Does income inequality contribute to credit cycles?

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Abstract

Recent literature has presented arguments linking income inequality on the financial crash of 2007 - 2009. One proposed channel is expected to work through bank credit. We analyze the relationship between income inequality and bank credit in panel cointegration framework, and find that they have a *long-run* dependency relationship. Results show that income inequality has contributed to the increase of bank credit in developed economies after the Second World War.
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Keywords: top 1% income share, bank loans, cointegration

1 Introduction

Historically the most prominent factor behind financial crises has been the abnormal growth of bank credit or leverage (Gorton 2012; Schularik and Taylor 2012). After the financial crisis of 2007-2009, the relation between income inequality and financial crises has also become under scrutiny. Rajan (2010) argues

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that rising inequality in developed economies caused redistribution in the form of subsidized housing finance, which led to a boom in mortgages and later to a crash with known consequences. Iacoviello (2008) shows that income inequality was the main driver of increasing household debt in the United States during the 1980s and 1990s using a simulated theoretical model. Kumhof and Rancière (2010) argue in their theoretical model that there is a a long-run relationship between inequality and credit, where higher inequality leads to higher level of bank loans. Inequality raises the indebtedness of middle-income and poor households as a result of consumption smoothing. This article shows that there is a long-run *steady-state* relationship between income inequality and bank loans in developed economies, where inequality leads to higher levels of bank credit.

In a recent article, Bordo and Meissner estimate the effect of change in income inequality on the growth of bank loans and find "very little evidence linking credit booms and financial crises to rising inequality" (Bordo and Meissner 2012, p. 2148). Atkinson and Morelli (2011) find that there seems to be only an ambiguous causal relation of changes in income inequality on economic crises. Atkinson and Morelli (2011, p. 48) 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) refer to the hypothesis, where banks take higher risks in extent to higher income inequality through securitization. But, the level of income inequality also plays a role in the model by Kumhof and Rancière (2010). In the model investors (the top 5% of income earners) own the whole stock of physical capital and derive their income from the physical capital and from interest on loans to workers. The bargaining power between investors and workers determines the distribution of income in the economy. In this setup, decrease in the bargaining power of workers leads to higher income inequality by lowering the wages of workers, which induces higher lending from investors as they have surplus funds to invest. The more the real income of the workers drops, the more they have to borrow to maintain their level of consumption. This creates a *trending* relation between income inequality and bank credit, where higher income income inequality leads to higher levels of credit. However, income inequality tends to grow very rapidly in the face of the decreasing bargaining power of workers, whereas leverage, or the debt-to-real income ratio of workers tends to grow more steadily. The process of leveraging is gradual because borrowing matches the decreasing real income of workers as they do not increase their consumption, but just try to maintain their original level consumption. That is why short-run changes in income inequality may not have an effect on the growth of bank credit. What matters for bank credit is the long-run, trending relationship between credit and income inequality.[1]

The analysis of this possible long-run relationship is complicated by the fact that bank loans tend to grow over time, whereas the generally used measures of income inequality, like the top 1% income share, are bounded from above. This creates a problem, because it is not possible for something that is not trending to have a long-run *equilibrium* relation with something that is upward trending, in the first two moments at least. There are two ways around this problem: the trending series can be detrended or it can be bounded using some suitable transformation. Detrending of the series is problematic, because it will remove the very thing under interest, that is, the trend. Fortunately, there is a natural candidate by which the series can be transformed. The top 1% income share measures the share of national income concentrated on the hands of the highest percentile of income

[1] See Perugini *et al.* (2013) for a thorough discussion about the theoretical linkages between income inequality and financial stability.

earners. As GDP is, in practice, the national income of a country, the share can be presented as $\frac{\text{income of the top 1\%}}{\text{GDP}}$. Therefore, it would be natural to convert bank loans the same way, i.e., $\frac{\text{bank loans}}{\text{GDP}}$. This transformation would make the measures comparable, as both would be expressed as a percentage of total income, or GDP, without removing the possible long-run relationship that may exist between inequality and credit. As explained above, household leverage is modeled as workers debt-to-income ratio in the theoretical model by Kumhof and Rancière (2010). Thus, credit-to-GDP ratio is also a more accurate statistical approximation of the measure of leverage used by Kumhof and Ranciére than the level or the first difference of bank credit.

In this article, we test and estimate the relationship of income inequality and credit as ratios to real GDP. We use data on the income share of top 1% income earners and bank loans on eight developed economies. Results indicate that both the top 1% income share and the share of credit are driven by stochastic trends. The two series are also found to be cointegrated of order one implying that they have a long-run *equilibrium* relation. The long-run elasticity of the share of bank loans with respect to income inequality is estimated with panel DSUR and it is found to be positive. Top 1% income share is also found to predict the share of credit, but not the other way around, using a Granger non-causality test.

