Inequality and household debt: a panel cointegration analysis (preliminary version)

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Abstract

This study investigates whether there exists an empirical long-run relationship between income inequality and household debt. By using panel cointegration techniques, we find that inequality and leverage are cointegrated of order one and therefore share a common trending relation. Removing this trend by first differencing the series leads to biased inference. Our results are robust to different indicators for household debt and alternative inequality measures.

Keywords: Income inequality, household debt, panel cointegration
JEL-Classification: C23, D31, E25, G21

1 Introduction

Several authors have attributed the recent financial crisis of 2008/09 to a considerable rise in income inequality (e.g. Rajan, 2010; Atkinson and Morelli, 2011). In a speech given by Sarah Bloom Raskin, member of the Board of Governors of the Federal Reserve System, she mentioned that "The effects of increasing income and wealth disparities - specificially, the stagnating wages and sharp increase in household debt in the years leading up to the crisis, combined with the rapid decline in house prices and contraction in credit that followed - may have resulted in dynamics that differ from historical experience and which are threfore not well captured by aggregate models." (p.14).

Rajan (2010) argues that rising inequality in the United States pressured different governments to enact redistribution policies aimed at improving the lot of those low- and middle-income voters being left behind. In combination with a relaxation of underwriting standards, rising income disparity led to an increasing use of credit unsupported by greater income. The resulting credit bubble is seen as one of the foundations for the subsequent crisis (Schularick and Taylor, 2012).

Following this argumentation, Kumhof and Rancière (2010) study the relationship between income inequality, household debt and the likelihood of a financial crisis within a DSGE framework. In this model, as a consequence of a decreasing bargaining power of workers who make up the lower deciles of the income distribution, inequality rises and workers demand more credit in order to maintain their desired level of consumption. As inequality increases further, these households become increasingly indebted but continue to borrow more to maintain their consumption. By assuming a convex relationship between household debt and the probability of a financial crisis, this increased leverage makes a crisis more likely. Kumhof et al. (2012) build on Kumhof and Rancière (2010) by extending this model to an open economy framework.

Based on the correlation between household debt and income inequality in the United States, Iacoviello (2008) develops a heterogenous agents DSGE model which consists of so-called patient and impatient agents. This model is able to capture the trend and cyclical behavior of debt and income dispersion. Moreover, the model attributes the long-run increase in household debt to the pronounced rise in inequality. In contrast, business cycle fluctuations are detected as the main determinant for short-run changes in household debt.

Despite this growing interest and theoretical debate about the inequality-leverage-crisis nexus, the empirical research in this area is still scanty - besides calculating simple correlation coefficients. One exception is the study by Bordo and Meissner (2012). They explicitely test the empirical support for the hypothesis set up by Rajan (2010) and Kumhof and Rancière (2010) within a panel dataset covering 14 advanced economies. By estimating the effect of changes in income inequality on the change of bank loans, the authors do not find a significant relationship between inequality and bank loans growth. The results of Bordo and Meissner coincide with those of Atkinson and Morelli (2011) who fail to find a causal relation between changes in income inequality and economic crises.

Our study differs from those by Bordo and Meissner (2012) and Atkinson and Morelli (2011) in three ways. First, a more precise measure of household debt offered by the Bank for International Settlements (BIS) is used. The BIS credit variable measures the outstanding amount of credit to private households and therefore does not include credit to the business sector as the series used in Bordo and Meissner (2012) does. Second, in order to check for the robustness of the results, we consider four different inequality indicators. Three of these series, namely the top 1% income share, the inverted Pareto-Lorenz coefficient and the Gini index measure the income distribution within one economy while the fourth one, labor income share, includes information about the distribution of factor incomes. Third and most importantly, this study differs from Bordo and Meissner (2012) and Atkinson and Morelli (2011) in the underlying hypothesis tested. While Bordo and Meissner (2012) and Atkinson and Morelli (2011) investigate the relationship between changes in income inequality and financial stability, we test the level hypothesis between inequality and credit. As shown by Engle and Granger (1987), first differencing may remove the long-run relation between two non-stationary variables if the variables share a common stochastic trend. Therefore, if a trending relationship between inequality and credit exists, using changes of the variables of interest may lead to a loss of information in the data and biased inference on the effect of inequality on leverage (Johansen and Juselius, 1990). Moreover, as already shown in Iacoviello (2008), short-run dynamics in household debt can mainly be explained by business cycle fluctuations and, thus, no direct relation between inequality and household debt could be expected in the short-run. However, when turning to a long-run perspective, Iacoviello (2008) directly relates the trend increase in household debt to the persistent rise in income dispersion. Furthermore, the argumentation of Rajan (2010) and the model of Kumhof and Rancière (2010) are based on the levels of inequality and household debt and not on the changes of the two variables.

By using panel cointegration methods, we test whether the levels of income inequality and household debt share a common long-run relationship. This approach coincides with Malinen (2013) who finds that income inequality is associated with increased leverage in the economy. However, similar to Bordo and Meissner (2012), Malinen (2013) also uses the broader bank loans measure offered by Schularick and Taylor (2012) as debt indicator and just considers one inequality variable; the top 1% income share. Based on all these considerations, our study can be seen as a more precise and general approach for testing the existence of a long-run relationship between income inequality and household debt hypothesized in Rajan (2010) and theoretically modeled in Kumhof and Rancière (2010) and Iacoviello (2008).

The remaining chapters of the paper are organized as follows. Section 2 will review the existing literature on the connection between inequality, credit and financial crises. Section 3 describes the panel cointegration tests used in the study. Section 4 presents the data and addresses the problem of unit root tests on bounded variables because some of the inequality measures considered in this paper have a limited value range. Cointegration test results are reported in section 5 and section 6 concludes.

2 Related Literature

Focussing on the relationship between credit expansions and financial crises, Schularick and Taylor (2012) show that credit aggregates are a reliable indicator for the likelihood of future crises. By using data on aggregate bank loans, covering 14 developed countries from 1870 to 2008, they estimate Logit regressions in order to explain the occurrence of a banking crisis. However, they do not address the question what determines credit expansions and therefore also indirectly the outburst of a crisis.

