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Structure of Income Inequality and Household Leverage: Theory and Cross-Country Evidence

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Highlights

- We extend the theoretical framework by Kumhof et al. (2015) to show that most of the predicted positive impact of inequality on credit should be driven by the share of income owned by middle classes.
- The model is brought to the data using a 44 countries dataset over the period 1970-2012, and a new instrumental variable (the total number of ILO conventions signed at the country-level) to identify exogenous variations of inequality.
- We support a positive impact of inequality concentrated on household leverage, mostly driven by middle classes, rather than low-income households.
- Consistently, our results hold mostly for developed countries.

Abstract

How do income inequality and its structure affect the volume of credit? We extend the theoretical framework by Kumhof et al. (2015) to distinguish between upper, middle and low-income classes, and show that most of the positive impact of inequality on credit predicted by Kumhof et al. (2015) should be driven by the share of total output owned by middle classes. These theoretical predictions are empirically confirmed by a study based on a 44 countries dataset over the period 1970-2012. Exogenous variations of inequality are identified with a new instrument variable, the total number of International Labor Organization conventions signed at the country-level. Using various indicators of inequality, we support a positive impact of inequality concentrated on household leverage, and investigate how this average impact is distorted along income distribution. Consistently with the theoretical setting, our results tend to show that most of the impact is driven by middle classes, rather than low-income households. Consistently, our results hold mostly for developed countries.

Keywords

Credit, Finance, Income Inequality, Inequality structure.

JEL

D31, E25, E44, G01.

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RESEARCH AND EXPERTISE
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Structure of Income Inequality and Household Leverage: Theory and Cross-Country Evidence[1]

Rémi Bazillier * and Jérôme Hericourt † and Samuel Ligonniere‡

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1. Introduction

It has only been recently (less than a decade) that academic attention has been paid to the regular rise in both income and wealth inequalities. In this context, Atkinson, Piketty and Saez (see Piketty, 2003, Piketty, 2014 or Atkinson et al., 2011) have made seminal contributions emphasizing the rise in the top income, and the concentration of wealth over the past 30 years, in developed but also in some emerging economies. Stiglitz (2012) warned of the huge cost of rising inequality in the US. Less expected has been the direct, causal relationship between those rising inequalities, the excess leverage of low- and middle-income households, and the financial crisis increasingly advocated by academic economists at the beginning of 2010. Debate entered the public sphere based on Rajan (2010)'s and Galbraith (2012)'s arguments that rising income inequality forced low- and middle-income households to increase their indebtedness in order to maintain their consumption levels.

Since then, this relationship has been the focus of a burgeoning academic literature. On the conceptual side, van Treeck (2014) and Bazillier and Hericourt (2017) survey different potential theoretical channels through which a rise in income inequalities[2] may endogenously have triggered an expansion of credit. An important issue relates to the type of income shock at stake. If income shocks are *transitory* and the volatility of transitory income is increasing (reflecting higher income inequalities in the short run), smoothing consumption through credit may be a rational answer for consumers facing a negative income shock. It is the theoretical framework chosen by Krueger and Perri (2006), Krueger and Perri (2011) or Iacoviello (2008) to analyze the link between inequalities and leverage or between income and consumption inequalities. But if income shocks are *permanent*, Piketty and Saez (2013) argue that households should adjust their consumption accordingly. If it is not the case, for instance if households cannot completely adjust their consumption to their income because of a too large welfare loss induced by such a consumption cut (Bertrand and Morse, 2013), the increase in leverage might lead to financial instability and possibly financial crises. Evidence from various countries tend to show that the rise of inequalities is more likely to be explained

[2] Consistently with the literature and the mechanisms at stake, in the remainder of the paper, inequality will refer to income inequality.

by permanent shocks.[3] Consistently with these stylized facts pointing to permanent income shocks associated with a long-term increase in between-group inequality, Kumhof et al. (2015) provide a formal discussion within a DSGE model relying on inequalities between household groups, and where a more unequal income distribution leads to higher leverage of low- and middle-income households; calibrated on US data, the framework replicates fairly well the profiles of the income distribution and the debt-to-income ratio for the three decades preceding the Great Recession.

On the empirical side, literature has also been scarce, and to some extent inconclusive. Based on quarterly US data from 1980 to 2003, Christen and Morgan (2005) find evidence consistent with a positive impact of inequality on household indebtedness, triggered by an increase in credit demand from individuals. Based on data of individual mortgage applications, still from the US, Coibion et al. (2014) find that low-income households in high-inequality regions borrowed relatively less than similar households in low-inequality regions. However, they do find a significant impact of the level of income on debt accumulation in both regions. On a cross-country-perspective, Bordo and Meissner (2012) rely on a panel of 14 mainly advanced countries for 1920 to 2008 to study the determinants of total bank credit growth using macroeconomic variables and the level of inequality measured by the 1% top income share. They find no significant relation between inequality and credit growth. However, based on a sample of 18 OECD countries over the period 1970-2007, Perugini et al. (2016) find very different results, concluding to a positive impact of income inequality on credit. Both studies do not use the same measure of credit (log of real bank loans to the private sector for Bordo and Meissner, 2012, credit over GDP for Perugini et al., 2016), but more importantly Perugini et al. (2016) provide an explicit treatment for the various endogeneity issues plaguing the

[3] On the US case, Kopczuk et al. (2010) show that income mobility decreased slightly since the 1950s. A decreasing social mobility is inconsistent with inequalities explained by *transitory* income shocks. Moffitt and Gottschalk (2002) and Moffitt and Gottschalk (2011) also find that the variance in transitory income declined or remained constant after 1980 unlike the variance in permanent income. Cappellari and Jenkins (2014) and Jenkins (2015a) report very similar evidence (lack of changes in social mobility over time, decrease in income volatility observed) for the UK. On a cross-country perspective, Andrews and Leigh (2009) confirm this negative link between income inequality and social mobility over a sample of 16 countries. Similar evidence of an increase in between-group inequality, reflecting permanent income shocks, has also been found in emerging countries (see Ferreira and Litchfield, 2008 on Brazil; Kanbur and Zhuang, 2014 on some Asian countries including China, and India)

relationship between inequality and credit.

These contradictory outcomes emphasize the difficulties inherent to the identification of a causal relationship between inequality and finance, due to the multiplicity of circular linkages and intertwined mechanisms - the latter are surveyed in Bazillier and Hericourt (2017).[4] Besides, the existing literature tend to focus almost only on the role of top incomes, which are opposed to a "bottom category" which actually mixed low and middle-incomes. This paper aims at filling these different gaps. We first provide an extension of Kumhof et al. (2015)'s framework, by distinguishing explicitly between low and middle-class incomes, versus top incomes. The model is then brought to the data to empirically investigate the existence of a causal relationship between inequality and the expansion of credit. As previously said, endogeneity is a major issue in the proper identification of such a relationship, as both variables are likely to be simultaneously determined by common shocks, and also due to the obvious reverse causality from finance to inequality. We propose a strategy based on variations in ratifications of International Labor Organization (ILO) at the country-level to predict exogenous changes of inequality, and estimate their effect on credit dynamics. Our approach relies on the exogeneity of the waves of ratifications at the international level in the 1970s and the 1990s, while controlling for the other standard macro determinants of credit. The strategy of ILO has changed over time. They have expanded their technical cooperation at the end of the seventies, and have adopted a strategy of active promotion of core labor standards and decent work in the nineties (see the conclusions of the Social Summit of Copenhagen in 1995 and the Declaration on Fundamental Principles and Rights at Work in 1998). Both evolutions have lead to a substantial increase in countries' ratification which is arguably orthogonal to country-specific developments. As the implementation of international labor standards has been shown to be inequality-reducing, this exogenous increase in ILO conventions' ratification allows us to identify the causal effect of inequalities on credit.

[4] They investigate various channels, which can be classified in two categories. On the one hand, demand-side arguments put emphasis on the proactive will of low/middle income household to maintain their consumption level relatively to the one of top income households. On the other hand, supply-side arguments emphasize the role of top incomes and of government, the former by savings and the latter in promoting the credit to those households with declining relative incomes.

Our empirical analysis relies on a country-level yearly dataset for 44 countries over the period 1970-2012, based on two building blocks. Income inequality data come from World Income Inequality Database (WIID). Credit (household, aggregate, firm) come from various sources, such as the Bank of International Settlements, Central banks, OECD, Datastream. In both cases, data have been cleaned and harmonized through a transparent process which is detailed in the Data section. Besides, various robustness checks are implemented in order to ensure the stability of our estimates.

We find that an exogenous increase in inequality coming from ILO ratification shocks triggers an expansion of household credit. However, we show that the size of this effect varies substantially with the structure of income inequality. Starting with the Gini index (scaled between 0 and 1), which can be understood as a synthetic measure of inequality over the whole distribution, a 0.01 point increase (a half standard deviation) is associated with a significant 3 percentage points increase in the household credit to GDP ratio. Effects differ quite substantially when we focus on specific parts of the income distribution. When inequality is measured through the Palma index, which relates the share in total income of the richest 10% with the one of the poorest 40%, a 0.1 point increase (also corresponding to a half standard deviation) lifts household credit over GDP up by 2 percentage points. Besides, and maybe more importantly, we show that a major part of the effect is driven by middle classes (defined as individuals between 50% and 70% of the income distribution): when their share in total income increases by 1 percentage point, credit to GDP decreases by 13 percentage points, whereas the same increase in low-income share only cuts credit to GDP ratio by 3 percentage points. Therefore, we provide theory-based empirical evidence that inequality is a driver of household credit, not total private credit. Besides, we show that the middle of the income distribution is the key driver of this effect at the aggregate level, much more than low incomes.