The rest of the paper is organized as follows. Section 2 presents the data and gives the results of panel unit root tests. Results of estimations, cointegration and Granger non causality tests are reported in section 3, and section 4 concludes.

2 Data and unit root tests

The annual data on bank loans include end-of-year amount of lending by domestic banks to domestic households and nonfinancial corporations in domestic currency excluding lending within the financial system (Schularik and Taylor 2012). Banks are defined as monetary institutions and they include savings banks, postal banks, credit unions, mortgage associations, and building associations. The data on bank loans comes from the dataset of Schularik and Taylor (2012).

We use the top 1% income share of the population to proxy the income inequality. Leigh (2007) has demonstrated that the top 1% income share series have a high correlation with other measures of income inequality, like the Gini index, which makes the series a comparable measure of income inequality. The data on top income share is obtained from the World Top Income Database (Atkinson *et al.* 2011). In addition to income concentration we use several macroeconomic aggregates attributed as factors behind credit growth as control variables. These include real GDP per capita, investments as a share of GDP, short-term interest rates, and broad money (M2) as a share of GDP (Bordo and Meissner 2012; Borio and White 2003; Mendoza and Terrone 2008). The data on investment as a share of GDP, short-term interest rates, and broad money (M2) as a share of GDP is obtained from the dataset of Schularik and Taylor (2012). The data on real GDP is taken from the Maddison dataset of the Groningen Growth and Development Centre.

Leverage is modeled as a debt to real income ratio in the theoretical model by Kumhof and Rancière (2010). Thus, to test the hypotheses by Kumhof and Ranciere, we use bank loans to real GDP as our dependent variable. Descriptive statistics of the data are presented in Appendix I.

Due to limitations of the data on top 1% income share, we are able to construct a balanced panel on eight countries.[2] The baseline dataset spans from 1959 to 2008, whereas the dataset including short-term interest rate spans from 1972 to

[2]Countries included in the panel are: Australia, Canada, France, Japan, Norway, Sweden, the United Kingdom and the United States.

2008. Figure 1 presents the time series of the share of credit to real GDP and the mean of the top 1% income share in our data. Figure shows a roughly similar

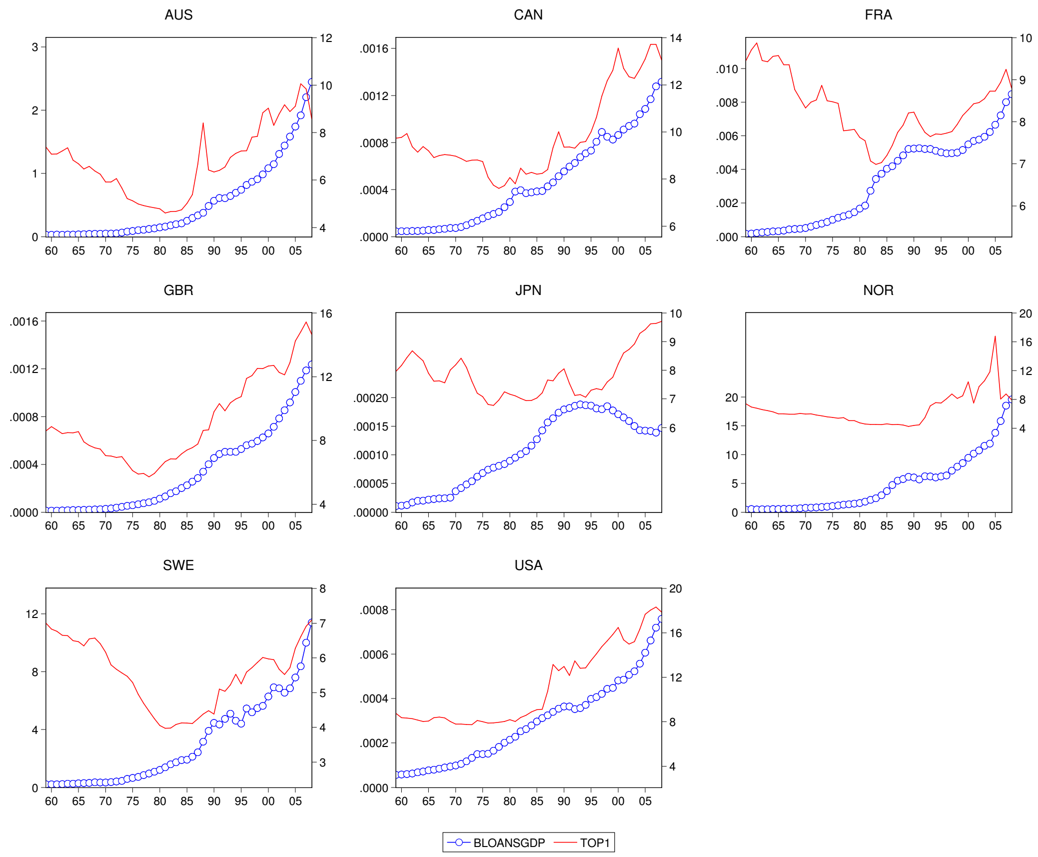

Figure 1. Shares of bank loans to real GDP and the top 1% income share in eight developed economies. Sources: Atkinson *et al.* (2011); Schularik and Taylor (2012).

