*, Cambridge University Press, pp 80–108.

Sufi, A (2015): "Out of many, one? Household debt, redistribution and monetary policy during the economic slump", Andrew Crockett Memorial Lecture delivered at the Annual General Meeting of the Bank for International Settlements, June, Basel.

Appendix 1. Data sources on household debt

We use quarterly data on household debt, GDP and other macroeconomic variables, financial variables and institutional variables for 54 economies over the period ranging from Q1 1990 (or the earliest period of data availability) to Q1 2015. The 54 economies include 23 advanced economies (AEs) and 31 emerging market economies (EMEs). Table A1.1 shows the 54 economies we selected.

Sample economies

Table A1.1

Region (number)	Economy
Asia-Pacific (12)	Australia, China, Hong Kong SAR, India, Indonesia, Japan, Korea, Malaysia, New Zealand, Philippines, Singapore, Thailand
Central and eastern Europe (15)	Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Russia, Serbia, Slovakia, Slovenia, Turkey, Ukraine
Latin America (5)	Argentina, Brazil, Colombia, Mexico, Peru
Middle East and Africa (2)	Israel, South Africa
Western Europe (18)	Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, Malta, Netherlands, Norway, Portugal, Spain, Sweden, United Kingdom
North America (2)	Canada, United States

Household debt data were collected from various national sources. It should be noted that the definition of the total amount of loans extended by banks to households, which is our proxy for household debt, differed across economies. Table A1.2 provides the exact definitions and sources of our data as well as the period of data availability.

In Table A2.5, we use total credit to households and non-profit institutions serving households (NPISHs) from the BIS database on total credit to the non-financial sector for 39 of the economies comprised in our sample.

In the empirical analysis, we use the ratio of household debt to GDP as a proxy for household indebtedness. Here we use GDP instead of household disposable income due to data availability considerations.