A substantial part of the paper is devoted to exploring the sensitivity of our results to robustness and falsification tests. The quantitative prevalence of middle classes in the positive link between inequality and credit is robust to various definitions of middle incomes. Consistently with theoretical intuitions, income inequality does not have any impact on the ratio of credit granted to firms over GDP. The positive impact of inequality is found again on ratios of bank credit and total credit over GDP, which is consistent with Perugini et al. (2016)'s results; however, our own findings tend to show that this results on total private credit is driven by credit to household. Besides, when we split our sample between developed and developing/emerging countries, we find that our results hold only for advanced countries, most inequality indicators displaying an insignificant impact on credit dynamics when the sample is restricted to developing countries. Once again, this is consistent with our result that most of the impact of income inequality on credit is driven by middle-class incomes. According to Kochhar (2015) who defines the middle and middle-upper classes as the group of individuals living with 10-50$ a day, they account for 15% of the population in Asia or 8% in Africa, against 60% in Europe or 39% in North America. One complementary explanation relies on financial market imperfections in developing countries. The poor and the middle income cannot respond to lower incomes by borrowing (Kumhof et al., 2012). Furthermore, our results are mostly not impacted by the dynamics arising with the financial crisis and the Great Recession of 2007-2008. Finally, we do not find any impact on average of income inequality on (the log of) real household credit, when used as a dependent variable instead of the ratio of household credit over GDP. This is interesting because it tends to support the idea that inequality has a positive impact only on the variation of credit which is not matched by a corresponding increase in potential output, i.e. the one that creates potentially an increased macroeconomic risk.

Our work has important implications regarding financial crises prevention. Indeed, there is a bunch of recent academic papers supporting that household leverage (i.e. housing credit and short-term finance) is the main driving factor of banking and financial crises (see Buyukkarabacak and Valev, 2010; Jordá et al., 2013; Jordá et al., 2015a; Jordá et al., 2015b; Mian and Sufi, 2010; Mian and Sufi, 2014).[5] In order to avoid financial crises such as the one of 2007-2008, which triggered afterwards the Great Recession, one has therefore to prevent the creation of household leverage bubbles. Our findings suggest that the reduction of inequality

[5]Using the database by Schularick and Taylor (2012) on 14 developed countries from 1870 to 2008, Kirschenmann et al. (2016) show that income inequality tends to be a better predictor of financial crises than bank loan growth. However, this does not mean inequality *directly* triggers financial crises, but merely that bank loans are not the best way to measure excessive leverage induced by income inequality. We will provide evidence throughout this paper that household credit is a more consistent and stronger candidate.

is an important prerequisite of such a policy, especially at the middle of the income distribution. Hence, an implication of our results is that middle classes drive most of the financial cycle. This is consistent with a recent literature, like e. g. Gourinchas and Rey (2016) who show that the consumption to wealth ratio predicts real interest rates movements over the long run: periods of low consumption-wealth ratios are following periods of rapid asset price increases, subsequently followed by extended periods of low real (risk-free) interest rates.[6] That is consistent with our own idea of a permanent negative (positive) income shock on middle (high) incomes, which afterwards impacts aggregate credit.

The next section presents the model and the main theoretical predictions. Section 3 presents the data and some descriptive statistics. Section 4 details our empirical methodology and our identification strategy. Section 5 reports our baseline results and a number of robustness checks and falsification tests. The last section concludes.

2. The model

Our approach extends the model by Kumhof et al. (2015). In the latter, the economy is made of two kinds of agents, top and bottom earners, corresponding roughly to the top 5% and bottom 95% in the US case. Therefore, bottom earners in Kumhof et al. (2015) involve *de facto* low and medium-income households.

Our model consists of three groups of infinitely-lived households, referred to respectively as top earners, with population share χ_T, middle-class earners with χ_M and low-income earners with χ_L. Here, an increase of inequalities could be driven by rises in both incomes of top earners z^T and middle class z^M, or the rise in only one of them. As stressed by Atkinson and Morelli (2010), there is a potential heterogeneous role of income distribution changes. The remaining part of our model follows Kumhof et al. (2015), by including endogenous and rational default decision from middle- and low-income earners.

Total aggregate output y_t follows an autoregressive stochastic process around the steady-

[6] Krishnamurthy and Muir (2016) also find that unusually low interest rate spreads, combined with unusual credit growth, are symptomatic of a credit market exuberance preceding a financial crisis.

state $\overline{y}$. The share of output received by the three groups is also an autoregressive stochastic process and we test various cases about the shift in inequalities, from one group to another one or both two groups. The model respects the following conditions:

$$\chi^T + \chi^M + \chi^L = 1 \tag{1}$$

$$z_t^T + z_t^M + z_t^L = 1 \tag{2}$$

2.1. Middle Class Households

The representative middle class earner maximizes the intertemporal utility function

$$V_t^M = \mathbb{E}_t \sum_{k\geq 0}^{\infty} \beta_M^k \left[\frac{(c_{t+k}^M)^{1-\frac{1}{\sigma}}}{1-\frac{1}{\sigma}} - \gamma \frac{(\frac{1}{\chi^M} z_{t+k}^M b_{t+k}^M)^{1-\frac{1}{\theta}}}{1-\frac{1}{\theta}} \right] \tag{3}$$

where β_M^k is the time-discount factor for middle-class earners and σ is the intertemporal elasticity of substitution. The first part of consumption preferences is the standard case of CRRA consumption preference. The second part represents the credit demand-side mechanism. γ is the weight of this effect and we assume that $\gamma > 0$. θ parameterizes the curvature of utility function with respect to this demand-side effect. If there are low inequalities, meaning a high z^M, the household is incited to sharply reduce his demand for loans. Conversely, this decreasing utility effect goes down when there are high inequalities with a low z^M. This mechanism provides a trade-off between consumption smoothing through debt and incentive effect through inequalities.

This intertemporal utility function is subject to three conditions. First, middle-class earners' budget constraint is as follows:

$$c_t^M = y_t z_t^M (1 - u_t^M) \frac{1}{\chi^M} + b_t^M p_t^M - l_t^M \tag{4}$$

The first part is the per capita income of middle class households where u^M is the fraction of middle class earners' endowment that is absorbed by a penalty for current or past defaults. The second part refers to debt flows: the household receives b_t^M and reimburses l_t from previous debt contracted in period $t-1$. These debt flows are specific to Kumhof et al. (2015): when top earners lend to middle earners, they offer p_t^M units of consumption today in exchange for 1 unit of consumption tomorrow if middle earners do not default. Similarly, when top earners lend to low-income earners, they offer p_t^L units of consumption, following the same mechanism. The smaller the amount p_t, the more expensive the implicit interest rate. The amount of debt per middle earners repaid in period t is given by:

$$l_t^M = b_{t-1}^M(1 - h\delta_t^M) \tag{5}$$

where $h \in [0, 1]$ is the haircut parameter. In case of default from bottom earners, top earners receive (1-h) units of consumption tomorrow and not 1 unit. Middle class earners maximize (3) subject to (4) and (5). Their optimal condition is as follows:

$$p_t^M = \beta_M \mathbb{E}_t \left[(\frac{c_{t+1}^M}{c_t^M})^{-\frac{1}{\sigma}}(1 - h\delta_{t+1}^M) \right] + \gamma \frac{(z_t^M \frac{1}{\chi^M})^{1-\frac{1}{\theta}}(c_t^M)^{\frac{1}{\sigma}}}{(b_t^M)^{\frac{1}{\theta}}} \tag{6}$$

This condition highlights a trade-off between costs and benefits of a marginal increase of debt. Benefits are linked to intertemporal consumption choices while costs are explained by our specific demand-side argument. The increase in borrowing leads to a higher implicit interest rate, but high inequalities dampen this effect. When z_t^M increases, meaning that inequalities around middle-incomes go down (that is, when the share of total income earned by middle-class households increases), p_t^M goes up. It means a reduction of middle class earners' demand with lower implicit interest rate. Symmetrically, an increase in inequalities implies higher implicit interest rate and consequently, higher demand for loans from middle-class earners. This demand-side argument holds only if $\theta > 1$. By comparison, Kumhof et al. (2015) provides a flat bottom earners' demand price as a function of debt, p_b.

2.2. Low-Income Households

Low-income households display the same behavior than middle-class ones. Their utility has the same functional form and the same elasticities σ and θ. The key difference is relative to the access to financial markets. Consistently, we do not assume either the same penalty for defaults u_t^L or the same discount factor for low- and middle-income[7]. Consequently, we expect potential different price and level of debt, which in turn reflect various discount factors and/or not the same trade-off about rational default decision[8].

Calculations similar as previously give this optimal condition:

$$p_t^L = \beta_L \mathbb{E}_t \left[(\frac{c_{t+1}^L}{c_t^L})^{-\frac{1}{\sigma}} (1 - h\delta_{t+1}^L) \right] + \gamma \frac{(z_t^L \frac{1}{\chi^L})^{1-\frac{1}{\theta}} (c_t^L)^{\frac{1}{\sigma}}}{(b_t^L)^{\frac{1}{\theta}}} \tag{7}$$

2.3. Top Income Households

Top earners' utility from consumption has the same functional form and has the same parameter σ. By contrast with low- and middle-income earners, top earners provide loans to these two previous groups. This financial wealth is directly incorporated into their utility function, which implies a positive marginal propensity to save out of permanent income shock, following Carroll (2000) and Kumhof et al. (2015), among others. This wealth preference alters the arbitrage between consumption and debt in favor of supplying loans to other types of households. φ^L and φ^M are the weights of wealth in utility when top earners lend to low-income and middle-income earners, respectively. η parameterizes the curvature of the utility function with respect to wealth.

$$V_t^T = \mathbb{E}_t \sum_{k \geq 0}^{\infty} \beta_T^k \left[\frac{(c_{t+k}^T)^{1-\frac{1}{\sigma}}}{1-\frac{1}{\sigma}} + \varphi^L \frac{(1 + \frac{\chi^L}{\chi^T}(b_{t+k}^L))^{1-\frac{1}{\eta}}}{1-\frac{1}{\eta}} + \varphi^M \frac{(1 + \frac{\chi^M}{\chi^T}(b_{t+k}^M))^{1-\frac{1}{\eta}}}{1-\frac{1}{\eta}} \right] \tag{8}$$

[7] We could assume that $\beta_L > \beta_M > \beta_T$ but this condition is not necessary. See Iacoviello (2005), among others.