pattern in all eight countries. During the period of 1959-1980 the share of income of the top 1% decreased, but at the same time the share of bank loans increased, although only marginally. During that period income inequality decreased the most in Sweden and in France. After 1980 the share of income earned by the top 1% and the share of bank loans to real GDP grew at a very similar pace in all countries. This period after 1980 gives some evidence in favor of the level hypothesis stating that bank credit is increased with inequality. During this period bank loans diminished only in Japan, which suffered from a decade long recession that began in 1991. Because of the country related heterogeneity, the best way to analyze the possible relationship between the two variables is to test are the different trend processes driven by the same factor(s).

The data on bank loans is extremely heterogeneous, as described by Schularik and Taylor (2012). Credit, money and banking institutions differ profoundly across countries and in some cases historical data on credit covers only commercial banks. As Schularik and Taylor, we tackle the issue of heterogeneity by using country-related constants. There are few yearly observations missing from the top 1% income share data, which we replace by averages of the values preceding and following the missing observation.

We start by testing the time series properties of the data. As the time series extent of the data (50 annual observations) is too short for a country related time series testing, we use two sets of panel unit root tests to test for the possible stochastic trends. The first two are the so called first-generation tests, by Im et al. (2003) (IPS) and the Fisher type ADF test by Maddala and Wu (1999). These tests assume that there is no cross-sectional correlation between the units of the panel. The second generation panel unit root tests by Pesaran (2007) and Phillips and Sul (2003) allow for cross-sectional correlation within the panel. In all tests the null hypothesis is that the series is trend-stationary. A more detailed introduction on the used tests is provided in the Appendix II. Table 1 presents the results of panel unit root tests for the six included variables.

According to results presented in table 1, all panel unit root tests find the share of credit to real GDP to be an unit root process, i.e., tests cannot reject the null hypothesis of an unit root. Three out of four tests find the top 1% income share and the share of broad money to GDP to be unit root processes. Two out of the

Table 1: Panel unit root tests

variable	IPS	ADF	PS	Pesaran
credit/RGDP	2.973	7.157	5.908	2.135
	(0.998)	(0.970)	(0.969)	(0.984)
top 1%	3.075	3.631	8.470	-3.891
	(0.999)	(0.997)	(0.863)	(<.001)
investments/GDP	-3.077	36.646	14.978	-1.792
	(0.001)	(0.002)	(0.380)	(0.037)
M2/GDP	3.543	8.127	25.954	-0.629
	(0.999)	(0.945)	(0.026)	(0.265)
ln(real GDP per capita)	-1.947	27.268	11.772	-0.833
	(0.0258)	(0.0386)	(0.625)	(0.203)
short term interest rate*	-2.880	34.090	40.484	-.866
	(0.002)	(0.005)	(0.002)	(0.002)

In the unit root tests, the tested model is: $\triangle y_{it} = \rho_i y_{i,t-1} + \delta_i + \eta_i t + \theta_t + \epsilon_{it}$, and $H_0 : \rho = 0$. The p-values of the test statistics are presented in parentheses. All other test are done with the eight country panel ranging from 1959 to 2008, except tests for short term interest rates are done with a panel with yearly observations from 1972 to 2008.

four tests find the real GDP per capita to be an unit root process and one out of the four tests find the share of investments to GDP to be an unit root process. According to all tests, the short-term interest rate is a trend-stationary process.[3]

3 Cointegration test and estimations

3.1 Panel cointegration testing

According to unit root tests presented in table 1, stochastic trends would drive the time series of the top 1% income share and the share of credit to real GDP. Next we test if the stochastic trends are linear combinations of one and another, that is, we test are the series cointegrated. To this end, we use two panel cointegration tests

[3]According to all second generation panel unit root tests, the first differences of log of credit to real GDP, top 1% income share, investments to GDP, money to GDP and GDP per capita are trend-stationary. Results are available upon request.

proposed by Pedroni (2004) and by Banerjee and Carrion-i-Silvestre (2011) (from now on BC). The biggest difference between these tests is that while Pedroni's test assumes uncorrelated residual structure, BC's test allows for cross-sectional correlation through common factors and it also controls for possible structural breaks in the cointegration relation. Appendix III gives more detailed description of the used tests.