Definitions and data sources of household credit by banks

Table A1.2

Economy	Definition	Source
Argentina	Credit institutions: credit (=loans) to households: total, M-end NSA	BIS databank
Australia	Bank assets: loans to households: total, M-end NSA	BIS databank
Austria	Households & NPISHs: liabilities: total (Esa95), NSA	BIS databank
Belgium	Credit institutions: loans to households (including NPISHs): M-end NSA	BIS databank
Brazil	Financial system: credit (=loans) to households: market and non-market conditions: M-end NSA	BIS databank
Bulgaria	Banks (MFIs): credit (=loans) to households and NPISHs: M-end NSA	BIS databank
Canada	Households liabilities: residential mortgage credit and consumer credit: NSA	BIS databank
China	Consumer loan: local and foreign currency	CEIC
Croatia	Banks (MFIs): credit (=loans) to households: total, M-end, Q-end NSA	BIS databank
Colombia	Credit institutions: consumer credit	Datastream
Czech Republic	Bank (MFI) assets: credit to households: total (Esa95), M-end NSA	BIS databank
Denmark	Monetary financial institution lending: households etc: total	Datastream
Estonia	Depository corporation excluding central bank: assets: loans to households: NSA	BIS databank
Finland	Depository corporation excluding central bank: assets: loans to households: NSA	BIS databank
France	Credit institutions: credit (=loans) to households: total, M-end NSA	BIS databank
Germany	Banks (MFIs): credit (=loans) to households: total, NSA	BIS databank
Greece	Credit institutions and central bank: credit to households: Total, NSA	BIS databank
Hong Kong SAR	Bank assets: credit to the household sector: Q-end NSA	BIS databank
Hungary	Households & NPISHs: liabilities: loans	BIS databank
Iceland	Deposit money banks: loans to households, backdated with total lending to households	National data, Datastream
India	Scheduled commercial banks: credit outstanding: personal loans	CEIC
Indonesia	Commercial banks outstanding credits to individuals	Datastream
Ireland	Credit institutions: assets: loans to households: M-end NSA	BIS databank
Italy	MFIs excluding central bank: credit (=loans) to households: total, M-end NSA	BIS databank
Israel	Credit: debt outstanding: households	Datastream
Japan	Flow of funds: liabilities: households: loans	BIS databank
Korea	Loans of commercial and specialised banks: household	CEIC
Latvia	Banks (MFIs): credit (=loans) to households: Total, M-end NSA	BIS databank
Lithuania	Other MFI loans to residents: households	Datastream
Luxembourg	Bank loans: households and NPISHs	Datastream
Malaysia	Loans: banking system: by type: including Cagamas and excluding Danaharta: term: Personal loans and housing loans	CEIC
Malta	Deposit money banks: loans and advances: Personal	Datastream
Mexico	Banks: credit (=loans) to households: total, Q-end NSA	BIS databank
Netherlands	Depository corporation excluding central bank: loans to households: NSA	BIS databank
New Zealand	Deposit-taking corporation and other fin. Institutions: credit to households: M-end SA	BIS databank
Norway	Banks: assets: credit to households: total, M-end NSA	BIS databank
Peru	Credit to the private sector: consumer credit and mortgage loan	National data
Philippines	Philippine banking system: consumer loans	CEIC
Poland	Monetary financial institution loans and other claims on the non-financial sector: households: total	Datastream
Portugal	Depository corporation excluding central bank: assets: credit to households and NPISHs: M-end NSA	BIS databank
Romania	Credit: households: total	Datastream
Russia	Credit institutions: credit to households: Total, NSA	BIS databank
Serbia	Assets: domestic credit: credit to non-government sectors: households	Datastream
Singapore	Domestic banking units: loans and advances: consumer loans	CEIC
Slovakia	Monetary financial institutions: balance sheet: assets: loans to households	Datastream
Slovenia	Other monetary financial institutions domestic ASS (households and NPISHs)	Datastream
South Africa	Credit extended to the domestic private sector: loans and advances: Households	Datastream
Spain	MFIs excluding central bank: credit (=loans) to households: total, M-end NSA	BIS databank
Sweden	Credit institutions: loans to households: total, M-end NSA, backdated with monetary financial institutions: lending to households excluding NPISHs: total	BIS databank, Datastream
Thailand	Banks: assets: loans to individuals: NSA	BIS databank
Turkey	Credit institutions: loans: households (including NPISHs): M-end NSA	BIS databank
Ukraine	Loans: banks: households	Datastream
United Kingdom	Net lending to individuals: total (amounts outstanding): SA	Datastream
United States	Flow of funds balance sheet: household and NPISH: liabilities: credit market instruments total	Datastream

Appendix 2. Further robustness checks

To check the robustness of our results from threshold regressions, we repeated the exercise on the alternative models employed in Table 3. For the sake of brevity, we only report the results from the first two models corrected for cross-sectional dependence in Table 6. In all cases, the coefficient on the level dummy for GDP growth remains negative and statistically significant (Table A2.1). This means that, even after controlling for additional long-run drivers of household indebtedness, there is no alteration to the negative effect of household indebtedness on growth. We also find that the coefficient on the slope dummy for GDP growth when considered together with the level dummy for the 20% threshold remains positive for all additional explanatory variables and statistically significant for most additional explanatory variables. For consumption, the results are less clear-cut, and some specifications produce non-significant coefficients on the level dummy, although the signs of the coefficients are almost always negative. By contrast, in all cases the coefficient on the slope dummy for consumption when considered with the level dummy for the 20% threshold is positive and statistically significant. This means that, even after controlling for additional long-run drivers of household indebtedness, there is no alteration to the positive effect of increasing household indebtedness above the 20% threshold on consumption growth.