[8] It is beyond the scope of this paper, but we can expect a higher penalty in case of default for low-income than middle-class earners.

With condition (5), we can write top earners' budget constraints as follows

$$c_t^T = y_t z_t^T \frac{1}{\chi_t} + \frac{\chi^L}{\chi^T}(b_{t-1}^L(1-h\delta_t^L) - b_t^L p_t^L) + \frac{\chi^M}{\chi^T}(b_{t-1}^M(1-h\delta_t^M) - b_t^M p_t^M) \tag{9}$$

The first part represents the per capita income of top earners. The second and third part are debt flows towards the two other household groups[9]. The first order conditions for b_t^M and b_t^L are logically close to the ones from Kumhof et al. (2015).

$$p_t^L = \beta_T \mathbb{E}_t \left[(\frac{c_{t+1}^T}{c_t^T})^{-\frac{1}{\sigma}} (1-h\delta_{t+1}^L) \right] + \varphi^L \frac{(c_t^T)^{\frac{1}{\sigma}}}{(1+\frac{\chi^L}{\chi^T} b_t^L)^{\frac{1}{\eta}}} \tag{10}$$

$$p_t^M = \beta_T \mathbb{E}_t \left[(\frac{c_{t+1}^T}{c_t^T})^{-\frac{1}{\sigma}} (1-h\delta_{t+1}^M) \right] + \varphi^M \frac{(c_t^T)^{\frac{1}{\sigma}}}{(1+\frac{\chi^M}{\chi^T} b_t^M)^{\frac{1}{\eta}}} \tag{11}$$

As suggested by Kumhof et al. (2015), these conditions reflect the trade-off between benefits and costs of acquiring an additional unit of financial wealth. They also suggest a no-arbitrage condition between loans to low-income earners and those to middle-class earners. It depends on the debt distribution among these two groups and their rational decision to default.

2.4. Equilibrium

In equilibrium the three groups maximize their respective lifetime utilities, the market for borrowing and lending clears and the market clearing condition for goods holds:

$$y_t(1 - z_t^M u_t^M - z_t^L u_t^L) = \chi^T c_t^T + \chi^M c_t^M + \chi^L c_t^L \tag{12}$$

Two properties appear in equilibrium. First, the Euler equations (6), (7), (10) and (11) can be interpreted as the price of demand and supply of these loans while keeping their consumption constant. The following condition holds:

$$l_t^i - b_t^i p_t^i = b_{t-1}^i(1-h\delta_t^i) - b_t p_t = b^i(1-p^i(b^i)) \tag{13}$$

[9] $\frac{\chi_L}{\chi_T}$ and $\frac{\chi_M}{\chi_T}$ are explained by per capita wealth transfers.

So the optimal consumption of the three groups changes with $\overline{y}$ as output in steady-state. There are given by

$$c^T = \overline{y}\overline{z^T}\frac{1}{\chi^T} + \frac{\chi^L}{\chi^T}(b^L(1-p^L(b^L))) + \frac{\chi^M}{\chi^T}(b^M(1-p^M(b^M))) \tag{14}$$

$$c^M = \overline{y}\overline{z^M}\frac{1}{\chi^M} + b^M(p^M(b^M)-1) \tag{15}$$

$$c^L = \overline{y}\overline{z^L}\frac{1}{\chi^L} + b^L(p^L(b^L)-1) \tag{16}$$

Second, as noted by Kumhof et al. (2015), *"default has negligible effect on the Euler equations in the neighborhood of the original steady state."*. Therefore, we simplify these demands and supplies to yield

$$p^L(b^L) = \beta_L + \gamma\frac{(\overline{z^L}\frac{1}{\chi^L})^{1-\frac{1}{\theta}}(c^L)^{\frac{1}{\sigma}}}{(b^L)^{\frac{1}{\theta}}} \tag{17}$$

$$p^L(b^L) = \beta_T + \varphi^L\frac{(c^T)^{\frac{1}{\sigma}}}{(1+\frac{\chi^L}{\chi^T}b^L)^{\frac{1}{\eta}}} \tag{18}$$

$$p^M(b^M) = \beta_M + \gamma\frac{(\overline{z^M}\frac{1}{\chi^M})^{1-\frac{1}{\theta}}(c^M)^{\frac{1}{\sigma}}}{(b^M)^{\frac{1}{\theta}}} \tag{19}$$

$$p^M(b^M) = \beta_T + \varphi^M\frac{(c^T)^{\frac{1}{\sigma}}}{(1+\frac{\chi^M}{\chi^T}b^M)^{\frac{1}{\eta}}} \tag{20}$$

We aim to obtain same steady state relationships as Kumhof et al. (2015). By combining (14), (16), (17) and (18), we are nearing our goal with

$$\beta_L - \beta_T = \varphi^L\frac{(\overline{y}\overline{z^T}\frac{1}{\chi^T} + \frac{\chi^L}{\chi^T}(b^L(1-p^L(b^L))) + \frac{\chi^M}{\chi^T}(b^M(1-p^M(b^M))))^{\frac{1}{\sigma}}}{(1+\frac{\chi^L}{\chi^T}b^L)^{\frac{1}{\eta}}} \tag{21}$$

$$-\gamma\frac{(\overline{z^L}\frac{1}{\chi^L})^{1-\frac{1}{\theta}}(c^L)^{\frac{1}{\sigma}}}{(b^L)^{\frac{1}{\theta}}} \tag{22}$$

Table 1 – Baseline Case

Symbol	Parameter	Value	Source
$\overline{y}$	Steady-State Output Level	1	
χ^T	Population Share of Top Income Households	0.10	Literature.
χ^M	Population Share of Middle Class Households	0.50	See Discussion.
χ^L	Population Share of Low-Income Class Households	0.40	See Discussion.
$\overline{z^T}$	Steady-State Top 10% Output Share	0.30	WIID
$\overline{z^M}$	Steady-State Middle Class Output Share	0.55	WIID
$\overline{z^L}$	Steady-State Low-Income Class Output Share	0.15	WIID
σ	IES in Consumption	0.05	Literature.
$\varphi^L = \varphi^M$	Top Income Households' Weight on Wealth in Utility	0.05	Kumhof et al. (2015)
η	Top Income Households's Wealth Elasticity	1.09	Kumhof et al. (2015)
γ	Bottom Classes Households' Weight on Demand-Side Argument	0.05	See Discussion.
θ	Bottom Classes Households' Elasticity on Demand-Side Argument	1.09	See Discussion.
β_T	Discount Factor for Top Income Households	0.92	See Discussion.
β_M	Discount Factor for Middle Class Households	0.95	See Discussion.
β_L	Discount Factor for Low-Income Class Households	0.98	See Discussion.

In a similar fashion, we obtain this relationship for middle-class loans with (14), (15), (19) and (20)

$$\begin{aligned} \beta_M - \beta_T &= \varphi^M \frac{(\overline{y}\overline{z^T}\frac{1}{\chi^T} + \frac{\chi^L}{\chi^T}(b^L(1-p^L(b^L))) + \frac{\chi^M}{\chi^T}(b^M(1-p^M(b^M))))^{\frac{1}{\sigma}}}{(1+\frac{\chi^L}{\chi^T}b^L)^{\frac{1}{\eta}}} && (23) \\ &\quad -\gamma \frac{(\overline{z^M}\frac{1}{\chi^M})^{1-\frac{1}{\theta}}(c^M)^{\frac{1}{\sigma}}}{(b^M)^{\frac{1}{\theta}}} && (24) \end{aligned}$$

Nevertheless, we cannot provide the level of debts in steady state because there are still implicit both prices. Equations (12) and (14)-(20) can solve for eight variables $\{y_t, c_t^T, c_t^M, c_t^L, b_t^L, b_t^M, p_t^L, p_t^M\}$.

2.5. Comparative Statics

We investigate the impact of shift in inequalities between low or middle-income groups on the one side and the top income group on the other side. We use the list of parameters of Table 1.

The steady-state output is normalized to one. The decomposition of bottom earners into low and middle-class incomes follow Palma (2011) and our empirical strategy. We use our inequality data from WIID in similar fashion to determine steady-state output shares for the three classes. There are obviously some differences across countries, but our parameters match

US data, following Kumhof et al. (2015).

The parameter σ determines the curvature of utility function with respect to consumption. The literature traditionally uses $\sigma = 0.5$ and so do we for all groups. The parameters φ and η calibrate the top earners' wealth preference. Kumhof et al. (2015) analyze micro-level data to determine marginal propensity to save of top 5%. By contrast, we focus on top 10% households and we do not have micro-level data to replicate their approach. Because of the same supply-side mechanism, we follow Kumhof et al. (2015) in a conservative way to preserve results comparability. One key difference with their paper is the distinction between low- and middle-class households, but we do not have any reason to believe that top earners discriminate between the two kinds of borrowers if they pay the same interest rate, so we choose to equalize φ^L and φ^M.

As far as we know, there is no consensus on the size of the demand-side mechanism. Consequently, we assume that our parameters θ and γ provide the same weight and the same curvature of the utility function of bottom earners than their supply-side counterparts in the utility function of top earners. The parameter θ is higher than 1, satisfying the condition of demand-side argument from equation (6). For the sake of simplicity, we do not distinguish these parameters across the low and middle-class.

We also follow similar time-discount factor for top earners from Kumhof et al. (2015) and we use $\beta_T = 0.92$. They replicate the steady-state debt-to-income ratio, but we do not have the amount of debt per low-income earners and per middle-class earners repaid in each period. Time-discount factors reflect impatience degree and we expect that $\beta_L > \beta_M > \beta_T$.