The model for testing for cointegration between inequality and credit is:

$$credit/RGDP_{it} = \alpha_i + \gamma_i top1\%_{it} + \epsilon_{it}, \tag{1}$$

where the level of bank loans are explained by the level of inequality, and $(1, -\gamma_i)$ is the country-specific cointegration vector between bank loans and the top 1% income share. Under the null hypothesis $\gamma_i = 1 \; \forall \; i$ implying that variables are not cointegrated. We include individual constants due to heterogeneity of the data on bank loans discussed in the previous section. Results of panel cointegration tests based on the model (1) are presented in table 2.[4] 15 out of the 19 test statistics in table 2 find that the series of top 1% income share and credit to real GDP are cointegrated of order one at the 5% significance level. Results presented in the last four rows give some indication that deterministic trends may need to be incorporated in the estimated model. Still, the overall conclusions from cointegration tests is clear: the top 1% income share and credit to real GDP seem to be cointegrated indicating that the two series have a long-run *steady-state* relation.

3.2 Estimations

First differencing of cointegrated variables removes stochastic trends and eliminates the long-run dependency between the variables. What remains is a short-run

[4]The Pedroni's test was conducted with Eviews 6 and B&C's test was done with Gauss. We are grateful to Carrion-i-Silvestre for providing the program code.

Table 2: Panel cointegration test statistics for credit/RGDP and top 1% income share

Pedroni tests		
Within-dimension	Constants	Constants
panel v-statistic	-0.898	-1.392
	(0.267)	(0.1512)
panel ρ-statistic	2.112	2.444
	(0.043)	(0.020)
panel PP-statistic	3.606	3.604
	(<.001)	(<.001)
panel ADF-statistic	4.0827	3.529
	(0.001)	(<.001)
Between-dimension	Constants	
group ρ-statistic	3.059	
	(0.004)	
group PP-statistic	4.483	
	(<.001)	
group ADF-statistic	4.549	
	(<.001)	
BC tests		
	Constants	Trends
$Z_{\hat{t}_{NT}}(\hat{\lambda})$	2.900	-2.185
	(0.998)	(0.015)
$Z_{\hat{\rho}_{NT}}(\hat{\lambda})$	1.616	-5.806
	(0.947)	(<.001)
	Constants, ci. vector shift	Trends, ci. vector shift
$Z_{\hat{t}_{NT}}(\hat{\lambda})$	-3.164	-1.896
	(<.001)	(0.029)
$Z_{\hat{\rho}_{NT}}(\hat{\lambda})$	-11.88	-6.929
	(<.001)	(<.001)

The null hypothesis is that the variables are not cointegrated. In the test by Pedroni, lag length were determined with the Akaike information criterion. *Constants* states that individual constants were used in the test, and *trends* that individual constants and trends were used in the test. Tests with level and cointegration vector shifts allow for structural breaks to occur in the country-specific cointegration relations.

relation, which may or may not exist. To test for this, we first estimate a model where the variables are first differenced. More precisely, we estimate a model:

$$\Delta credit/RGDP_{it} = \alpha_i + \beta_1 \Delta top_{i,t-1} + \beta_2 \Delta ln(RGDP)_{i,t-1} \tag{2}$$
$$+\beta_3 \Delta investments/GDP_{i,t-1} + +\beta_4 \Delta M2/GDP_{i,t-1} + \beta_5 \Delta stir_{i,t-1} + u_{it},$$

where α_i are individual constants and u_{it} is the idiosyncratic error term. Explanatory variables are lagged with one period to control for the possible endogeneity of regressors. Results reported in table 3 indicate that income inequality would

Table 3: Regression results using first differenced variables

Dependent variable: Δ(credit/RGDP)		
	FE-OLS	FE-OLS
Δtop 1_{t-1}	-0.0004	-0.0019
	(0.0010)	(0.0029)
Δln(real GDP per capita)$_{t-1}$	-0.0069	0.1611
	(0.0049)	(0.1105)
Δinvestments/GDP$_{t-1}$	0.0419*	0.3944
	(0.0165)	(0.2479)
ΔM2/GDP $_{t-1}$	0.0077	0.0255
	(0.0060)	(0.0253)
Δshort term interest rate$_{t-1}$	-	0.0799
		(0.1332)
countries	8	8
years	1960-2008	1972-2008
observations	384	280

Estimations are done with country fixed-effects and White's heteroskedasticity-consistent standard errors are presented in parentheses.

not have a statistically significant short-run effect on credit. In the estimation presented in the last column, none of the parameter estimates of the explanatory variables is statistically significant at the 5% level.