In his book, Rajan (2010) proposes a linkage between inequality, credit expansion and financial crisis in the United States in the first decade of the 21st century and in the 1920s. Rajan argues that rising inequality led to political pressure for redistribution in the form of subsidized housing finance via institutions like Fannie Mae and Freddie Mac. The resulting lending boom created an unsustainable increase in housing-prices which reversed in 2007 and finally can be identified as one major reason for the crisis of 2008/09. Along these lines, Kumhof and Rancière (2010) model a relationship between inequality, household debt and the probability of a crisis within a DSGE framework. Their model consists of two representative agents: an investor, who owns all of the capital, earns only capital income, and saves and invests as well as consumes; and a worker who earns only wage income and uses this only for consumption. A negative shock on the bargaining power of workers leads to an increase in income differences between these two agents. Due to a subsistence level of consumption included in the worker's utility function the pronounced rise in inequality results in an increasing amount of loans demanded by workers, in order to maintain the desired level of consumption. Consequently, workers' household debt rises as well. Because the authors assume a convex relation between household debt and the probability of an economic crisis, they connect rising inequality to an increasing amount of leverage and, ultimately to a higher probability of a crisis. Kumhof et al. (2012) extend this model to an open economy framework.

By using a heterogenous agents model, Iacoviello (2008) is able to replicate the long-term and short-run dynamics of household debt and income inequality in the United States from 1963 to 2003. Based on the model by Krusell and Smith (1998), agents face aggregate and idiosyncratic income shocks and accumulate real and financial assets. In the model there are so-called patient agents which have a low discount rate and do not face borrowing constraints and impatient agents which discount the future more heavily and face a collateral constraint. In response to a negative idiosyncratic income shock, unconstrained agents reduce consumption by a small amount but increase their debt. Instead, constrained agents behave like hand-to-mouth consumers by reducing consumption and borrowing less. The model successfully captures the observed income inequality and household debt series. Additionally, the model attributes the trend increase in debt to the pronounced rise in inequality whereas business cycle fluctuations can account for the short-run changes in household debt.

Although models like those by Kumhof and Rancière (2010) or Iacoviello (2008) explicitly make use of a connection between inequality and household debt, there is only a small literature testing for this relationship empirically. Atkinson and Morelli (2011) study the question whether economic crises were preceded by rising inequality. By using a dataset covering 25 countries over the period from 1911 to 2010, they find no clear relationship between changes in income inequality and banking crises. Nevertheless, they conclude that "[...] we have not investigated whether inequality level was relatively higher before identified macroeconomic shocks. Therefore, the level hypothesis cannot be ruled out at this stage." (Atkinson and Morelli, 2011, p. 49). Following this considerations, Bellettini and Delbono (2013) show that between 1982 and 2008, a large majority of banking crises have been preceded by persistently high levels of income inequality. They consider the Gini index for incomes after-tax as well as before-tax and transfers as inequality indicators. However, Atkinson and Morelli (2011) and Bellettini and Delbono (2013) focus on the relationship between income inequality and the occurence of a banking crisis and not on the connection between inequality and household debt which is essential in the models of Kumhof and Rancière (2010) and Iacoviello (2008).

Bordo and Meissner (2012) empirically study the relationship between changes in inequality and credit growth. Based on the dataset by Schularick and Taylor (2012) they use the amount of outstanding bank loans to the private sector as indicator for household debt. The inequality measure in their study is the share of income of the top 1%. By using panel data on 14 advanced countries for the period from 1920 to 2000 they do not find a significant relationship between inequality growth and credit changes. Instead, interest rates and gdp per capita growth are robust determinants of credit booms. However, this study suffers from several limitations in order to test for the inequality-household debt relation set up by Rajan (2010) and used in Kumhof and Rancière (2010) and Iacoviello (2008). First, the theoretical frameworks by Kumhof and Rancière (2010) and Iacoviello (2008) model the connection between inequality and debt of private households. By using total loans to the private sector, credit to businesses is also included in the dependent variable used by Bordo and Meissner (2012). Given an increase in bank loans to business, the times series of Schularik and Taylor (2012) rises, while, ceteris paribus, credit to the household sector which is central for the works by Kumhof and Rancière (2010) and Iacoviello (2008) stays constant. Therefore, by using time series which explicitely measure credit to the household sector, we can more precisely investigate the relationship between inequality and household debt compared to Bordo and Meissner (2012). Second, the authors just consider one inequality measure in their study and do not check whether their results still hold when alternative inequality variables are considered. Finally and most importantly, the theoretical works by Kumhof and Rancière (2010) and Iacoviello (2008) show that there exists a trending long-run relation between income inequality and household debt. By using growth rates this trend is removed and finally just short-run dynamics remain. If, however, there is a long-run relationship between inequality and household debt, using growth rates of the variables of interest may lead to biased inference on the effect of inequality on leverage (Engle and Granger, 1987; Johansen and Juselius, 1990). In addition, as pointed out by Iacoviello (2008) short-run dynamics of household debt can well be explained by business cycle fluctuations while debt and inequality are mainly connected in the long-run. Therefore, it should not be surprising that short-run changes in gdp per capita and interest rates are significant regressors in explaining loans growth as shown by Bordo and Meissner (2012). For testing the existence of a long-run relationship between household debt and inequality both variables should be considered in levels which is possible within the cointegration approach applied in our study.

Malinen (2013) tests if there is a cointegration relationship between income inequality and credit. The author uses a panel dataset covering nine countries and also considers total bank loans to the private sector and the top 1% income share as measures for household debt and inequality, respectively. By using panel cointegration tests the null hypothesis of no cointegration can not be rejected in most cases. Nevertheless, this study also suffers from the same data limitation as the one by Bordo and Meissner (2012). Thus, the contribution of this study is, first, to test for the relationship hypothesized by Rajan (2010) and modeled by Kumhof and Rancière (2010) and Iacoviello (2008) by using explicit time series on private household debt as dependent variable and, second, considering different inequality indicators in order to check for the robustness of the results.

3 Panel Cointegration tests

The cointegration approach which allows for testing the presence of long-run relationships among integrated variables is a popular tool in the empirical literature (Breitung and Pesaran, 2005). However, most of the tests have only low power when applied to single unit time series mainly available just after World War II (Pedroni, 2004). Due to this dilemma it seems natural to expand the underlying sample by including additional cross-sectional data and studying cointegration relationships within a pooled time series panel. Moreover, by applying cointegration tests we are able to consider the variables of interest measured in levels. Therefore, our approach can be seen as more precise way for studying the existence of a long-run relationship between levels of income inequality and household debt used in Rajan (2010), Kumhof and Rancière (2010) and Iacoviello (2008) than considering growth rates as applied by Bordo and Meissner (2012).

In the following we will present two common panel cointegration tests: the Pedroni (1999, 2004) and Westerlund (2007) test.