The baseline case provides steady-state values with strong differences across various consumers. There are different debt flows and interest rates. Credit quantity per capita and implicit interest rate are higher for low-income household than middle class household, but these values crucially depend on the calibration, notably on our time-discount factors. The first scenario is a one standard deviation increase of output share from middle class to top earners. This increase in inequality leads to a drop of output and consumption of all groups. This is only comparative statics and we cannot say anything about the transition dynamics,

Table 2 – Comparative Statics

	Baseline	Scenario 1	Scenario 2	Scenario 3	Scenario 4
		$\uparrow \overline{z^T}$	$\uparrow \overline{z^T}$	$\downarrow \overline{z^T}$	$\downarrow \overline{z^L}$
		$\downarrow \overline{z^M}$	$\downarrow \overline{z^L}$	$\uparrow \overline{z^M}$	$\uparrow \overline{z^M}$
y	0.96	0.77	0.81	1.07	0.99
c_T	3.05	2.70	2.75	3.55	3.22
c_M	1.06	0.80	0.86	1.15	1.10
c_L	0.33	0.26	0.25	0.35	0.31
b_M	1.22	1.47	1.31	2.42	1.56
b_L	1.97	1.48	1.54	2.87	2.28
p_M	0.9969	0.9725	0.9790	0.9794	0.99
p_L	0.9827	0.9823	0.9820	0.9821	0.9820

but they are consistent with Kumhof et al. (2015). Nevertheless, the channel here is not the effect of rational default from bottom earners but only due to the restriction of consumption from lower share of output for the main consumer group, that is, middle-class households. About the finance-inequality nexus, supply-side and demand-side arguments do play a role. The increase of output share of top earners increases credit supply whereas the credit demand goes up with the middle-class earners' loss. They push up credit volume addressed to this middle class and generate two opposite effects on the implicit interest rate. The decrease of p_M means an increase in implicit interest rate, so the demand effect appears higher than the other. Because of no-arbitrage condition, they also affect the volume and the interest rate for low-income borrowers. There is higher competition for loanable funds and the supply effect provides higher credit supply. At the end, the first effect is higher than the second one with an increase of their interest rate and a reduction of their actual credit.

The second scenario is a one standard deviation increase of output share from low-income class to top earners. The story is generally similar with a decrease of consumption and output. The two effects still generate some conflicting stories. Quantity of credit goes down for low-income class while this quantity for middle class goes up. Implicit interest rates for all borrowers increase, especially for middle-class. It suggests that the demand effect from the poorest household first goes through prices. The demand-effect seems to work on credit quantity for middle-class whereas this effect goes through interest rates for low-income group.

The third scenario is symmetric to the first and provides a one standard deviation increase of output share from top earners to middle class. The negative demand and supply effects clearly lead to an increase in interest rates. But this change of output shares also alters consumption behavior which in turn significantly increases consumptions and output through large credit volume.

The fourth scenario explores one standard deviation increase of output share from low-income class to middle class. It has positive effect on output and on top earners' consumption. It is a redistribution of consumption from poorest household to middle class households. This positive demand-side effect from the first and negative demand-side effect from the second sharply increases credit quantity and generates a positive pressure on interest rates.

2.6. Testable Predictions

We can derive from this short theoretical exercise two main theoretical predictions, that we will subsequently bring to the data:

Testable Prediction 1: An increase in inequality leads to an expansion on household credit at the aggregate level. This is consistent with both Kumhof et al. (2015) and our own setting.

Testable Prediction 2: The bulk of the positive impact of inequality on household credit is driven by middle classes.

3. Data

Our empirical analysis relies on a country-level yearly dataset for 44 countries over the period 1970-2012, based on two building blocks, income inequality and credit.

3.1. Inequality

The use of inequality data in cross-countries studies raises several challenges. The use of one specific index of inequality and one specific database is not neutral. Jenkins (2015b), among others, show how it can have major implications on empirical results. One contribution of this paper is to rely on several alternative indexes of inequalities focusing on different part of the income distribution. Furthermore, we apply a very rigourous process to choose the relevant primary source in order to ensure comparability among countries.

Bordo and Meissner (2012) and Perugini et al. (2016), among others, use top income shares from the World Top Income Database (WTID). This database built by Alvaredo et al. (2014) is available for 31 countries with high time coverage for some countries. It uses fiscal data and is based on *pretax* income. The main advantage of this database is that it provides much better estimates of the tail of income distribution (top 1% and beyond). However, one serious limitation is that it is based on pre-tax income and not *disposable* income. As we would like to focus on saving and borrowing behaviour of households, it represents a serious drawback as these data do not take into account the effect of fiscal redistribution on the disposable income. Also, by definition, this database only focus on top incomes. Leigh (2007) admittedly argue that "*panel data on top income shares may be a useful substitute for other measures of inequality over periods when alternative income distribution measures are of low quality, or unavailable.*" (p. 619). However, one condition has to be fulfilled: factors affecting inequalities should have an impact on both the top and the bottom of income distribution. In our case, it is unlikely to be the case. As stated by Atkinson and Morelli (2010) in the context of banking crises, "*different parts of the income distribution react differently, and the conclusions drawn regarding the origins and the impact of the crisis may depend which part of the parade we are watching. The top and the bottom may be the most affected; depending on the theoretical model adopted, either the top or the bottom may be more relevant to understand the origins of the crisis*" (p. 66). Here, our aim is to focus on the potential heterogenous role of different shocks along the income distribution on the inequality-credit relationship. Any distributional change *within* the bottom 90% will not be captured by top income share indexes.

By contrast with the literature, we consequently focus on different indexes of inequalities, namely: the Gini coefficient, the Palma Index and income shares per decile. The use of the Gini index will give a more general picture as it takes into account the whole distribution of income and not only the dynamics at both tails. We complement this by the Palma index that combines the top 10% income share with the bottom 40% income share. Palma (2011) argues that Gini is "*supposed to be more responsive to changes in the middle of the distribution. That is, the most commonly used statistic for inequality is one that is best at reflecting distributional changes where changes are least likely to occur.*" (p.105). The Palma index is therefore focusing on top income and lower income. Nevertheless, if lower incomes are highly credit-constrained, i.e., if they have a more difficult access to credit, income dynamics of the middle-class is more likely to have an effect on credit dynamics. The detailed analysis with income share per decile allows us to disentangle the specific effect of income shocks for the poorest and income shocks for the middle-class. This will allow us to test the second prediction of the theoretical model.

For the Gini index and statistics per decile, we follow Jenkins (2015b), recommending the use of the World Income Inequality Database (WIID) instead of the Standardized World Income Inequality Database (SWIID). The former has updated and extended the Deininger and Squire (1996) database and corrected some of the inconsistencies pointed out by Atkinson and Brandolini (2001, 2009). It also includes new estimates from National Survey statistics, TransMonEE (2011), the Commitment to Equity Project (CEQ) ,the Socio-Economic Database for Latin America and the Caribbean (SEDLAC, 2012), the Luxembourg Income Study, OECD and EUROSTAT. It covers 161 countries between 1867 and 2013. By comparison, the SWIID from Solt (2009) has broader coverage than the WIID, with a lower number of missing observations. We choose not to use this data, mostly because of potential problems raised by the imputation procedure that is used to fill missing data in the WIID[10].

We provide a transparent process to use WIID rigorously. The use of several data types (gross versus net income data, household versus individual income data and income versus expenditure data) may alter the comparability of the inequality measures (Atkinson and Brandolini, 2001; Jenkins, 2015b), so it is necessary to use comparable data across sources. Our rules of selection ensure high quality data within and between countries. We keep only observations with specific characteristics: they are coded as high (or medium) quality, and they concern

[10]This debate falls within the trade-off between the geographical coverage and the reliability of the data. See Jenkins (2015b) and Solt (2015).

post-tax income. They are also consistent according to the income share unit, the unit of analysis, the geographical, age and population coverages and they use similar equivalence scale. Our selection promotes the use of one unique dataset but also provides arguments in favor of some datasets mix. To ensure high quality, we generally prefer to use only one dataset.[11] In some cases, we face a trade-off between the use of one particular dataset with potential linear intrapolations and the use of multiple datasets, especially when these datasets come from the same institutions. We combine datasets if and only if the risk of structural break is very low[12]. Appendix A summarizes the primary sources used for each country. 25 percent (11 countries) of our sample use series mixing different primary sources. These are mainly countries where deciles data are missing. When we focus on deciles data, we use different primary sources only for 5 countries[13] out of 35.

3.2. Credit

By contrast with the existing works based on cross-country samples, we refer to household credit[14] but there is no unique data source according to our time and geographical coverages. Data reported by different sources may exhibit discrepancy under mutually consistent definitions. We build a general data map to ensure comparability and to achieve a reliable identification of the link between household credit and inequality.

Our main datasource for household credit is the Bank for International Settlements (BIS): Over 75% (33 countries) of household credit directly comes from BIS. The remainder of household credit data comes from Central Banks and Oxford Economics from Datastream, and has been carefully checked and harmonized (see Appendix A). Note that aggregate private credit computed by the BIS involves loans from both domestic and international financial sector. In robustness checks, we check how inequality impacts total credit to the private sector, using

[11] In some limited cases, we fill missing data by using a linear intrapolation. We use this technique only if the time span between two observations is limited.

[12] These following conditions should be met: (1) same (or very close) definition of welfare; (2) same share unit; (3) same unit of analysis; (4) same equivalence scale; (5) the Gini and deciles should follow same trends before and after the risk of structural break, (6) the Gini should be similar in the year of matching the two datasets.

[13] Italy, Netherlands, Poland, Sweden and United Kingdom.

[14] Bordo and Meissner (2012) use the log of bank credit to the private section, and Perugini et al. (2016), the ratio of total private credit to GDP.

the corresponding variable form the BIS database, and also two alternatives indexes from the World Bank (WB), which are restricted, respectively, to private credit from domestic financial sector, and from domestic banks. We also use credit granted to private firms as a falsification test, since the theoretical underlying intuitions do not imply it will be impacted by inequality.

We investigate the impact of inequality on the ratio of (household) credit of GDP, following Perugini et al. (2016). Indeed, the recent literature (see e.g. Mendoza and Terrones, 2008, Schularick and Taylor, 2012 or Atkinson and Morelli, 2015) emphasizes that it is the excessive level of credit compared to output that may lead to financial instability: therefore, the ratio of credit over GDP appears as a more relevant indicator than the mere growth of credit alone. Indeed, increasing levels of credit do not imply instability if productive investment is funded, triggering an increase in the long-run output: this is the conclusion reached for example by Buyukkarabacak and Valev (2010), who find that business credit is a much weaker predictor of financial crises. In other words, we are not that much interested in the growth of credit *per se*, but by the share of the latter which creates potentially an increased macroeconomic risk, i.e. which does not translate into a corresponding increase in potential output. This is why we focus on the use of credit as a percentage of GDP. However, we also check in additional estimates how our results behave when we use the log of household credit.