The picture somewhat changes, when the levels of credit to real GDP and top 1% income share are used. In this case, we use panel DSUR (dynamic seemingly unrelated regressions) estimator by Mark *et al.* (2005) to estimate the cointegration coefficient of top 1% income share using a model:

$$credit/RGDP_{it} = \alpha_i + \gamma' top1_{it} + \beta_p \mathbf{X}_{it} + \theta_t + u_{it}, \tag{3}$$

where α_i are individual constant, θ_t is the common time effect, $(1, -\gamma')$ is the cointegrating vector between bank loans and top 1% income share, $\mathbf{X_{it}}$ is the matrix of additional explanatory variables, and u_{it} is the idiosyncratic error. As the panel DSUR does not allow for cointegration between explanatory variables, all the other explanatory variables, besides top 1% income and short term interest rates, are first-differenced.[5] The panel DSUR estimator by Mark *et al.* (2005) controls for the possible endogeneity or the reverse causality of explanatory variables by including the leads and lags of the first differences of the explanatory variables in the estimated equation. Panel DSUR also allows for cross-sectional dependence.[6] More information about the panel DSUR can be found in Appendix IV.

Table 4 presents the results of panel DSUR estimations on equation (3) using the dataset spanning from 1959 to 2008.[7] First differences of the GDP per capita and shares of M2 and investment to GDP are included as additional explanatory variables.

According to the results presented in table 4, the cointegration coefficient of top 1% income share is positive and highly statistically significant.[8] The value of the cointegrating coefficient varies from around 0.12 to around 0.35. From the control variables GDP per capita growth and change in the level of money have

[5]There is no need to take the first difference of the short term interest rate, as all the panel unit root tests presented in table 1 found the series to be trend-stationary.

[6]In the reported panel DSUR estimates a long-run covariance matrix is used, which actually makes panel DSUR more efficient when cross-sections are dependent.

[7]DSUR estimations were done with Gauss. We are grateful to Donggyu Sul for providing the program code in his homepage.

[8]We also estimated a model including deterministic trends, but the main results did not change. Results are available upon request.

Table 4: DSUR estimates, 1959-2008

Dependent variable: credit/RGDP			
top 1%	0.281***	0.117***	0.348***
	(0.0219)	(0.0182)	(0.0048)
Δln(real GDP per capita)	-	-0.103	0.226***
		(0.0719)	(0.0869)
Δinvestment/GDP	-	-	-0.8614***
			(0.1746)
Δmoney/GDP	-	-	0.381***
			(0.0534)
countries	8	8	8
years	1959-2008	1959-2008	1960-2008
observations	400	400	392

* = p<.05, ** = p<.01, *** = p<.001. Standard errors are presented in parentheses. All DSUR estimations include individual constants and common time effects. First, second and third leads and lags of the first differences are used as instruments for the explanatory variables.

expected positive and statistically significant signs. The coefficient of investments as a share of GDP has an unexpected negative and statistically significant sign. However, this may be due to the possible correlation between investments and interest rate. Higher demand for investments may increase the short term interest rates, but higher interest rates are likely to diminish the demand for bank loans and investments. Therefore, the negative effect of interest rates to bank loans may be reflected to investments.[9]

Table 5 presents the results of panel DSUR estimations on model 3 using the dataset spanning from 1972 to 2008.[10] In addition to first differences of the GDP per capita, M2 share to GDP and investment share to GDP, short-term interest rate

[9] Correlation between short term interest rates and investments as a share of GDP is indeed positive and highly statistically significant. Results are available upon request.

[10] This is the period that Schularik and Taylor (2012, p. 1031) describe as a "era of unprecented leverage and risk" because the level of credit in developed economies surpassed pre-war levels around 1970 and trended up rapidly after that.

in levels is included as an explanatory variable.[11]

Table 5: DSUR estimates, 1972-2008

Dependent variable: credit/RGDP			
top 1%	0.212***	0.0264***	0.159***
	(0.0355)	(0.0023)	(0.0308)
Δln(real GDP per capita)	-	-0.302	0.395
		(0.2167)	(0.5739)
Δinvestment/GDP	-	-	-0.6754
			(0.3611)
Δmoney/GDP	-	-	-0.5923*
			(0.2355)
short term interest rate	-	-	-0.706***
			(0.1527)
countries	8	8	8
years	1972-2008	1972-2008	1972-2008
observations	296	296	296

* = p<.05, ** = p<.01, *** = p<.001. Standard errors are presented in parentheses. All DSUR estimations include individual constants and common time effects. First leads and lags of the first differences are used as instruments for the explanatory variables.