3.1 Pedroni test

Engle and Granger (1987) developed the cointegration idea for single unit time-series. The underlying test is based on an examination of the residuals of a regression performed using I(1) variables. A necessary condition for a cointegration relationship between these variables is that the residuals of the regression should be I(0). In contrast, if the residuals are I(1) then there does not exist cointegration and therefore no long-run steady-state relation between the variables of interest. Pedroni (1999, 2004) extend the Engle-Granger residual-based approach to the panel data setting.

The Pedroni test requires to compute the residuals from the hypothesized cointegration regression. Therefore, consider the following regression

$$y_{it} = \delta_i^{'} d_t + \beta_i x_{it} + e_{it} \ , \qquad (1)$$

where $t = 1, ..., T$ represents the time index and $i = 1, ..., N$ stands for the cross-sectional units. d_t contains the deterministic components, which can take three different specifications. When no deterministic trend is included in (1), then $d_t = 0$, while $d_t = 1$ in the case when y_{it} is modeled with an individual constant term. Finally, for $d_t = (1,t)^{'}$, y_{it} is modeled with a individual constant and a time trend. Note that individual specific fixed effects and deterministic trends are allowed via the parameter δ_i. Additionally, the slope coefficients β_i can vary across individuals.

Both variables of interest y_{it} and x_{it} are assumed to be I(1) for each cross-sectional unit i. Following the Engle-Granger approach, under the null hypothesis of no cointegration the error term e_{it} should also be I(1). This can be studied by first obtaining the residuals from equation (1) $\widehat{e_{it}} = y_{it} - \widehat{\delta_i^{'}} d_t - \widehat{\beta}_i x_{it}$ and then to test whether residuals are I(1) by running the auxiliary regression for every cross-section

$$\widehat{e_{it}} = \rho_i \widehat{e_{i,t-1}} + u_{it}$$

or

$$\widehat{e_{it}} = \rho_i \widehat{e_{i,t-1}} + \sum_{j=1}^{p_i} \psi_{ij} \Delta \widehat{e_{i,t-j}} + v_{it} \ ,$$

where $E\left[u_{it}u_{js}\right] = 0 \ \forall s,t,i \neq j$ and $E\left[v_{it}v_{js}\right] = 0 \ \forall s,t,i \neq j$. Thus, the individual processes are assumed to be independent and identically distributed cross-sectionally, i.e. the Pedroni test does not allow for cross-sectional correlation. Now Pedroni suggests seven different statistics for testing the null hypothesis of no cointegration ($\rho_i = 1$). Four out of these statistics test the null hypothesis $H_0 : \rho_i = 1$ for all i, versus the alternative hypothesis $H_1^p : \rho_i = \rho < 1$ for all i, so that a common autoregressive coefficient is presumed. Pedroni calls these four tests the within-dimension or panel cointegration statistics test. On the other hand if the autoregressive coefficients are allowed to vary between the cross-sectional units, the null hypothesis $H_0 : \rho_i = 1$ for all i is tested versus the alternative hypothesis $H_1^g : \rho_i < 1$ for all i. Pedroni terms these remaining three tests the between-dimension or group mean panel cointegration statistics tests. By allowing for individual specific autoregressive coefficients, the between-dimension-based statistics take one additional source of potential heterogeneity across individual members of the panel into account.

The four simple panel cointegration statistics are: a non-parametric panel variance ratio statistic, a panel rho-statistic that is analogous to the rho statistic developed by Phillips and Perron (1988) and Phillips and Ouliaris (1990), a type of the non-parametric t-statistic studied by Phillips and Perron (1988) and a parametric statistic which is based on the augmented Dickey-Fuller (1979) t-statistic. The other three group mean panel cointegration statistics are based on the Phillips and Perron (1988) and Phillips and Ouliaris (1990) rho-statistic, the Phillips and Perron (1988) t-statistic and the augmented Dickey and Fuller (1979) t-statistic, respectively. The Pedroni test belongs to the so called first generation panel cointegration tests (Breitung and Pesaran, 2005).

3.2 Westerlund test

While the first generation panel cointegration tests do not allow for cross-sectional correlation, tests of the second generation explicitly consider such dependencies. Another shortcoming of residual-based cointegration tests as the one by Pedroni is the so called common factor restriction (Kremers et al., 1992; Banerjee et al., 1998). Residual-based tests require that the long-run cointegration vector for the variables in their levels have to equal to the short-run error correction process for the variables in their differences (Westerlund, 2007). As shown by Kremers et al. (1992) and Banerjee et al. (1998) this common factor restriction can result in a significant loss of power for residual-based cointegration tests.

One example for a second generation panel cointegration test is the test proposed by Westerlund (2007). In contrast to the residual-based approach of the Pedroni test, Westerlund develops an error correction-based cointegration test for panel data. The null hypothesis of no cointegration is tested by inferring whether the error-correction term in a conditional panel error-correction model is equal to zero. This test does not rely on the common factor restriction and by employing a bootstrap approach inference is possible even under general forms of cross-sectional dependence. As simulation results in Westerlund (2007) show, the test has good small-sample properties.

The error-correction tests are based on the following data-generating process:

$$\Delta y_{it} = \delta_i^{'} d_t + \alpha_i (y_{i,t-1} - \beta_i^{'} x_{i,t-1}) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=-q_i}^{p_i} \gamma_{ij} \Delta x_{i,t-j} + e_{it} \ . \qquad (2)$$

Once again d_t contains the deterministic components, which can take one of the three specifications already described above. It is assumed that Δx_{it} and the error term e_{it} are independent and that these errors are independent across i and t.

Equation (2) can be rewritten as

$$\Delta y_{it} = \delta_i^{'} d_t + \alpha_i y_{i,t-1} + \lambda_i^{'} x_{i,t-1} + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=-q_i}^{p_i} \gamma_{ij} \Delta x_{i,t-j} + e_{it} \ , \qquad (3)$$

where $\lambda_i^{'} = -\alpha_i \beta_i^{'}$. The equilibrium relationship of the system is given by $y_{i,t-1} - \beta_i^{'} x_{i,t-1}$. Therefore, α_i captures the speed at which the system converts back to equilibrium after an exogenous shock occurred. Given that $\alpha_i > 0$, then error correction is present, which implies that there exists a cointegration relationship between y_{it} and x_{it}. However, if $\alpha_i = 0$, then error correction does not happen and, thus, there is no cointegration relationship. Following these considerations, Westerlund (2007) states the null hypothesis of no cointegration as $H_0 : \alpha_i = 0$ for all i. What is considered as the alternative hypothesis depends on the assumption about the homogeneity of α_i. If the α_i's are not required to be equal for all cross-sectional units, then H_0 is tested versus the alternative hypothesis $H_1^g : \alpha_i < 0$ for at least one i. This is done by the two so called group-mean tests. A second pair of tests, so called panel tests, make the assumption that α_i is equal across all cross-sectional units i. Thus, these panel tests are designed to test H_0 versus $H_1^p : \alpha_i = \alpha < 0$ for all units i. Note that the distinction between panel and group-mean cointegration tests is similar for the Pedroni and Westerlund test statistics.