3.3. Other variables

The classical determinants of credit pointed by the literature are financial liberalization, monetary dynamics and the level of economic development. Regarding financial liberalization, we use indexes of credit market deregulation provided by the Fraser Institute[15]. They are widely employed in the literature, notably Giannone et al. (2011) and Stankov (2012). We employ the summary index derived from the private ownership of banks, the existence of interest rate controls and negative interest rates, and the extent to which government borrowing crowds-out private borrowing.

Monetary dynamics are a key determinant of credit in various theoretical contexts. We proxy

[15]Data available at https://www.fraserinstitute.org/

the monetary environment by broad money supply, i.e. M2/GDP ratio from World Bank, following the previous literature, notably Elekdag and Wu (2011) and Perugini et al. (2016). The level of economic development also impacts the depth of the domestic financial system on the one hand and the level of the *financial exclusion* frontier in the flavor of French et al. (2013) on the other hand. We use the standard proxy, GDP per capita, provided once again by the World Bank.

4. Empirical methodology

4.1. Baseline specification

Our main objective is to identify how inequality, and its structure, affect the household credit at the country-level. In general, we want to estimate a specification of the following form:

$$Credit_{i,t} = \beta Ineq_{i,t} + \Gamma X_{i,t} + \mu_i + \lambda_t + \epsilon_{i,t} \tag{25}$$

where $Credit_{i,t}$ and $Ineq_{i,t}$ are respectively the household credit over GDP and inequality in country i during year t. Inequality impact will be assessed through various measures (Gini and Palma indexes, deciles of income) in order to enlighten the role of the structure of income distribution. $X_{i,t}$ is a vector of controls including M2/GDP, log(GDP per capita) and the index of financial deregulation. μ_i denotes country-specific fixed effects, and λ_t represent year dummies. The former captures all time-invariant country characteristics and the latter common trend and shocks, in particular common business cycle conditions. We are specifically interested in changes in credit driven by exogenous variations in inequality. Our coefficient of interest is β: our model predicts $\beta > 0$ when inequality rises, i.e. when the Gini index, the Palma index and the share of top incomes (top 10%, top 30%) in the total income increases, or when the share of low (share of the first to the fourth decile) and middle-incomes (share of the fifth to the seventh decile) decrease.

Table 3 below shows the results obtained when equation 25 is estimated by OLS. The correlation between domestic and foreign sales is correctly signed according to theoretical predictions, but insignificant. This echoes the findings of Bordo and Meissner (2012), who find insignificant correlations when using a similar specification - but with log of credit as a dependent variable.

Table 3 – OLS specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: Household Credit/GDP						
Inequality Measure	Gini	Gini	Palma	Top 10	Top 30	Middle	Bottom
Inequality	0.0782	0.385	0.0659	0.949	0.427	-2.462	-0.112
	(0.497)	(0.448)	(0.0459)	(0.654)	(0.594)	(1.617)	(0.789)
GDP per capita	0.224***	0.368***	0.400***	0.432***	0.374***	0.470***	0.340***
	(0.0772)	(0.0870)	(0.0856)	(0.0929)	(0.0896)	(0.110)	(0.0969)
M2 Ratio	0.158**	0.220***	0.221***	0.219***	0.224***	0.223***	0.230***
	(0.0613)	(0.0748)	(0.0693)	(0.0695)	(0.0728)	(0.0665)	(0.0738)
Credit Deregul.	-0.0200**	-0.0134	-0.0124	-0.0118	-0.0129	-0.0101	-0.0128
	(0.00901)	(0.0108)	(0.0104)	(0.0100)	(0.0106)	(0.00981)	(0.0106)
Obs.	774	571	571	571	571	571	571
Countries	44	35	35	35	35	35	35
adj. R^2	0.670	0.678	0.684	0.684	0.677	0.688	0.676

Constant not reported. Robust standard errors in parentheses.
Country and Year Fixed Effects.
*, ** and *** denote respectively significance at the 1, 5 and 10% levels.

However, a number of reasons may lead these OLS estimates to be heavily biased. First, credit and inequality are likely to be simultaneously determined by shocks, such as the deregulation waves in the 1980s and the 1990s[16], which increased simultaneously the two variables; in that case, β is positively biased. Another obvious issue relates to reverse causality: credit is very much likely to have an impact on inequality, even if the direction and size of the impact are quite debated in the literature (see Bazillier and Hericourt, 2017), making the extent and sign of the bias on β uncertain. Finally, Table 4 below shows that credit is much more volatile than inequality (as embodied by the Gini index): the standard deviation of the growth rate of our preferred indicator, the ratio of household credit over GDP is ten times higher than the one of Gini. For the growth rate of household credit, standard deviation is still a bit less

[16] As the deregulation wave occurs simultaneously in most developed countries, part of this effect is captured through the time dummies. However, differences in the timing of financial deregulation may still bias our OLS estimates.

than three times higher. This creates an attenuation bias driving β towards zero, and may be due to the fact that country-level idiosyncratic shocks on these variables are probably not the same. All these reasons imply that the sign and significance we obtain for β in Equation 25 when estimated by OLS is unclear.

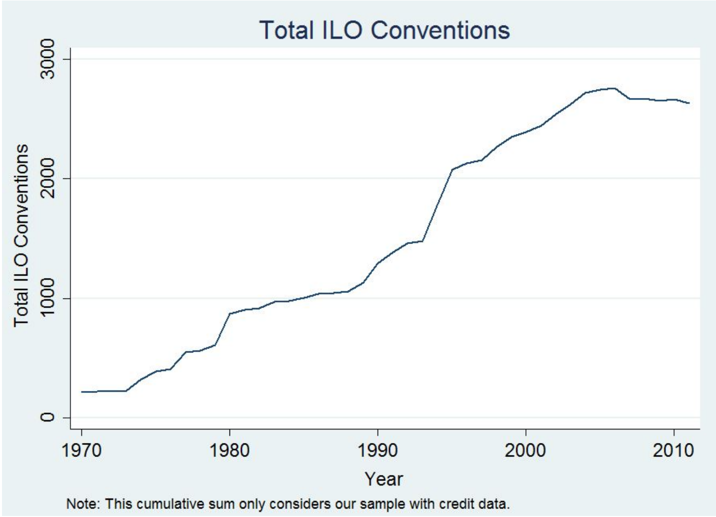
Table 4 – Descriptive Statistics: Credit and Inequality

	Mean	First quartile	Median	Third quartile	S.D.*within*
Levels					
Gini	0.345	0.273	0.325	0.377	0.0196
Palma	1.596	0.918	1.240	1.805	0.195
Top 10	0.270	0.219	0.250	0.293	0.0148
Top 30	0.539	0.479	0.523	0.576	0.0150
Middle 50-70	0.266	0.26	0.276	0.286	0.0066
Bottom 10-40	0.195	0.161	0.200	0.235	0.0104
Household credit/GDP	0.43	0.18	0.42	0.60	0.14
log(real household credit)	11.7	11.07	11.7	12.1	0.30
Variations					
d.log(Gini)	0.002	-0.014	0	0.015	0.027
d.log(real household credit)	0.35	0.009	0.027	0.05	0.068
d.(Household credit/GDP)	0.15	-0.0001	0.01	0.027	0.25

4.2. Identification strategy

To identify how variations in inequality driven by exogenous shocks affect household credit over GDP, we need an instrument that impacts inequality without influencing directly credit (exclusion restriction), and that is orthogonal to any country-specific characteristics which may have driven simultaneously both variables (inequality and credit). This notably excludes indicators of labor market flexibility and institutions. Indeed, labor market and financial liberalization often belong to the same policy package, with two consequences: an increase in the demand for credit due to the fall in workers' bargaining power, and an increase in credit supply explained by financial liberalization (see Tridico, 2012).

Therefore, we propose to exploit exogenous changes in the policies of the International Labor Organization (ILO). These changes were largely exogenous to specific country characteristics but had a direct impact on the number of ILO conventions ratified by a country. We will show that the ratifications of ILO conventions are likely to be correlated with the level of inequality in



Source: ILO website, compilation by the authors.

Figure 1 – ILO's Conventions Ratifications

one country. In other words, we propose to rely on a "quasi-natural experiment" environment provided by the strategy of the International Labor Organization. In normal times, one can argue that the ratification of ILO conventions is likely to depend on countries characteristics, which will violate the exclusion restriction in our identification strategy. Here, we identify two waves of ratifications that are likely to be exogenous to these national characteristics. As we can see in Figure 1, we can identify two waves of increase in ILO conventions ratifications: the first one starting in the seventies and the second one in the nineties. We argue that these two waves are largely exogenous to countries' characteristics.

The International Labour Organization and waves of ratifications

The International Labour Organization was created in 1919, as part of the Treaty of Versailles that ended World War I, *"to reflect the belief that universal and lasting peace can be accomplished only if it based on social justice"* (ILO Website)[17]. The ILO has 187 member States, is the oldest UN agency and is characterized by its tripartite structure: each State is represented by its government, by workers' representatives and by employers' representatives. They set international labor standards by adopting conventions and recommendations. The ratification of conventions is voluntary. Once one country has ratified a convention, it becomes binding. Ratifying countries commit themselves to applying the Convention in national law and prac-

[17] http://www.ilo.org/global/about-the-ilo/history/lang--en/index.htm

tice and to reporting on its application at regular intervals. Today, there are 189 conventions covering all fields related to labor relations (collective bargaining, forced labor, child labor, equality of opportunity and treatment, labor administration and inspection, employment policy, vocational guidance and training, job security, wages, working time, occupational safety and health, social security, maternity protections...). Areas covered by these conventions are therefore much broader than labor market market institutions.