According to the results of table 5, the cointegrating coefficient of top 1% income share is positive and highly statistically significant. The first differences of money share to GDP and the short-term interest rate have statistically significant negative parameter estimates. The negative effect of short-term interest rate to ratio of bank loans to real GDP is expected, as higher interest rates make borrowing more expensive. The negative parameter estimate of the share of M2 to GDP, on the other hand, is likely to result from reverse causality. That is, as bank loans increase, money held in deposit accounts (etc.) decreases, which will decrease the broad money in circulation.[12]

[11]DSUR estimations were done with Gauss. We are grateful to Donggyu Sul for providing the program code in his homepage.

[12]We also estimated a model including deterministic trends, but the main results did not change. Results are available upon request.

3.3 Granger causality tests

Roine *et al.* (2009) have shown that financial development, measured as the share of bank deposits and stock market capitalization, can have an effect on the income of the top 1%.[13] If the same applies to bank credit, there would be a reverse effect from credit to income inequality. Panel DSUR estimator by Mark *et al.* (2005) controls for this possible endogeneity by including the leads and lags of the explanatory variables to the estimated model. The drawback of this method is that it is sensitive to the selection of leads and lags. If some or all of the explanatory variables are endogenous, and if the number of leads and lags has not been sufficient to eliminate the correlation between them and the error term, estimates will not be asymptotically unbiased.

Testing for this possible bias without strictly exogenous instruments is difficult. However, Granger non-causality test can be used to assess whether income inequality helps to forecast the share of credit and *vice versa*. Although this is not an actual test for causality, it will show the direction of the flow of statistical (predictive) information, which can be used to assess whether there are reasons to suspect a reverse effect or causality running from bank credit to income inequality.

We use the Granger non-causality test by Emirmahmutoglu and Kose (2011) developed for heterogeneous cointegrated panels. It conducts N separate time series tests and then calculates Fisher test statistics by Fisher (1932) using the obtained individual p-values. Cross-sectional correlation is controlled by using bootstrap method for obtaining the empirical distribution of the Fisher statistic and associated critical values. Table 6 presents results for Granger non-causality test between the share of bank credit to RGDP and top 1% income share.[14]

[13] See also D'Onofrio and Murro (2013).

[14] Testing was carried out with Matlab. We are grateful to Furkan Emirmahmutoglu for providing the program in runmycode.org.

Table 6: Tests for Granger non causality between credit/RGDP and the top 1% income share

X	Y	Fisher statistic	5%	1%
credit/RGDP	top 1%	31.07	34.52	44.17
top 1%	credit/RGDP	62.54	33.25	42.36
countries	8			
years	1959-2008			
observations	384			

The null hypothesis is that X does not Granger cause Y. Lag lengths were determined using Akaike information criterion. The empirical distribution and the critical values based on the Fisher statistics were generated using 10000 bootstrap replications.

According to the results presented in table 6, there is no information on the share of credit to real GDP series that would help to forecast the top 1% income share series at the 5% level of significance. However, the information contained into the top 1% income series does help to forecast the share of credit to RGDP with 1% level of significance. Results thus indicate that the flow of information would run from income inequality to bank credit. This diminishes the endogeneity problem and shows that the estimation results presented in previous section are not driven by mere statistical correlation. That is, results indicate that income inequality has a positive long-run effect on the share of credit to real GDP.

4 Conclusion

Schularik and Taylor (2012, p. 1031) have described the period after the Second World War as the "age of unprecedented risk and leverage". Iacoviello (2008) shows that income inequality has contributed to the rise of household debt in the United States during this era. Kumhof and Rancière (2010) argue that there is a more general, long-run relationship between these variables, where income inequality will lead to increasing leverage in the economy. In this study, we have tested the existence of such a long-run relationship.

According to our results, there is a long-run *steady-state* relationship between income inequality and bank credit in developed economies. The long-run elasticity of credit with respect to income inequality was found to be positive. Income inequality was also found to have a one-way Granger causality relationship to bank credit. These results indicate that income inequality has contributed to the increase of leverage in accordance with the theories by Iacoviello (2008), Kumhof and Rancière (2010), and Rajan (2010).

Due to the pioneering nature of these findings, directions of future research are ample. The analysis presented herein concentrated on developed economies, but the relationship between inequality and credit may differ, for example, in developing economies. More importantly, future research should include the examination of the effect of income inequality on the probability of financial crises.[15] By disentangling the effect of income inequality and credit as predictors of financial crises, the channels through which income inequality may increase the probability of crises would be made clearer. Future research will also define the possible need of equalization of the distribution of income as a mean for achieving financial stability.