The group-mean tests of the Westerlund (2007) approach can be obtained by the following three steps: First equation (3) is estimated by least squares for each cross-sectional unit i. This leads to

$$\Delta y_{it}=\widehat{\delta}_i^{'} d_t+\widehat{\alpha}_i y_{i,t-1}+\widehat{\lambda}_i^{'} x_{i,t-1}+\sum_{j=1}^{p_i}\widehat{\alpha_{ij}}\Delta y_{i,t-j}+\sum_{j=-q_i}^{p_i}\widehat{\gamma_{ij}}\Delta x_{i,t-j}+\widehat{e_{it}}\ , \qquad (4)$$

where a caret $\hat{}$ reflects estimated parameters. Note that p_i and q_i which determine the lag and lead orders, respectively, are allowed to vary across individuals. By estimating equation (3) $\widehat{e_{it}}$ and $\widehat{\gamma_{ij}}$ are obtained. In a second step we compute

$$\widehat{u_{it}}=\sum_{j=-q_i}^{p_i}\widehat{\gamma_{ij}}\Delta x_{i,t-j}+\widehat{e_{it}}\ .$$

Based on $\widehat{u_{it}}$ and Δy_{it}, the usual Newey and West (1994) long-run variance estimators $\widehat{\omega_{ui}}$ and $\widehat{\omega_{yi}}$, respectively, can be constructed. These estimators are then used to obtain $\widehat{\alpha}_i(1) = \widehat{\omega_{ui}}/\widehat{\omega_{yi}}$. In the third and last step the group-mean tests are computed as follows:

$$G_\tau=\frac{1}{N}\sum_{i=1}^{N}\frac{\widehat{\alpha}_i}{SE(\widehat{\alpha}_i)}, \qquad G_\alpha=\frac{1}{N}\sum_{i=1}^{N}\frac{T\widehat{\alpha}_i}{\widehat{\alpha}_i(1)}\ ,$$

where $SE(\widehat{\alpha}_i)$ represents the usual standard error of $\widehat{\alpha}_i$.

The panel tests are also computed in three separate steps. Similar to the group-mean tests, the first step is to regress Δy_{it} and $y_{i,t-1}$ on d_t, the lagged values of Δy_{it}, and the contemporaneous and lagged realizations of Δx_{it}. Following this procedure, the projection errors can be obtained

$$\Delta\widetilde{y_{it}} = \Delta y_{it} - \widehat{\delta}_t^{'} d_t - \widehat{\lambda}_i^{'} x_{i,t-1} - \sum_{j=1}^{p_i} \widehat{\alpha_{ij}} \Delta y_{i,t-j} - \sum_{j=-q_i}^{p_i} \widehat{\gamma_{ij}} \Delta x_{i,t-j} \ ,$$

and

$$\widetilde{y_{i,t-1}} = y_{i,t-1} - \widetilde{\delta}_i^{'} d_t - \widetilde{\lambda}_i^{'} x_{i,t-1} - \sum_{j=1}^{p_i} \widetilde{\alpha_{ij}} \Delta y_{i,t-j} - \sum_{j=-q_i}^{p_i} \widetilde{\gamma_{ij}} \Delta x_{i,t-j} \ .$$

By using the values for $\Delta\widetilde{y_{it}}$ and $\widetilde{y_{i,t-1}}$, the common error-correction parameter, α, and its standard error are estimated in a second step.

$$\widehat{\alpha} = \left(\sum_{i=1}^{N} \sum_{t=2}^{T} \widetilde{y_{i,t-1}^2} \right)^{-1} \sum_{i=1}^{N} \sum_{t=2}^{T} \frac{1}{\widehat{\alpha}_i(1)} \widetilde{y_{i,t-1}} \Delta\widetilde{y_{it}} \ .$$

The standard error of $\widehat{\alpha}$ is given by

$$SE(\widehat{\alpha}) = \left((\widehat{S_N^2})^{-1} \sum_{i=1}^{N} \sum_{t=2}^{T} \widetilde{y_{i,t-1}^2} \right)^{-1/2} \quad \text{where} \quad \widehat{S_N^2} = \frac{1}{N} \sum_{i=1}^{N} \widehat{S_i^2} \ .$$

Now suppose $\widehat{\sigma_i}$ denotes the estimated regression standard error in equation (4). Then $\widehat{S_i}$ is defined as $\widehat{\sigma}_i / \widehat{\alpha}_i(1)$.

The last step consists of computing the panel statistics as

$$P_\tau = \frac{\widehat{\alpha}}{SE(\widehat{\alpha})}, \qquad P_\alpha = T\widehat{\alpha} \ .$$

To account for cross-sectional dependency within the panel, a bootstrap approach based on Chang (2004) can be applied. The method consists of the following steps.

First, the least-squares regression is fitted,

$$\Delta y_{it} = \sum_{j=1}^{p_i} \widehat{\alpha_{ij}} \Delta y_{i,t-j} + \sum_{j=-q_i}^{p_i} \widehat{\gamma_{ij}} \Delta x_{i,t-j} + \widehat{e_{it}} \ . \qquad (5)$$

By using the results of (5), the vector $\widehat{\omega_t} = (\widehat{e_t'}, \Delta x_t')'$ can be computed. Here $\widehat{e_t}$ and Δx_t are vectors which contain stacked observations on $\widehat{e_{it}}$ and Δx_{it}, respectively. In the next step bootstrap samples $\omega_t^* = (e_t^{*'}, \Delta x_t^{*'})'$ are generated by sampling with replacement the centered residual vector,

$$\widetilde{\omega_t} = \widehat{\omega_t} - \frac{1}{T-1}\sum_{j=1}^{T}\widehat{w_j} \ .$$

Then the bootstrap sample Δy_{it}^* is generated. This is done by first computing the bootstrap values of the composite error term, u_{it}, via

$$u_{it}^* = \sum_{j=-q_i}^{p_i}\widehat{\gamma_{ij}}\Delta x_{i,t-j}^* + e_{it}^* \ .$$