We also explored whether EMEs have specifically different thresholds and coefficients by excluding AEs from the sample. On average, the significance of the results tends to weaken not only because of the smaller cross-section, but also because the time-series dimension of the data shrinks substantially. In terms of the determination of the optimal threshold (Table A2.2), results are less clear cut. Starting from the high threshold for GDP growth, we find that all models point to a 50% threshold. But, for consumption growth, results are a bit more mixed, though they still hover around 50%. As far as the low threshold is concerned, results are more similar to those based on the full sample, and point to 35% when only the level dummy is included and 20% when also the interaction term appears. For the sake of completeness, we also computed the equivalent of Table 6 for EMEs. The results reported in Table A.2.3 look comparable to those in Table 6, even though their statistical significance weakens. We note, however, that the slope coefficient at the 20% threshold remains positive and significant, especially in the case of consumption growth.

We also tried to control for banking, financial and currency crises with dummies based on the dates provided by Laeven and Valencia (2013). The results remain virtually unchanged in terms of statistical significance (Table A2.4). Table A2.5 replicates the results of Table A2.4 for EMEs only by including the financial crisis dummies of Laeven and Valencia (2013). The results remain virtually unchanged.

As an additional robustness check, we also considered different breakdowns of debt and consumption, and tried to associate them with a relevant debt component. More specifically, we looked at consumption of durables and non-durables (which we tried to relate to consumer loans) and at residential investment (which we tried to relate to housing loans).

The results are reported in Table A2.6. It is important to stress that, due to data limitations, the cross-sectional dimension drops substantially. This is likely to heavily affect the statistical significance of the results. The economic significance, however, is unaltered: the coefficients are all positive and of the same order of magnitude as those in Table 2.

Finally, we also looked at a broader definition of household debt, ie, the BIS definition of total credit to households and NPISHs (Dembiermont et al (2013)). We do not use these data for the baseline regressions, since the cross-sectional coverage of 41 economies is narrower than that of 54 economies for the baseline regressions, but the results reported in Table A2.7 are in line with those reported in Table 2. The only difference is that cross-sectional averages do not seem to eliminate completely the cross-sectional dependence.

Results from threshold regressions with additional explanatory variables — Table A2.1

				GDP growth			
Threshold		Baseline	Inflation	House price	LT rate	ToT	DSR
20%	Level	–0.110^{+}	–0.216**	–0.053^{+}	–0.210**	–0.125*	–0.119^{+}
		(0.059)	*(0.065)*	*(0.030)*	*(0.065)*	*(0.053)*	*(0.071)*
	Level	–0.147^{+}	–0.275**	–0.086	–0.236*	–0.174*	–0.130^{+}
		(0.078)	*(0.080)*	*(0.065)*	*(0.095)*	*(0.078)*	*(0.077)*
	Interaction	0.058*	0.100*	0.123*	0.044	0.045^{+}	0.104**
		(0.029)	*(0.032)*	*(0.049)*	*(0.033)*	*(0.027)*	*(0.039)*
	N	3258	3258	2333	2624	3223	1664
70%	Level	–0.300**	–0.320**	0.005	–0.325**	–0.224**	–0.235*
		(0.089)	*(0.090)*	*(0.103)*	*(0.110)*	*(0.068)*	*(0.097)*
	Level	–0.289*	–0.342*	–0.037	–0.305*	–0.198	–0.200^{+}
		(0.139)	*(0.161)*	*(0.086)*	*(0.133)*	*(0.123)*	*(0.100)*
	Interaction	–0.060	–0.033	0.024	–0.068	–0.070	–0.022
		(0.068)	*(0.088)*	*(0.055)*	*(0.056)*	*(0.080)*	*(0.046)*
	N	818	818	656	748	808	528
				Consumption growth			
20%	Level	–0.149*	–0.095	–0.040	–0.221**	–0.069	–0.087
		(0.063)	*(0.067)*	*(0.039)*	*(0.067)*	*(0.063)*	*(0.054)*
	Level	–0.171*	–0.216**	–0.151^{+}	–0.376**	–0.277**	–0.175*
		(0.087)	*(0.082)*	*(0.090)*	*(0.114)*	*(0.092)*	*(0.083)*
	Interaction	0.120**	0.087*	0.127**	0.064^{+}	0.104**	0.098*
		(0.037)	*(0.036)*	*(0.046)*	*(0.036)*	*(0.034)*	*(0.042)*
	N	3258	3258	2333	2624	3223	1664
70%	Level	–0.207**	–0.221**	0.026	–0.206**	–0.214*	–0.179
		(0.054)	*(0.065)*	*(0.090)*	*(0.055)*	*(0.069)*	*(0.136)*
	Level	–0.234**	–0.197*	–0.068	–0.178*	–0.160*	–0.218^{+}
		(0.077)	*(0.079)*	*(0.068)*	*(0.090)*	*(0.078)*	*(0.112)*
	Interaction	–0.057	–0.096	0.056	–0.055	–0.118^{+}	–0.004
		(0.090)	*(0.068)*	*(0.122)*	*(0.079)*	*(0.063)*	*(0.107)*
	N	818	818	656	748	808	528