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APPENDIX I: Descriptive statistics

Table 7: Descriptive statistics

variable	mean	std. deviation	min.	max.
credit/RGDP	1.046	2.675	0.00004	19.578
top 1%	8.165	2.660	3.970	18.333
investments/GDP	0.227	0.0466	0.153	0.363
M2/GDP	0.945	1.944	0.00006	11.039
ln(real GDP per capita)	9.638	0.373	8.176	10.343
short term interest rate*	0.071	0.0379	0.0001	0.183

Countries included are: Australia, Canada, France, Japan, Norway, Sweden, the United Kingdom and the United States. Data is in annual time series ranging from 1959 to 2008, except data on short term interest rates which ranges from 1972 to 2008.

APPENDIX II: Panel unit root tests

All the used tests allow for individual unit root processes. That is, they allow the coefficient of unit root to differ across countries.

The traditional panel unit root tests, are based on the following regression:

$$\triangle y_{it} = \rho_i y_{i,t-1} + \eta_i t + \alpha_i + \theta_t + \epsilon_{it}, \tag{4}$$

where α_i are individual constants, $\eta_i t$ are individual time trends, and θ_t are the common time effects. The tests rely on the assumption that $E[\epsilon_{it}\epsilon_{js}] = 0 \ \forall \ t, s$ and $i \neq j$, which is required for calculating common time effects. Thus, if the different series are correlated, the last assumption is violated.

The second generation test is based on the regression

$$\triangle y_{it} = \rho y_{i,t-1} + \eta_i t + \alpha_i + \delta_i \theta_t + \epsilon_{it}, \tag{5}$$

where α_i are the individual constants, $\eta_i t$ are the individual time trends, and θ_t is the common time effect, whose coefficients, δ_i, are assumed to be non-stochastic, measure the impact of the common time effects of series i, and ϵ_{it} is assumed to be normally distributed with mean zero and variance of σ^2 and independent of ϵ_{js} and θ_s for all $i \neq j$ and s, t. Cross-sectional dependence is allowed through the common time effect, which generates the correlation between cross-sectional units. The matrix δ_i gives the non-random factor loading coefficients that determine the extent of the cross-sectional correlation.

The null hypothesis in all tests is that $\rho_i = 0 \ \forall \ i$, i.e. that the process in $I(1)$ nonstationary. The alternative hypotheses are:

$$H_1 : \rho_i < 0, \quad i = 1, 2, ..., N_1, \quad \rho_i = 0, \quad i = N_1 + 1, N_1 + 2, ..., N. \tag{6}$$

For consistency of panel unit root tests it is also required that, under the alternative, the fraction of the individual processes that are stationary is non-zero, formally $lim_{N\to\infty}(N_1/N) = \gamma$, $0 < \gamma \leq 1$ (Im et al. 2003).

Appendix III: Panel cointegration tests

Panel cointegration test developed by Banerjee and Carrion-i-Silvestre (2011) is based on the normalized bias and the pseudo t-ratio test statistics by Pedroni (2004). The data generating process behind Pedroni's test statistics is given by:

$$y_{it} = f_i(t) + x'_{it} + e_{it},$$

$$\triangle x_{it} = v_{it}, \tag{7}$$

$$e_{it} = \rho_i e_{i,t-1} + \epsilon_{it} \zeta_{it} = (\epsilon_{it}, v_{it})',$$

where $f_i(t)$ includes member specific fixed effects and deterministic trends.

The data generating process is described as a partitioned vector $z'_{it} \equiv (y_{it}, x_{it})$ where the true process is generated as $z_{it} = z_{i,t-1} + \zeta_{it}$, $\zeta'_{it} = (\zeta^y_{it} \zeta^X_{it})$ (Pedroni 2004). $\frac{1}{\sqrt{T}} \sum_{t=1}^{[Tr]} \zeta_{it}$ is assumed to converge to a vector Brownian motion with asymptotic covariance of Ω_i as $T \longrightarrow \infty$. The individual process is assumed to be $i.i.d.$ so that $E[\zeta_{it} \zeta'_{js}] = 0 \ \forall s, t, i \neq j$.