$\widehat{\gamma_{ij}}$ is obtained by the least-squares regression of equation (5). For a set of p_i initial values, Δy_{it}^* can then be generated recursively from u_{it}^* as follows:

$$\Delta y_{it}^* = \sum_{j=1}^{p_i}\widehat{\alpha_{ij}}\Delta y_{i,t-j}^* + u_{it}^* \ .$$

Once again $\widehat{\alpha_{ij}}$ results from the estimation of equation (5). In the final step y_{it}^* and x_{it}^* are generated as

$$y_{it}^* = y_{i0}^* + \sum_{j=1}^{t}\Delta y_{ij}^*, \qquad x_{it}^* = x_{i0}^* + \sum_{j=1}^{t}\Delta x_{ij}^* \ .$$

This step requires initiation through x_{i0}^* and y_{i0}^* which will be set to zero for simplicity. Following this method step by step leads to the bootstrap sample y_{it}^* and x_{it}^* and to the bootstrapped error-correction test of interest. Let t_1^* denote the initial bootstrap test. By repeating this procedure S times, one will obtain $t_1^*, ..., t_S^*$, which represents the boostrap distribution of the test. The null hypothesis is then rejected if the calculated sample value of the statistic is smaller than the critical value of a lower quantile (e.g. 1%) of the bootstrap distribution.

The Pedroni and Westerlund panel cointegration tests will be applied for testing the presence of a long-run relationship between inequality and household debt.

4 Data and unit root tests

The underlying panel of the study consists of nine industrialized countries: Australia, Canada, France, Great-Britain, Italy, Japan, Norway, Sweden and United States. The baseline dataset covers the period from 1953 to 2008. Nevertheless, due to data limitations some series are not available for all cross-sectional units or just for a shorter time span. The main data of this study are income inequality and household debt. As indicators for income inequality four different time series are used: the top 1% income share, the inverted Pareto-Lorenz coefficient, the labor income share and the Gini index. The top 1 % income share and the inverted Pareto-Lorenz coefficient are taken from the World Top Incomes Database (Atkinson et al., 2011), while the Gini index data come from the University of Texas Inequality Project (Galbraith and Kum, 2004). In his study, Leigh (2007) showed that there exists a significant relationship between top 1% income shares and alternative inequality measures, such as the Gini coefficient. The inverted Pareto-Lorenz coefficient measures the ratio between the average income $y^*(y)$ of individuals with income above threshold y and the threshold y (Atkinson et al., 2011). Additionally, the value of the inverted Pareto-Lorenz coefficient does not depend on the threshold y. That is, if the coefficient equals two, the average income of individuals with income above \$100,000 is \$200,000 and the average income of individuals with income above \$1 million is \$2 million. Intuitively, a higher inverted Pareto-Lorenz coefficient leads to a fatter upper tail of the income distribution. Data on the labor share of incomes are provided by the Organisation for Economic Co-operation and Development. While the top 1% income share, inverted Pareto-Lorenz coefficient and Gini index measure income distributions between persons or households, the labor income share indicates the distribution between the two factors capital and labor.

As an indicator for household debt we use series on the outstanding amount of credit to private households and non-profit institutions serving households offered by the Bank for International Settlements (BIS). These series measure credit to the household sector and therefore are a more precise indicator for household debt than the bank loans variable offered by Schularick and Taylor (2012) which also includes bank loans to the business sector. However, for most of the countries included in the sample, the BIS data cover only a relatively short time-span (early 1970s to 2007). Therefore, the loans series from Schularick and Taylor (2012) which is available for a longer time horizon will also be considered as a second indicator for household debt. Nevertheless, in order to accurately test for a long-run relationship between inequality and household debt, the BIS credit series will be of primary importance in the following. There are few yearly observations missing within the dataset, which are replaced by averages of the values preceding and following the missing observations.

Figure 1 presents the time series of sample averages of the yearly growth rate of log of real household debt per capita based on the BIS dataset and on real loans per capita calculated from the Schularick and Taylor (2012) data. To obtain real variables, household credit as well as total bank loans are deflated by the Consumer Price index also included in the Schularick and Taylor (2012) dataset. As can be seen, at cyclical frequencies, both series move together and are strongly correlated (the overall correlation coefficient equals 0.63 and is highly significant). This observation suggests, while the BIS credit series more precisely measures credit to private households, the total bank loans variable by Schularick and Taylor (2012) follows a similar growth pattern over time.

[FIGURE 1 about here]

Figure 2 shows the series of the mean of the log of real household credit per capita and the mean of the different inequality measures. Differences in the pattern of real household credit per capita between the graphs are due to data limitations as some series are not available for all cross-sectional units or just for a shorter time span. Real household credit per capita increased steadily over the whole observation period. During the period 1953 to 1980 the share of top 1% income share and the inverted Pareto-Lorenz coefficient decreased, but after 1980 both variables grow considerably indicating an increasing income disparity. While the labor income share shows a decreasing pattern from 1953 to 2008, the Gini index increased over the period of interest. At least for the years 1980 to 2008, all inequality measures grew at a similar pace to household debt. When comparing the evolutions of the different inequality series to the total bank loans variable, similar patterns can be observed.

[FIGURE 2 about here]

4.1 Unit root tests on bounded variables

In order to study whether there exists a cointegration relationship between inequality and household debt both variables should mimic a unit root process, which is non-mean reverting. Clearly, it does not make much sense to model the data generating process for variables like the top 1% income share, labor income share and Gini index as pure unit root processes, since ultimately these variables are bounded between the values zero and 100. It is well known that a unit root process crosses any finite bound with probability one (Jones, 1995). To overcome this dilemma, in the empirical literature it is preferred to think of the unit root process as a feature which describes the local behavior of the bounded series within the sample (e.g. Pedroni, 2007; Herzer and Vollmer, 2012; Guest and Swift, 2008; Young and Dove, 2013; Jones, 1995; Malinen, 2012; Francis and Ramey, 2005; Hurlin, 2010). Consequently, the unit root process is not seen as a global property but rather as a valid approximation of the underlying bounded time series. As pointed out by Pedroni (2007), if the determining factors of these bounded variables, such as taste, time preferences, and government policies, change over time, the series will show permanent movements that can be well described by a unit root process.

Following this line of reasoning Pedroni (2007), Young and Dove (2013), Francis and Ramey (2005), Jones (1995) and Hurlin (2010) do not reject the unit root hypothesis for several bounded variables such as investment shares, unemployment rates, bank reserve ratios, government shares of output, hours per capita, and tax rates. Herzer and Vollmer (2012), Guest and Swift (2008) and Malinen (2012) used unit root tests for studying the local behavior of different inequality measures for several countries and finally treat these series as non-stationary.