ILO strategy has evolved over time (see Rodgers et al., 2009 for a global overview of ILO history). The launching of the World Employment Programme in 1969 "*marked the formal beginning of an ILO concern with problems of poverty reduction in developing countries*" (Rodgers et al., 2009, p. 186). Then, under the leadership of the Director-General Francis Blanchard, the ILO expands significantly technical cooperation programs (such as the PIACT , the French acronym for the International Programme for the Improvement of Working Conditions and Environment, launched in 1975) in order to assist countries in the implementation of international labor standards. Regional employment teams were established in Africa, Latin America and the Caribbean, and Asia during the 1970s. This led to a substantial increase in ILO ratifications, particularly in developing countries. Clearly, these ratifications became possible because of the ILO policy and were not related to policy changes within countries.

The ILO model of tripartite dialogue was contested in the eighties with the increasing influence of free-market economics in international economic policies. But the fall of the Eastern European socialist regimes and the disintegration of the Soviet Union created new demands for the ILO, notably to strengthen independent workers' and employers' organizations in the countries concerned. And a debate started in the middle of the nineties around the social costs of globalization and the Washington consensus. This created a new political space for ILO actions. The 1995 Social Summit of Copenhagen and the 1998 Declaration on Fundamental Principles and Rights at Work gave a new focus on Human Rights at Work with the recognition of the core labor standards (freedom of association and collective bargaining, elimination of forced labor and child labor, and eradication of discrimination at work). This led to a new dynamic of ratifications, once again more related to global trends than specific national contexts. Once more, technical cooperation programs played a role, with the implementation of the International Program on the Elimination of Child Labor (IPEC), starting in 1992, targeting more than 90 countries. Part of the impulsion came from additional funding from a growing number of donors countries (Rodgers et al., 2009, p. 73).

ILO conventions and inequalities

For all these reasons, we argue that some dynamics in ILO conventions ratifications are explained by global policies and strategies, exogenous to countries' characteristics, and consequently should not violate the exclusion restriction in our IV strategy. On the other side, the ratification of ILOs conventions is likely to have an effect on inequalities, ensuring the strength of our instrument. This assumption is confirmed by Calderón and Chong (2009) in a cross-country study on the effect of labor regulations on inequality. They find a negative and statistically significant link between labor regulation measures and the distribution of income and argue that *"there appears to be an impact on the distribution of income as a result of a country having accumulated an increasing number of International Labour Organization conventions ratified by a country over time"* (Calderón and Chong, 2009, p.75). This negative link between labor market institutions and inequalities has been confirmed by Checchi and García-Peñalosa (2008) on a panel of OECD countries over the 1969-2004 period, even when taking into account the potential adverse effect in terms of unemployment.[18]

Therefore, we are going to use as instrumental variable the number of ILO conventions ratified, which is both time and country-varying. Our main econometric strategy estimates the effect of exogenous changes in inequality (through variations in this number of ILO conventions ratified) on the ratio of household credit to GDP:

$$Ineq_{i,t} = \alpha ILO_{i,t} + \delta X_{i,t} + \lambda_i + \lambda_t + \mu_{i,t} \tag{26}$$

[18] In this paper, they focus on a narrower definition of labor market institutions: union density, unemployment benefit, employment protection, wage coordination, tax wedge and minimum wage.

$$Credit_{i,t} = \beta \widehat{Ineq}_{i,t} + \Gamma X_{i,t} + \lambda_i + \lambda_t + \epsilon_{i,t} \tag{27}$$

where $\widehat{Ineq}_{i,t}$ is the predicted value of the inequality index from Equation 26. Given that they give higher protection and bargaining power to workers, we expect a negative association between this variable and inequality. This is what confirms Table B.1 in appendix B: Inequality decreases when the number of ILO conventions ratified increases. In other words, α is negative when Gini, Palma, or the share of the Top 10% increases (columns (1) to (6)), and positive when the share of middle-class (column (7)) or low-incomes (column (8)) rises. This result holds when we include lagged values in the first stage, to take into account potential reverse causality from inequality to the ratifications of ILO conventions (see table B.2).

In Appendix B, we provide further evidence that $ILO_{i,t}$ is not likely to seriously violate exclusion restrictions. Table B.3 reports estimates of a modified Equation 27, including the number of ILO conventions ratified $ILO_{i,t}$, for different subsamples when the dependent variable is either household credit over GDP (columns (1) to (3)) or the log of household credit (columns (4) to (6)). In all cases but one, we see that the exclusion restrictions seem to be respected: in columns (2) to (6), our IV does not have any impact on household credit. However, it is negative and significant in column (1).

Although most estimates are consistent with the validity of the exclusion restriction, we implement a methodology proposed by Conley et al. (2012) to take into account for this indication of a potential violation of exclusion restrictions in column 1. Basically, it consists in assessing to which extent the parameter of interest β is actually biased if the coefficient on $ILO_{i,t}$ is non-null in equation 27 (Conley et al., 2012 call this "plausible exogeneity"). Figure B.1 in Appendix B show that β is not fundamentally altered by a non-null coefficient on $ILO_{i,t}$ (δ), whatever the size of the latter. Therefore, our IV can be considered as "plausibly exogenous", and reliable on that ground.

Finally, we performed the Durbin-Wu-Hausman test for exogeneity of regressors ("Durbin-Wu" statistics, together with p-value , are reported at the bottom of each Table). Unsurprisingly, the null hypothesis of exogeneity is rejected in most cases, which confirms the need to use IV methodologies. In all estimations, we will also report the F-stat form of the Kleibergen-Paap statistic ("KFP" at the bottom of each Table), the heteroskedastic and clustering robust version of the Cragg-Donald statistic suggested by Stock and Yogo (2005) as a test for weak instruments. Most statistics are comfortably above the critical values, confirming that our instrument is a strong predictor of inequality.

5. Results

5.1. Baseline Results

We present in Table 5 our baseline results for equation 27, in which various indicators of income distribution are instrumented by the number of ILO conventions ratified at the country-level. Column (1) relies on the Gini, which gives an idea of the "average" inequality of the income distribution. Column (2) checks the stability of the estimates of column (1) on a restricted subsample, common with the other indicators of inequality. Column (3) uses the Palma index, which relates the share of the Top 10 with the one of the Bottom 40, giving a first insight on how the structure of inequality impacts the dynamics of credit. Columns (3) to (7) go into more details of that structure, first by focusing on top incomes (top 10 in column (4) and top 30 in column (5)), then on middle incomes (those from the 5^{th} to the 7^{th} decile, in column (6)) and low incomes (those from the 1^{th} to the 4^{th} decile, in column (7)).

Positive changes in inequality, as predicted by changes in the number of ILO conventions ratified, are positively related with the ratio of household credit to GDP. This result holds whatever the inequality indicator used, even if the size of the effect varies significantly along the distribution of income (see below). In all cases, the strength of our instruments is confirmed by the Kleibergen-Paap statistics. Given the first stage coefficients (Table B.1, column (1)), the ratification of one additional ILO convention is found to generate a -0.0017 decrease in the Gini (on a [0-1] scale), which in turn implies a 0.5 percentage point decrease in credit/GDP.

Regarding control variables, GDP per capita and M2 over GDP have the expected positive signs. Conversely, financial deregulation exhibits a negative impact on credit, which seems

Table 5 – Baseline

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.				Household Credit/GDP			
Gini	2.833***	2.533***					
	(0.689)	(0.861)					
Palma			0.209***				
			(0.0548)				
Top 10				3.828***			
				(1.263)			
Top 30					2.773***		
					(0.867)		
Middle 50-70						-12.64***	
						(4.799)	
Bottom 10-40							-3.322***
							(1.000)
GDP per capita	0.475***	0.544***	0.537***	0.722***	0.582***	1.021***	0.447***
	(0.104)	(0.119)	(0.0816)	(0.163)	(0.115)	(0.295)	(0.0806)
M2 Ratio	0.102***	0.153***	0.199***	0.181***	0.181***	0.190***	0.178***
	(0.0255)	(0.0353)	(0.0277)	(0.0278)	(0.0289)	(0.0285)	(0.0299)
Credit Deregulation	-0.0257***	-0.0182***	-0.0119**	-0.00923*	-0.0145***	0.000235	-0.0193***
	(0.00511)	(0.00570)	(0.00518)	(0.00531)	(0.00514)	(0.00791)	(0.00548)
$DurbinWu-stat$	24.910	9.939	7.907	8.087	10.684	9.097	14.884
$P-value$	0.0000	0.0016	0.0049	0.0045	0.0011	0.0026	0.0001
$KPF-stat$	42.229	23.095	43.424	21.105	34.488	11.272	50.054
$Obs.$	774	571	571	571	571	571	571
$Countries$	44	35	35	35	35	35	35
adj. R^2	0.518	0.586	0.619	0.583	0.601	0.446	0.605

Robust standard errors in parentheses.

Country and Year Fixed Effects.

*, ** and *** denote respectively significance at the 1, 5 and 10% levels.

at first sight at odd with the intuition that financial liberalization supports credit expansion. However, remember that we use the ratio of credit over GDP as a dependent variable: in other words, the negative sign simply means that there is a stronger correlation between financial liberalization and GDP than between financial liberalization and credit. This is confirmed by the results displayed in Table 8, where the financial liberalization indicator shows the expected positive impact on the log of household credit.

Going into more details, a 0.01 point exogenous increase (a half standard deviation) in the Gini index is associated with a significant 2.83 percentage point increase in the household credit to GDP ratio. This result remains almost identical in column (2), when the sample is restricted to the one where all indicators of inequality are available. Interestingly, when we investigate specific parts of the income distribution, effects are substantially different: when inequality is measured through the Palma index (column (3)), a 0.1 point increase (also corresponding to a half standard deviation) lifts credit to GDP ratio up by 2 percentage points. Besides, and maybe more importantly, this effect is quantitatively much higher when the share of middle incomes is concerned: when their share in total income increases by 1 percentage point (meaning a *decrease* in the inequality of the distribution of income), credit to GDP decreases by 13 percentage points, whereas the same increase in low-income share only cuts credit to GDP ratio by 3 percentage points. This is consistent with the fact that middle-classes weigh significantly more on aggregate credit, due to higher solvency and borrowing capacities. This would suggest that expansion of household credit over the considered period is the consequence of deteriorating standards of living, at least in relative terms.