$^{+}$, *, and ** denote statistical significance at the 10 percent, 5 percent and 1 percent level, respectively. Standard errors are in parentheses. ToT represents terms of trade and DSR for the debt service ratio.

Determining the optimal threshold – EMEs Table A2.2

	GDP growth			Consumption growth		
Threshold	Level	Interaction	Both	Level	Interaction	Both
10%	0.424	0.000	0.884	0.349	0.927	1.953
15%	0.045	0.001	0.121	0.179	1.373	1.627
20%	1.363	0.001	**2.249**	0.038	**2.764**	**6.324****
25%	4.944*	0.420	1.562	0.025	1.007	1.053
30%	5.554**	0.332	1.376	3.543+	0.569	2.748
35%	**6.444****	1.304	2.022	**7.224****	0.287	1.048
40%	0.851	0.441	1.661	3.946+	3.499+	2.142
45%	5.928	3.536+	12.081**	4.407*	**4.656****	4.978**
50%	**8.091****	**4.683***	**14.761****	**6.050****	1.156	5.987**
55%	4.882*	3.110+	4.952*	3.310+	1.681	**11.899****
60%	5.716**	1.156	8.868**	3.595+	1.325	2.969

+, *, and ** denote statistical significance at the 10 percent, 5 percent and 1 percent level, respectively.

Results from threshold regressions – EMEs

Table A2.3

Threshold		Pooled	Mean group	Cross-section (CS)		
GDP growth						
20%	Level	–0.433**	–0.563**	–0.124	–0.177	
		(0.063)	*(0.136)*	*(0.106)*	*(0.146)*	
	Interaction				0.052	–0.001
					(0.040)	*(0.042)*
	t-/F-statistics			1.366	2.25	0.00
	N	2314	1594	1533	1533	1533
35%	Level	–0.315**	–0.558*	–0.304*	–0.111	
		(0.087)	*(0.228)*	*(0.120)*	*(0.138)*	
	Interaction				–0.067	–0.077
					(0.078)	*(0.068)*
	t-/F-statistics			6.44	2.02	1.30
	N	2314	943	914	914	914
50%	Level	–0.360*	–2.030*	–0.823**	–0.737	
		(0.175)	*(0.979)*	*(0.289)*	*(0.485)*	
	Interaction				–0.015	–0.236**
					(0.226)	*(0.109)*
	t-/F-statistics			8.09	14.76	4.68
	N	2314	398	386	386	386
Consumption growth						
20%	Level	–0.408**	–0.469**	–0.023	–0.158	
		(0.062)	*(0.134)*	*(0.117)*	*(0.144)*	
	Interaction				0.154*	0.104+
					(0.062)	*(0.031)*
	t-/F-statistics			0.04	6.32	2.76
	N	2314	1594	1533	1533	1533
35%	Level	–0.347**	–0.543**	–0.340**	–0.151	
		(0.077)	*(0.213)*	*(0.126)*	*(0.151)*	
	Interaction				0.061	0.052
					(0.111)	*(0.097)*
	t-/F-statistics			7.22	1.05	0.29
	N	2314	943	914	914	914
50%	Level	–0.247	–1.744+	–0.837*	–0.351*	
		(0.154)	*(0.963)*	*(0.340)*	*(0.145)*	
	Interaction				–0.061	–0.165
					(0.141)	*(0.153)*
	t-/F-statistics			6.05	5.99	1.16
	N	2314	398	386	386	386