By following the mentioned empirical literature, we will approximate persistent changes in the top 1% income share, labor share of income and Gini index within the sample as unit root processes. It seems reasonable to assume that the behavior of the bounded variables can be mimicked by a unit root data generating process (Francis and Ramey, 2005). This is done by applying two conventional panel unit root tests on the underlying inequality time series: the Fisher type ADF test by Maddala and Wu (1999) and the Pesaran (2007) test. While the Maddala and Wu (1999) test belongs to the so-called first generation panel unit root tests, the test developed by Pesaran (2007) is a second generation panel unit root test (Breitung and Pesaran, 2005). The Maddala and Wu (1999) test allows for heterogeneity in the autoregressive coefficient of the Dickey-Fuller regression but ignores cross-section dependence in the data. In contrast, the Pesaran (2007) test assumes individual unit root processes but also allows for cross-section correlation in the underlying sample.

4.2 Unit root test results

Table 1 presents results of the two panel unit root tests on the six variables of interest. All tests include individual constants and time trends. For all series the null hypothesis of unit root can not be rejected when the variables are measured in levels. In contrast, when first differences are used the Maddala and Wu test rejects the unit root hypothesis at the 1% level for all series. According to the Pesaran test statistics, first differences of the loans, top 1% income share and Gini series, reject the null hypothesis at the 1% level, while first differenced series on credit, inverted Pareto-Lorenz coefficient and, labor share of income can be approximated as trend-stationary processes at the 5% level. Thus, the test results do not differ significantly when cross-sectional correlation is taken into account as for the Pesaran test or not as the Maddala and Wu test does. Given the panel unit root test results we conclude that both credit variables as well as the four inequality series are integrated of order one. This finding is a first prerequisite for applying cointegration tests.

[TABLE 1 about here]

5 Cointegration test results

According to the unit root tests reported in Table 1, stochastic trends drive the times series of both debt series and of all four inequality measures. In a next step, it will be tested if there exists a stationary linear combination between the nonstationary household debt and inequality variables, i.e. if the series are cointegrated. Two panel cointegration tests will be used, where the first one is the panel cointegration test by Pedroni (1999, 2004) and the second is the cointegration test developed by Westerlund (2007). As described earlier, the biggest difference between these tests is that while Pedroni's test assumes an uncorrelated residual structure, the Westerlund test allows for cross-sectional dependency.

For the Pedroni test, we will just report the test results applying the augmented Dickey and Fuller (ADF) principle, because, as shown in Wagner and Hlouskova (2010), those test statistics are least affected by (short-run) cross-sectional correlation and in addition show good small sample properties. For the Westerlund test all four test statistics will be presented.

The model for testing for cointegration between inequality and household debt is:

$$\log(\textit{real credit per capita})_{it} = \delta_i^{'} d_t + \beta_i \textit{inequality}_{it} + e_{it} \ , \qquad (6)$$

where the level of real credit per capita is explained by the level of inequality, and $(1 - \beta_i)$ is the country-specific cointegration vector between credit and inequality. Due to heterogeneity of the data, individual constants and time trends are included in d_t. Real credit is either measured via real credit to private households from the BIS series or via real bank loans included in the Schularick and Taylor (2012) dataset. Inequality is measured by the top 1% income share, the inverted Pareto-Lorenz coefficient, the labor income share and the Gini index, respectively. Results of the panel cointegration tests based on specification (6) are reported in Table 2.

The upper part of Table 2 presents the results of cointegration tests based on the Pedroni (1999, 2004) ADF test statistics. While the panel ADF statistics assume a common autoregressive coefficient, group ADF statistics allow for individual specific autoregressive coefficients. Weighted panel ADF statistics refer to statistics weighted by country-specific long-run conditional variances.

19 out of the 24 test statistics reject the null hypothesis of no cointegration between real credit per capita, measured as real credit to private households or real bank loans, respectively, and one of the four inequality series considered at the 10% level. Even at the 5% significant level, 16 out of the 24 test statistics reject the no cointegration hypothesis. When real credit to private household is used as dependent variable, the null hypothesis can be rejected at the 10% level for 10 out of the 12 test statistics. However, the hypothesis of no cointegration between real credit to private households per capita and the inverted Pareto-Lorenz coefficient can only be rejected for the group ADF statistics which allows for individual specific autoregressive coefficients. Given that real bank loans are considered as measure for credit, the null hypothesis is rejected in nine out of the 12 cases. None of the Pedroni ADF statistics reject the no cointegration

hypothesis between real bank loans per capita and labor share of incomes at common significant levels.

The lower part of Table 2 reports the test results based on Westerlund's (2007) panel cointegration test which explicitly allows for cross-sectional correlation within the panel. p-values for the cointegration tests are calculated by bootstrap methods, where 800 replications are used. For each possible cointegration relationship two group mean tests ($G\tau$, $G\alpha$) and two panel tests ($P\tau$, $P\alpha$) as proposed by Westerlund (2007) are shown. While the group mean specifications test the null hypothesis of no cointegration against the alternative hypothesis of cointegration for at least one cross-sectional unit, the panel unit root statistics test no cointegration against the hypothesis of cointegration for all members of the panel.

When allowing for cross-sectional dependency the test statistics mainly support the hypothesis of cointegration between credit per capita and inequality. Thus, 26 out of the 32 test statistics reported reject the no cointegration hypothesis at the 10% level. When real credit to private households per capita is considered as dependent variable, the null hypothesis can be rejected at the 10% level for 12 out of the 16 test statistics. If, in contrast, real bank loans per capita are considered as endogenous, 14 out of the 16 test statistics reject the no cointegration hypothesis. Cointegration between both real credit per capita measures and income disparity is present for all four inequality series considered here.

[TABLE 2 about here]

When taking the Pedroni as well as the Westerlund cointegration results together, 47 out of the 56 test statistics calculated find that inequality and real credit per capita are cointegrated of order one at the 10% level. 26 out of the 32 panel test statistics and 19 out of the 24 group-mean test statistics reject the no cointegration hypothesis at the 10% significant level. There are no significant differences whether real credit to private households or real total bank loans is used as measure for real credit. This finding seems surprising as it implies that including credit to the business sector in the household debt variable does not lead to different results when investigating the existence of a long-run relation between household leverage and income inequality. Explaining this strong connection between total bank loans and household credit could be the subject of future research. The test results also indicate that cointegration is present for all four inequality series considered here. Therefore, one can conclude that there exists a long-run relationship between inequality and credit per capita, i.e. that both variables have a long-run steady-state relation. This relation is present for different measures of real credit per capita and alternative inequality indicators. The reported results are in line with those by Malinen (2013) and do support the existence of a long-run relationship between inequality and household debt modeled in Kumhof and Rancière (2010) and Iacoviello (2008).