5.2. Robustness and Falsification Tests

Definition of Middle Classes. A key result reported above is the quantitative prevalence of middle classes in the positive causal impact of inequalities on household credit over/GDP. However, it could be argued that this is mainly due to the specific definition of middle classes we use, i. e., the share of income held by the 5^{th} to the 7^{th} decile. Therefore, Table 6 reports the results of estimates testing the validity of this definition, based on two strategies. First, columns (1) and (4) substitute to our preferred definition of middle classes on the right-hand side of our estimated equation two alternatives : the share of income owned by the 4^{th} to the 8^{th} decile (the definition proposed by Easterly, 2001) in column (1), and the share of income owned by the 4^{th} to the 7^{th} decile in column (4). While slightly lower, elasticities are still two to three times higher than the one found for low incomes in Table 5. Second, columns (3) to (6) report estimates that, on the contrary, have to be understood more as falsification tests, to the extent the variables they are based on mix explicitly low (2^{nd} and 3^{rd} decile) and middle incomes. As expected, the estimated coefficients (still negative and significant) are no longer different from the one reported in column (7) in Table 5. Finally, columns (2) and (5) display estimates which are compromises between these two strategies, by putting the lower bound on the 3^{rd} decile. Also as expected, elasticities remain negative and significant, somewhat higher than the one found on low incomes, but still lower than when the estimation restricts to consistent definitions of middle incomes. All in all, Table 6 does confirm the importance of middle classes in the positive dynamics linking inequality to credit.

Table 6 – Baseline with various definitions of middle-class

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.			Household Credit/GDP			
Middle 40-80	-8.767***					
	(3.354)					
Middle 30 -80		-5.348***				
		(1.858)				
Middle 20-80			-3.664***			
			(1.195)			
Middle 40-70				-7.346***		
				(2.536)		
Middle 30-70					-4.783***	
					(1.587)	
Middle 20-70						-3.390***
						(1.081)
GDP per capita	1.126***	0.874***	0.692***	0.900***	0.753***	0.620***
	(0.334)	(0.220)	(0.152)	(0.225)	(0.172)	(0.128)
M2 Ratio	0.180***	0.184***	0.187***	0.182***	0.184***	0.187***
	(0.0294)	(0.0273)	(0.0271)	(0.0279)	(0.0275)	(0.0277)
Credit Deregulation	0.00000733	-0.00711	-0.0108**	-0.00734	-0.0111**	-0.0134***
	(0.00797)	(0.00586)	(0.00526)	(0.00588)	(0.00533)	(0.00518)
$DurbinWu-stat$	8.891	8.190	8.027	8.366	8.504	8.967
$P-value$	0.0029	0.0042	0.0046	0.0038	0.0035	0.0027
$KPF-stat$	10.457	16.479	23.672	17.291	22.496	29.234
$Obs.$	571	571	571	571	571	571
$Countries$	35	35	35	35	35	35
adj. R^2	0.439	0.551	0.593	0.549	0.584	0.601

Robust standard errors in parentheses.
Country and Year Fixed Effects.
*, ** and *** denote respectively significance at the 1, 5 and 10% levels.

Impact of the Great Recession. One may argue that our results may be influenced by the Great Recession, which has been notably characterized by an abrupt credit crunch. Table 7 replicates estimates from Table 5 but excluding all years after 2007. Reported results are basically identical to those presented in Table 5, indicating that no impact of the Great recession on our key mechanism can be detected.

Table 7 – Baseline without the Great Recession (years after 2007 excluded)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.				Household Credit/GDP			
Gini	3.097***	2.506***					
	(0.853)	(0.845)					
Palma			0.226***				
			(0.0587)				
Top 10				3.717***			
				(1.191)			
Top 30					2.877***		
					(0.894)		
Middle 50-70						-12.42***	
						(4.594)	
Bottom 10-40							-3.587***
							(1.075)
GDP per capita	0.555***	0.623***	0.622***	0.811***	0.682***	1.138***	0.535***
	(0.121)	(0.131)	(0.0935)	(0.173)	(0.133)	(0.315)	(0.0960)
M2 Ratio	0.101***	0.200***	0.258***	0.232***	0.227***	0.253***	0.217***
	(0.0327)	(0.0389)	(0.0294)	(0.0303)	(0.0311)	(0.0324)	(0.0334)
Credit Deregulation	-0.0291***	-0.0251***	-0.0193***	-0.0167***	-0.0228***	-0.00937	-0.0278***
	(0.00681)	(0.00779)	(0.00631)	(0.00579)	(0.00653)	(0.00698)	(0.00740)
$DurbinWu-stat$	26.152	13.031	12.572	10.121	14.763	9.671	22.567
$P-value$	0.0000	0.0003	0.0004	0.0015	0.0001	0.0019	0.0000
$KPF-stat$	29.240	24.022	44.115	23.571	33.108	12.708	43.602
$Obs.$	649	474	474	474	474	474	474
$Countries$	42	33	33	33	33	33	33
adj. R^2	0.362	0.520	0.533	0.530	0.537	0.381	0.529

Robust standard errors in parentheses.

Country and Year Fixed Effects.

*, ** and *** denote respectively significance at the 1, 5 and 10% levels.

Dependent Variable. We provided several arguments in the data section advocating the ratio of household credit over GDP as a dependent variable. To sum it up, our focus in on the part of the rise in credit which is not matched by a corresponding increase in output. Still, it can be interesting to see what happens when we substitute the log of household credit to its ratio over GDP as a dependent variable in equation 27. The results of this modification are reported in Table 8, which replicates the structure of Table 5. Column (1) seems to show a reversion of our main result: an increase in the Gini index (still predicted by the number of ILO conventions ratified) actually shows a negative impact on household credit. However, column (2) shows that this is mainly a statistical artefact driven by the a few countries in the sample, most likely emerging ones (see paragraph "Developed versus Developing countries"

Table 8 – Baseline with log(credit) as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.	log(Household Credit)						
Gini	-6.336***	-0.366					
	(1.710)	(0.771)					
Palma			-0.0309				
			(0.0676)				
Top 10				-0.559			
				(1.189)			
Top 30					-0.408		
					(0.868)		
Middle 50-70						1.823	
						(3.912)	
Bottom 10-40							0.490
							(1.043)
GDP per capita	1.089***	1.857***	1.869***	1.839***	1.857***	1.805***	1.875***
	(0.278)	(0.141)	(0.129)	(0.172)	(0.143)	(0.238)	(0.119)
log (M2)	0.432***	0.302***	0.292***	0.295***	0.297***	0.288***	0.299***
	(0.0870)	(0.0534)	(0.0453)	(0.0469)	(0.0481)	(0.0446)	(0.0498)
Credit Deregulation	0.0448***	0.0164**	0.0156**	0.0152**	0.0159**	0.0138*	0.0166**
	(0.0106)	(0.00708)	(0.00675)	(0.00676)	(0.00684)	(0.00753)	(0.00723)
$DurbinWu-stat$	9.368	0.138	0.052	0.013	0.488	0.450	3.086
$P-value$	0.0022	0.7103	0.8189	0.9077	0.4847	0.5025	0.0790
$KPF-stat$	43.752	23.673	44.869	21.762	34.714	12.161	49.435
$Obs.$	774	571	571	571	571	571	571
$Countries.$	44	35	35	35	35	35	35
adj. R^2	0.683	0.866	0.865	0.865	0.866	0.861	0.867

Robust standard errors in parentheses.
Country and Year Fixed Effects.
*, ** and *** denote respectively significance at the 1, 5 and 10% levels.

and Table 11 below): when restricted to the common sample, the impact of Gini becomes insignificant, and the subsequent columns highlight it is the case whatever the measure of inequality chosen. On average over the sample, it appears that exogenous variations or inequality do not impact the dynamics of credit independently of output.

Falsification tests. Most theoretical frameworks, including ours, predict that only household credit should be driven by inequality. A simple falsification test is therefore to check the impact on other credit aggregates, for which there should be no impact. A straightforward example is credit granted to private firms. On the other hand, what should be the impact of inequality on total credit is less clear, since it is the sum of both household and business credit.

Therefore, Table 9 reports estimates of equation 27 where the inequality indicator is the Gini (predicted by our IV), and the dependent variable is alternatively total credit from the World Bank (column (1)), total bank credit form the BIS (column (2)), firm credit (column (3)) and household credit (column (4)). Columns (5) to (8) replicate columns (1) to (4) on a period excluding years after 2007, once again to premune against any influence from the Great Recession. As expected, inequality does not have any impact on firm credit (columns (3) and (7)). The impact remains positive on total credit (as in Perugini et al., 2016) and bank credit, whatever the period considered.

However, the way total credit is measured may be non-neutral on the result. This is what shows Table 10, which introduces total credit as computed by the BIS (column (2), the most legitimate for us since household and firm credit also come from the BIS), and rerunning regressions from Table 9 on a common sample. All results remain identical (indicating that the sample alteration cannot be invoked), but the impact of inequality on total credit as computed by BIS is statistically insignificant. A possible explanation comes from the fact that the World Bank aggregate excludes credit form the international financial sector, which may create a bias in the results. In any case, these "falsification evidence" points out that the positive causal impact of inequality is mainly concentrated on household credit.