+, *, and ** denote statistical significance at the 10 percent, 5 percent and 1 percent level, respectively. Standard errors are in parentheses.

Results from threshold regressions with crisis dummies

Table A2.4

Threshold		Pooled	Mean group	Cross-section (CS)		
		GDP growth				
20%	Level	–0.492**	–0.341**	–0.110+	–0.147+	
		(*0.042*)	(*0.082*)	(*0.059*)	(*0.078*)	
	Interaction				0.023	0.021
					(*0.115*)	(*0.031*)
	N	4163	3355	3258	3258	3258
35%	Level	–0.420**	–0.365**	–0.202**	–0.203*	
		(*0.039*)	(*0.097*)	(*0.066*)	(*0.090*)	
	Interaction				0.026	–0.009
					(*0.042*)	(*0.038*)
	N	4163	2704	2639	2639	2639
70%	Level	–0.453**	–0.503**	–0.300**	–0.289*	
		(*0.048*)	(*0.169*)	(*0.089*)	(*0.139*)	
	Interaction				–0.060	–0.141**
					(*0.068*)	(*0.049*)
	N	4163	826	818	818	818
		Consumption growth				
20%	Level	–0.486**	–0.319**	–0.072	–0.171*	
		(*0.045*)	(*0.083*)	(*0.064*)	(*0.087*)	
	Interaction				0.120**	0.080*
					(*0.037*)	(*0.038*)
	N	4163	3355	3258	3258	3258
35%	Level	–0.425**	–0.362**	–0.241**	–0.241**	
		(*0.038*)	(*0.092*)	(*0.068*)	(*0.084*)	
	Interaction				0.068	0.034
					(*0.046*)	(*0.042*)
	N	4163	2704	2639	2639	2639
70%	Level	–0.359**	–0.305**	–0.239**	–0.234**	
		(*0.044*)	(*0.102*)	(*0.052*)	(*0.077*)	
	Interaction				–0.057	–0.126+
					(*0.090*)	(*0.075*)
	N	4163	826	818	818	818

+, *, and ** denote statistical significance at the 10 percent, 5 percent and 1 percent level, respectively. Standard errors are in parentheses.

Results from threshold regressions for EMEs with crisis dummies

Table A2.5

Threshold		Pooled	Mean group	Cross-section (CS)		
				GDP growth		
20%	Level	–0.394**	–0.432**	–0.081	–0.141	
		(*0.070*)	(*0.128*)	(*0.089*)	(*0.154*)	
	Interaction				0.008	–0.024
					(*0.037*)	(*0.028*)
	N	2146	1502	1449	1449	1449
35%	Level	–0.315**	–0.558*	–0.304*	–0.111	
		(*0.087*)	(*0.228*)	(*0.120*)	(*0.138*)	
	Interaction				–0.067	–0.077
					(*0.078*)	(*0.068*)
	N	2314	943	914	914	914
50%	Level	–0.145	–0.314+	–0.470*	–0.569**	
		(*0.107*)	(*0.181*)	(*0.211*)	(*0.111*)	
	Interaction				0.167	–1.12
					(*0.167*)	(*1.228*)
	N	2146	162	162	162	162
				Consumption growth		
20%	Level	–0.382**	–0.415**	–0.001	–0.136	
		(*0.070*)	(*0.140*)	(*0.089*)	(*0.146*)	
	Interaction				0.085+	0.051
					(*0.050*)	(*0.044*)
	N	2146	1502	1449	1449	1449
35%	Level	–0.347**	–0.543*	–0.340**	–0.151	
		(*0.077*)	(*0.213*)	(*0.126*)	(*0.151*)	
	Interaction				0.061	0.052
					(*0.111*)	(*0.097*)
	N	2314	943	914	914	914
50%	Level	–0.186	–1.079+	–0.838*	–0.900**	
		(*0.194*)	(*0.629*)	(*0.372*)	(*0.309*)	
	Interaction				0.105	–2.126
					(*0.105*)	(*2.045*)
	N	2146	162	162	162	162