6 Conclusion

Several recent studies have assessed the relationship between income inequality, household debt and the outburst of a financial crisis (e.g. Atkinson and Morelli, 2011; Rajan, 2010). Although in theoretical works by Kumhof and Rancière (2010) and Iacoviello (2008), rising income inequality leads to an increase in household debt, there is only a small literature testing for this relationship empirically. By studying the effect of changes in income inequality on bank loans growth, Bordo and Meissner (2012) find that rises in top income shares are no significant determinant in explaining credit booms. Similar Atkinson and Morelli (2011) conclude that there is no causal relationship between rising income inequality and economic crises. However, both studies do not investigate whether there exists a relation between the levels of income inequality and credit or economic crises, respectively. Moreover, the models developed by Kumhof and Rancière (2010) and Iacoviello (2008) explicitely use a connection between levels of income inequality and household debt. Therefore, the results by Bordo and Meissner (2012) and Atkinson and Morelli (2011) should not be seen as a rejection for the inequality/credit/crisis nexus hypothesized by Rajan (2010) and modeled by Kumhof and Rancière (2010) and Iacoviello (2008).

By applying panel cointegration techniques, we study whether there exits an empirical long-run relation between the levels of income inequality and household debt. We use two different measures for household debt; the private household credit series offered by the BIS and the broader total bank loans series which also includes loans to the business sector and is available from the Schularick and Taylor (2012) dataset. Additionally, four alternative inequality indicators are considered; the top 1% income share, the inverted Pareto-Lorenz coefficient, the Gini index and the labor share of income. In testing for a cointegrated relationship between inequality and household debt, the Pedroni (1999, 2004) and Westerlund (2007) panel cointegration tests are applied. While the Pedroni test does not allow for cross-sectional correlation, a bootstrapped version of the Westerlund test makes inference under cross-sectional dependence possible.

47 out of the 56 test statistics calculated reject the null hypothesis of no cointegration at the 10% significant level. The results show no significant differences whether the household credit or total bank loans series is used as dependent variable. Additionally, the test results are robust to all four inequality measures considered. Therefore, it seems reasonable to conclude that there exists a long-run relationship between income inequality and leverage in developed economies which is in accordance with the theories by Kumhof and Rancière (2010), Rajan (2010) and Iacoviello (2008). Our results coincide with that of Malinen (2013) who finds that the top 1% income share and bank loans are cointegrated of order one.

Finally, the results by Bordo and Meissner (2012) may be considered as biased as they use first differenced variables hence remove the long-run trend and mainly focus on the short-term effects of changes in inequality on credit growth. Following this consideration, the finding by Bordo and Meissner (2012) is in line with Iacoviello (2008), who points out that in the short-run there is no significant relation between income inequality and household debt. At cyclical frequencies, economic activity can account for the short-run changes in household debt. In contrast, the finding by Iacoviello (2008) that the trend increase in debt is attributed to the rise in income inequality is supported by our panel cointegration results. Therefore, the cointegration approach which allows to use levels of the variables of interest seems to be more appropriate to test for the inequality-credit relation than using growth rates as done in Bordo and Meissner (2012).

In future work we aim to consistently estimate the long-run effect of inequality on household debt. This will allow us to precisely quantify the impact of rising income disparity on household debt observed in most developed economies over the last decades.