Let $\hat{e}_{it}$ denote the estimated residuals of obtained from (7) and $\hat{\Omega}_i$ the consistent estimator of Ω_i. The two test statistics can now be defined as :

$$\tilde{Z}_{\hat{\rho}_{NT}-1} \equiv \sum_{i=1}^{N}\left(\sum_{t=1}^{T}\hat{e}_{i,t-1}^{2}\right)^{-1}\sum_{t=1}^{T}(\hat{e}_{i,t-1}\Delta\hat{e}_{it}-\hat{\lambda}_i),$$

$$\tilde{Z}_{\hat{t}_{NT}}^{*} \equiv \sum_{i=1}^{N}\left(\sum_{t=1}^{T}\hat{s}_i^{*2}\hat{e}_{i,t-1}^{*2}\right)^{-1/2}\sum_{t=1}^{T}(\hat{e}_{i,t-1}^{*}\Delta\hat{e}_{it}^{*}),$$

where $\hat{\lambda}_i = 1/T\sum_{s=1}^{k_i}(1-s/(k_i+1))\sum_{t=s+1}^{T}\hat{\mu}_{it}\hat{\mu}_{i,t-s}$, $\tilde{\sigma}_{NT}^2 \equiv 1/N\sum_{i=1}^{N}\hat{L}_{11i}^{-2}\hat{\sigma}_i^2$, $\hat{s}_i^{*2} \equiv 1/t\sum_{t=1}^{T}\hat{\mu}_{it}^{*2}$, $\tilde{s}_{NT}^{*2} \equiv 1/N\sum_{i=1}^{N}\hat{s}_i^{*2}$, $\hat{L}_{11i}^2 = 1/T\sum_{t=1}^{T}\hat{\vartheta}_{it}^2+2/T\sum_{s=1}^{k_i}(1-s/(k-i+1))\sum_{t=s+1}^{T}\hat{\vartheta}_i,\hat{\vartheta}_{i,t-s}$. The residuals $\hat{\mu}_{it}$,$\hat{\mu}_{it}^{*}$ and $\hat{\vartheta}_{it}$ are attained from regressions: $\hat{e}_{it} = \hat{\gamma}\hat{e}_{i,t-1}+\hat{\mu}_{it}$, $\hat{e}_{it} = \hat{\gamma}_i\hat{e}_{i,t-1}+\sum_{k=1}^{K-i}\hat{\gamma}_{ik}\Delta\hat{e}_{i,t-k}+\hat{\mu}_{it}^{*}$, $\Delta y_{it} = \sum_{m=1}^{M}\hat{b}_{mi}\Delta x_{mi,t} = \hat{\vartheta}_{it}$. (Pedroni 1999, 2004)

The statistics pool the between dimension of the panel and they are constructed by computing the ratio of the corresponding conventional time series statistics and then by computing the standardized sum of the N time series of the panel. Pedroni (1999, 2004) shows that under the null of no cointegration the asymptotic distributions of the two statistics presented above converge to normal distributions with zero mean and variance of one as N and T sequentially converge to infinity.

Banerjee and Carrion-I-Silvestre (2006) extend the model by Pedroni (2004) to include common factors:

$$\begin{aligned} y_{i,t} &= f_i(t)+x_{i,t}'+u_{i,t}, \\ \triangle x_{i,t} &= v_{i,t}, \\ f_i(t) &= \mu_i+\beta_i t \\ u_{it} &= F_t'\pi_i+e_{it}, \end{aligned} \tag{8}$$

where $e_{i,t} = \rho_i e_{i,t}+\epsilon_{i,t}$ and F_t':s are the common factors which are used to account for the possible cross-sectional dependence.

APPENDIX IV: Panel DSUR estimator

The data generation process in Mark *et al.* (2005) DSUR estimator is of the form

$$y_{it} = \alpha_i + \lambda_i t + \theta_t + \beta' x_{it} + u_{it}, \tag{9}$$

$$\triangle x_{it} = e_{it} \tag{10}$$

where there are n cointegrating regression each with T observations, $(1 - \beta')$ is the cointegration vector between y_{it} and x_{it}, and x_{it} and e_{it} are $k \times 1$ dimensional vectors. Panel DSUR eliminates the possible endogeneity between explanatory variables and the dependent variable by assuming that u_{it} is correlated at most with p_i leads and lags of $\triangle x_{it}$ (Mark *et al.* 2005). The possible endogeneity can be controlled by projecting u_{it} onto these p_i leads and lags:

$$u_{it} = \sum_{s=-p_i}^{p_i} \delta'_{i,s} \triangle x_{i,t-s} + u_{it}* = \delta'_i z_{it} + u^*_{it}. \tag{11}$$

The projection error u^*_{it} is orthogonal to all leads and lags of $\triangle x_{it}$ and the estimated equation becomes:

$$y_{it} = \alpha_i + \lambda_{it} + \theta_t + \beta' x_{it} + \delta_i z_{it} + u^*_{it}, \tag{12}$$

where $\delta'_i z_{it}$ is a vector of projection dimensions. Panel DSUR estimates a long-run covariance matrix that is used in estimation of equation (9). This makes panel DSUR more efficient when cross-sections are dependent. The efficiency of panel DSUR actually improves as the correlation between cross-sections increases. Asymptotics properties of the estimator are based on $T \longrightarrow \infty$ with N fixed.