+, *, and ** denote statistical significance at the 10 percent, 5 percent and 1 percent level, respectively. Standard errors are in parentheses.

Results using granular data

Table A2.6

	Durables		Non-durables		Residential investment	
	CS–ARDL	CS–DL	CS–ARDL	CS–DL	CS–ARDL	CS–DL
			1 lag			
Theta	–0.014	–0.044	–0.009	0.010	0.104	0.111^{+}
	(0.054)	*(0.057)*	*(0.014)*	*(0.017)*	*(0.073)*	*(0.064)*
N	1715	1720	1715	1720	2511	2521
CSD test	–1.18	–1.46	–1.27	–1.45	–1.71^{+}	–2.32*
			2 lags			
Theta	0.002	–0.036	–0.005	0.007	0.082	0.099
	(0.055)	*(0.066)*	*(0.019)*	*(0.019)*	*(0.091)*	*(0.065)*
N	1689	1698	1689	1698	2492	2512
CSD test	–2.00*	–1.74^{+}	–0.93	–1.31	–1.82^{+}	–2.60**
			3 lags			
Theta	–0.007	–0.041	0.020	0.012	0.027	0.065
	(0.079)	*(0.083)*	*(0.020)*	*(0.018)*	*(0.099)*	*(0.068)*
N	1663	1676	1663	1676	2473	2503
CSD test	–1.48	–1.83^{+}	–0.72	–1.22	–1.66^{+}	–2.27*

CS–ARDL stands for cross–section augmented autoregressive distributed lag, and CS–DL for cross–section augmented distributed lag. $^{+}$, *, and ** denote statistical significance at the 10 percent, 5 percent and 1 percent level, respectively. Standard errors are in parentheses.

Results using total credit to households and NPISHs

Table A2.7

	GDP growth			Consumption growth	
	ARDL	CS–ARDL	CS–DL	CS–ARDL	CS–DL
			1 lag		
Theta	–0.161**	–0.098**	–0.083**	0.023	0.039*
	(0.022)	*(0.017)*	*(0.016)*	*(0.019)*	*(0.018)*
N	3187	3187	3187	3187	3187
CSD test	24.36**	13.38**	12.89**	5.04**	6.09**
			2 lags		
Theta	–0.143**	–0.099**	–0.078**	–0.010	0.041*
	(0.022)	*(0.018)*	*(0.016)*	*(0.034)*	*(0.030)*
N	3171	3171	3171	3171	3171
CSD test	23.97**	13.57**	12.26**	4.66**	6.30**
			3 lags		
Theta	–0.127**	–0.088**	–0.076**	–0.040	0.037⁺
	(0.022)	*(0.018)*	*(0.016)*	*(0.068)*	*(0.019)*
N	3155	3155	3155	3155	3155
CSD test	22.79**	13.55**	12.46**	4.58*	6.53**

NPISHs stand for non-profit institutions serving households. ARDL stands for autoregressive distributed lag, CS–ARDL for cross–section augmented ARDL, and CS–DL for cross–section augmented distributed lag. ⁺, *, and ** denote statistical significance at the 10 percent, 5 percent and 1 percent level, respectively. Standard errors are in parentheses.