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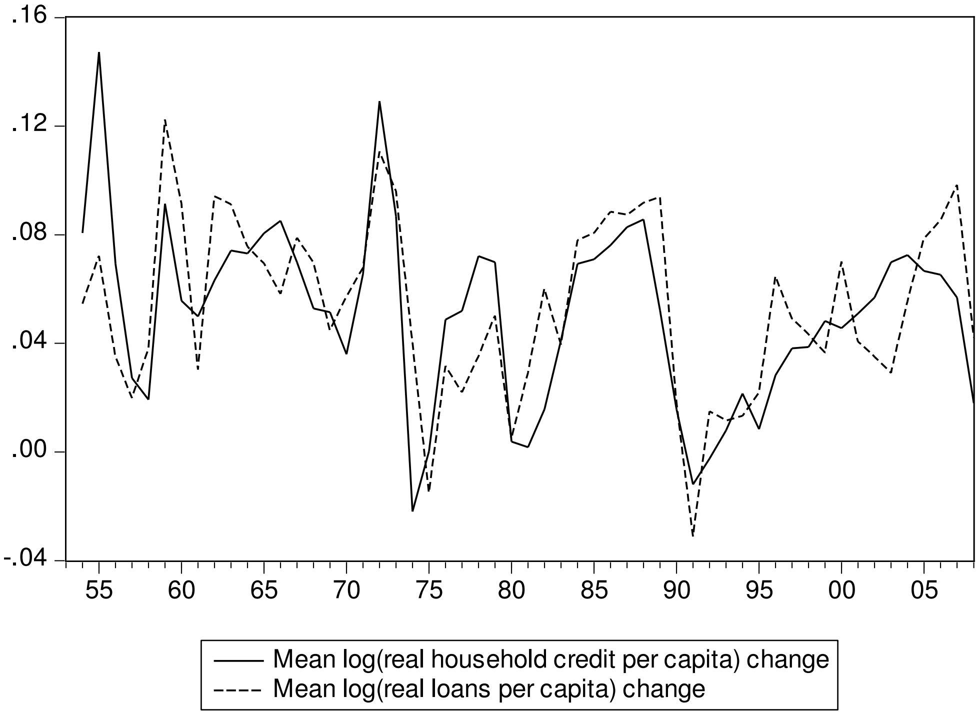
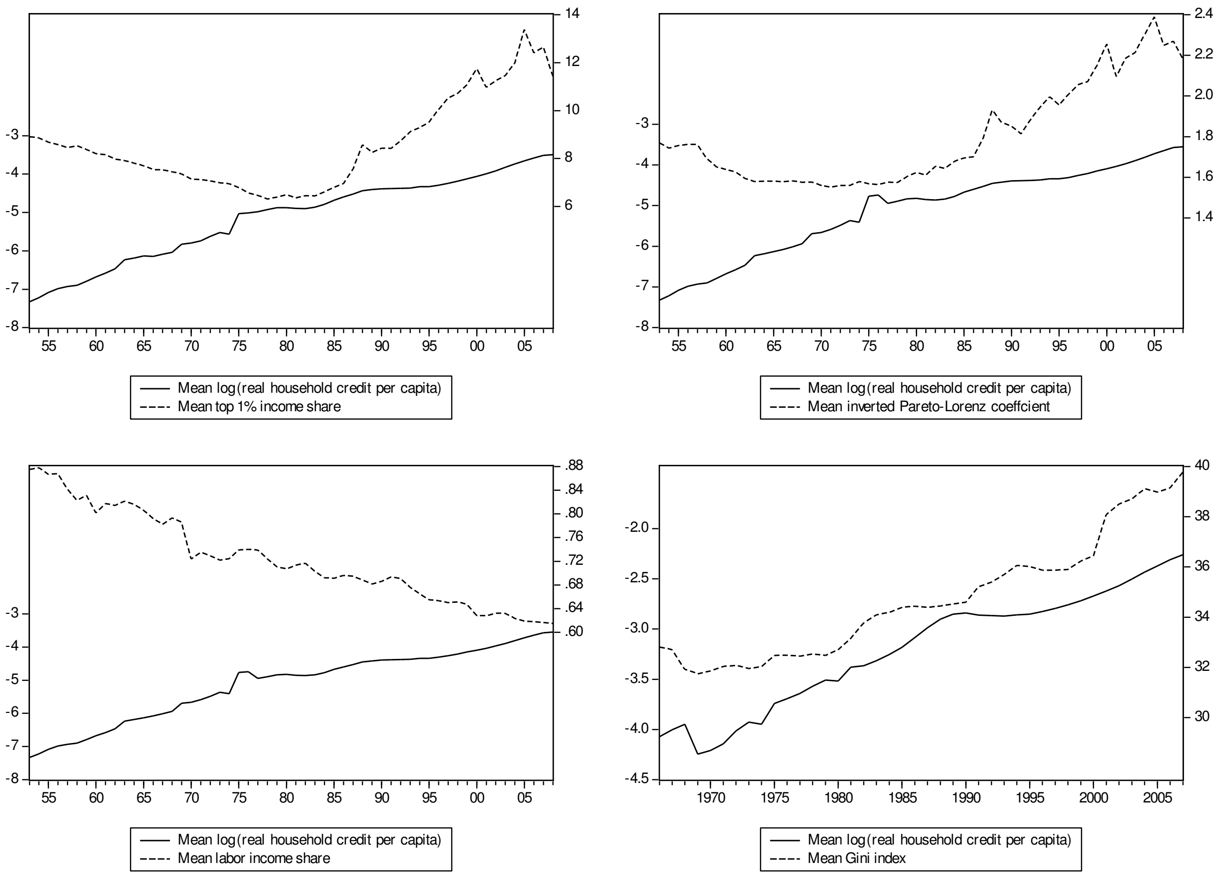
Figure 1: Household debt and bank loans



Sources: Bank for International Settlements; Schularick and Taylor (2012).

Figure 2: Private household debt (left scale) and inequality (right scale)



Sources: Bank for International Settlements; Schularick and Taylor (2012); Atkinson et al. (2011); Organisation for Economic Co-operation and Development; Galbraith and Kum (2006).

Table 1: Panel unit root tests

	Levels		First differences	
Variable	Maddala/Wu	Pesaran	Maddala/Wu	Pesaran
Credit	16.02	1.03	40.67***	-1.61**
Loans	17.27	1.58	82.25***	-6.87***
Top 1%	6.58	-1.17	55.72***	-4.51***
Ilc	8.26	-0.63	70.47***	-1.75**
Labor share	14.47	0.36	54.06***	-1.93**
Gini	17.59	0.32	58.89***	-4.41***

"Credit" stands for the log of real credit to private households per capita, "Loans" for the log of real total bank loans per capita, "Top 1%" for top 1% income share, "Ilc" for inverted Pareto-Lorenz coefficient, "Labor share" for labor share of income and "Gini" for Gini index. All tests include individual constants and time trends. The underlying sample consists of nine countries and covers the period from 1953 to 2008. Due to data limitations some series are not available for all cross-sectional units or just for a shorter time span. The null hypothesis is that the variable has a unit-root. Lag length were determined by the Akaike information criterion. *** Rejection at the 1% significant level; ** Rejection at the 5% significant level.

Table 2: Panel cointegration test statistics

Pedroni ADF statistics

Dependent variable	Credit				Loans			
Exogenous variable	Top 1%	Ilc	Labor share	Gini	Top 1%	Ilc	Labor share	Gini
Panel ADF stat	-2.14**	-0.54	-2.06**	-2.72***	-1.97**	-2.59***	-1.01	-1.35*
weighted	-2.32***	-0.99	-2.19***	-2.71***	-2.03**	-3.04***	-0.75	-1.28*
Group ADF stat	-2.25***	-1.89**	-1.29*	-3.91***	-1.85**	-2.52***	0.39	-1.68**

Westerlund test statistics

Dependent variable	Credit				Loans			
Exogenous variable	Top 1%	Ilc	Labor share	Gini	Top 1%	Ilc	Labor share	Gini
Gτ	-2.89*	-2.86**	-2.96**	-2.25*	-2.99*	-3.06**	-3.29***	-2.77*
Gα	-12.65	-11.66	-11.04	-8.83**	-13.80**	-13.98*	-11.32	-15.06**
Pτ	-5.84*	-7.88**	-7.07*	-5.32*	-6.86**	-7.44***	-7.15*	-6.41
Pα	-12.13	-12.37*	-11.17*	-6.53*	-13.50**	-14.13***	-12.85*	-14.88**

"Credit" stands for the log of real credit to private households per capita, "Loans" for the log of real total bank loans per capita, "Top 1%" for top 1% income share, "Ilc" for inverted Pareto-Lorenz coefficient, "Labor share" for labor share of income and "Gini" for Gini index. All tests include individual constants and time trends. Weighted refers to statistics weighted by country-specific long-run conditional variances. Gτ and Gα represent group mean tests, while Pτ and Pα show panel tests. The underlying sample consists of nine countries and covers the period from 1953 to 2008. Due to data limitations some series are not available for all cross-sectional units or just for a shorter time span. The null hypothesis is that the variables are not cointegrated. Lag and lead length were determined by the Akaike information criterion. *** Rejection at the 1% significant level; ** Rejection at the 5% significant level; * Rejection at the 10% significant level.