Developed versus Developing countries. Our sample includes a majority of developed countries, but also a significant number of emerging countries. Theoretically speaking, the causal impact of inequality on household credit dynamics in these countries may differ from the one stated on average, because the channels explaining the positive link between inequality and credit (both supply and demand) are certainly not activated the same way. On the supply side, the financial system is on average less developed in emerging countries, meaning more binding credit constraints and less credit available. On the demand side, it is also plausible than the mechanism relative to the relative income hypothesis and mimetic consumption is less at play in economies where the middle-class is not developed as it is in the advanced countries; it is important since a key result of this paper is the quantitative importance of the

Table 9 – Falsification tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Whole Sample				Before 2008			
Dep. Var: Credit/GDP	TotalWB	Bank	Firm	Household	TotalWB	Bank	Firm	Household
Gini	6.82***	3.12***	-0.466	2.81***	7.58***	2.55***	-0.472	3.08***
	(0.0147)	(0.00895)	(0.00861)	(0.00696)	(0.0185)	(0.00909)	(0.00881)	(0.00862)
GDP per capita	0.186	0.661***	-0.117	0.472***	0.273	0.871***	0.179	0.552***
	(0.207)	(0.142)	(0.146)	(0.105)	(0.248)	(0.142)	(0.134)	(0.122)
M2 Ratio	0.488***	0.164***	0.209***	0.102***	0.534***	0.198***	0.168***	0.101***
	(0.0614)	(0.0444)	(0.0421)	(0.0255)	(0.0761)	(0.0511)	(0.0490)	(0.0326)
Credit Deregul.	-0.00956	0.0153	0.00710	-0.0255***	-0.0423***	0.00335	0.0265***	-0.0290***
	(0.0157)	(0.0105)	(0.00949)	(0.00512)	(0.0157)	(0.00861)	(0.00903)	(0.00685)
$DurbinWu - st$	18.469	8.654	3.327	24.188	20.267	5.659	2.422	25.375
$P - value$	0.0000	0.0033	0.0681	0.0000	0.0000	0.0174	0.1196	0.0000
$KPF - stat$	41.249	41.249	41.249	41.249	28.516	28.516	28.516	28.516
$Obs.$	773	773	773	773	648	648	648	648
$Countries$	44	44	44	44	42	42	42	42
adj. R^2	0.457	0.348	0.386	0.520	0.371	0.367	0.365	0.365

Robust Standard errors in parentheses.

Country and Year Fixed Effects.

*, ** and *** denote respectively significance at the 1, 5 and 10% levels.

Table 10 – Additional falsification tests

	(1)	(2)	(3)	(4)	(5)
Dep. Var: Credit/GDP	TotalWB	TotalBIS	Bank	Firm	Household
Gini	6.16***	1.80	2.97***	-0.795	2.49***
	(0.0151)	(0.0124)	(0.00993)	(0.00981)	(0.00733)
GDP per capita	0.136	0.271	0.659***	-0.142	0.448***
	(0.202)	(0.176)	(0.151)	(0.156)	(0.104)
M2 Ratio	0.566***	0.331***	0.158***	0.222***	0.109***
	(0.0666)	(0.0717)	(0.0572)	(0.0570)	(0.0314)
Credit Deregulation	-0.0445***	-0.0238*	-0.00429	0.0119	-0.0339***
	(0.0109)	(0.0123)	(0.00879)	(0.0103)	(0.00524)
$DurbinWu - stat$	12.507	0.195	6.419	3.707	15.009
$P - value$	0.0004	0.6588	0.0113	0.0542	0.0001
$KPF - stat$	33.169	33.169	33.169	33.169	33.169
$Obs.$	701	701	701	701	701
$Countries$	38	38	38	38	38
adj. R^2	0.576	0.620	0.412	0.382	0.581

Robust Standard errors in parentheses.

Country and Year Fixed Effects.

*, ** and *** denote respectively significance at the 1, 5 and 10% levels.

share of middle incomes to explain the aggregate dynamics of credit.

Table 11 – Advanced versus emerging economies

	(1)	(2)	(3)	(4)
Dep. Var.	Household Credit/GDP		log(Household Credit)	
	Adv	Eme	Adv	Eme
Gini	2.562**	0.00697	1.063	-17.22***
	(0.997)	(0.409)	(0.959)	(5.269)
GDP per capita	0.502***	0.470***	1.917***	2.803
	(0.129)	(0.0880)	(0.143)	(1.760)
M2	0.0512*	0.147***	0.0579	0.488
	(0.0264)	(0.0283)	(0.0519)	(0.427)
Credit Deregulation	-0.0282***	-0.00687*	0.0122	0.0974**
	(0.00666)	(0.00353)	(0.00790)	(0.0439)
$DurbinWu-stat$	13.423	0.090	8.000	12.119
$P-value$	0.0002	0.7636	0.0047	0.0012
$KPF-stat$	23.411	14.248	24.160	11.197
$Obs.$	572	202	572	202
$Countries$	29	15	29	15
adj. R^2	0.641	0.569	0.887	-0.378

The variable M2 is a ratio over GDP in columns (1)-(2).
The variable M2 is log-linearized in columns (3)-(4).
Robust Standard errors in parentheses.
Country and Year Fixed Effects.
*, ** and *** denote respectively significance at the 1, 5 and 10% levels.

This is indeed what shows Table 11, which splits our sample between advanced (Adv) and emerging (Eme) economies. Columns (1) and (2) estimate exactly equation 27, while columns (3) and (4) substitute log of household credit to the ratio of household credit over GDP as the dependent variable. In all cases, the inequality indicator is the Gini index. For advanced countries (columns (1) and (3)), evidence keeps pointing to a positive impact of inequality on household credit as share of GDP, but not on (log of) real household credit: coefficient is still positive, but insignificant. This is consistent with the evidence of no impact reported in columns (2) to (6) of Table 8. For emerging countries, as expected, the effect is different: column (2) points that inequality does not impact household credit over GDP dynamics, but column (4) exhibits a *negative* impact on the log of household credit, reminding of the negative coefficient found in column (1) of Table 8. The limited size of the sample for emerging economies should make interpretation cautious, but in any case they tend to show that our results hold for developed countries. One potential explanation for the negative sign found in column (4) may be given by the theoretical argument proposed by Kumhof et al. (2012). Focusing on the effect of inequality on the current account, Kumhof et al. (2012) model a potential different effect of increasing inequalities in developing countries where access to credit is strongly constrained, especially for low and middle-income households. When inequalities are rising, one potential effect is the fall of borrowing needs for the richest, while the low and middle-income do not have access to credit to compensate their falling income.

Table 12 – Baseline with only advanced economies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.				Household Credit over GDP			
Gini	2.562**	2.484**					
	(0.997)	(1.264)					
Palma			0.225**				
			(0.0931)				
Top 10				3.319**			
				(1.601)			
Top 30					2.353**		
					(1.082)		
Middle 57						-11.89*	
						(6.567)	
Bottom 10-40							-2.736**
							(1.213)
GDP per capita	0.502***	0.525***	0.511***	0.678***	0.563***	0.997***	0.447***
	(0.129)	(0.116)	(0.0793)	(0.165)	(0.109)	(0.357)	(0.0717)
M2	0.0512*	0.0684	0.139***	0.128***	0.118***	0.156***	0.109***
	(0.0264)	(0.0512)	(0.0280)	(0.0288)	(0.0320)	(0.0277)	(0.0344)
Credit Deregulation	-0.0282***	-0.0193***	-0.0135**	-0.0101	-0.0144**	0.000972	-0.0192***
	(0.00666)	(0.00690)	(0.00584)	(0.00629)	(0.00600)	(0.0107)	(0.00638)
$DurbinWu-stat$	13.423	6.085	8.583	6.162	8.549	5.610	9.805
$P-value$	0.0002	0.0136	0.0034	0.0131	0.0035	0.0179	0.0017
$KPF-stat$	23.411	12.474	58.217	16.490	25.315	7.589	35.058
$Obs.$	572	446	446	446	446	446	446
$Countries$	29	26	26	26	26	26	26
adj. R^2	0.641	0.667	0.704	0.664	0.685	0.536	0.697

Robust standard errors in parentheses.
Country and Year Fixed Effects.
*, ** and *** denote respectively significance at the 1, 5 and 10% levels.

These dissimilar results for advanced and emerging economies are confirmed by Tables 12, 13, and 14. Tables 12 and 13 replicate Table 5 on a sample restricted to advanced economies,

Table 13 – Baseline with advanced economies without the Great Recession (years after 2007 excluded)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.			Household Credit over GDP				
Gini	2.646**	2.306*					
	(1.084)	(1.290)					
Palma			0.208**				
			(0.0917)				
Top 10				2.831**			
				(1.434)			
Top 30					2.186**		
					(1.083)		
Middle 50-70						-9.432*	
						(5.209)	
Bottom 10-40							-2.754**
							(1.336)
GDP per capita	0.537***	0.565***	0.558***	0.712***	0.610***	0.983***	0.492***
	(0.134)	(0.129)	(0.0913)	(0.173)	(0.125)	(0.334)	(0.0855)
M2 Ratio	0.0855**	0.147**	0.237***	0.220***	0.212***	0.255***	0.197***
	(0.0351)	(0.0736)	(0.0329)	(0.0372)	(0.0408)	(0.0317)	(0.0469)
Credit Deregulation	-0.0331***	-0.0310***	-0.0245***	-0.0213***	-0.0263***	-0.0131	-0.0321***
	(0.00879)	(0.0108)	(0.00721)	(0.00720)	(0.00810)	(0.00855)	(0.00951)
$DurbinWu - stat$	12.869	5.889	8.521	5.259	8.523	4.011	12.112
$P - value$	0.0003	0.0152	0.0035	0.0218	0.0035	0.0452	0.0005
$KPF - stat$	19.196	11.181	51.617	17.406	22.484	9.864	26.586
$Obs.$	478	367	367	367	367	367	367
$Obs.$	28	24	24	24	24	24	24
adj. R^2	0.554	0.615	0.660	0.635	0.637	0.565	0.636

Robust standard errors in parentheses.
Country and Year Fixed Effects.
*, ** and *** denote respectively significance at the 1, 5 and 10% levels.

respectively on our whole period of estimation and on a subperiod stopping in 2007, before the Great Recession. They highlight that our results, both about the impact of inequality and its structure, hold strongly for developed economies, where middle-classes have access to credit and are important enough to drive the dynamics of aggregated household credit. Conversely, Table 14 confirms that no such effect can be observed for emerging economies, possibly due to credit constraints (as suggested by Kumhof et al., 2012) and too small middle-classes (see Kochhar, 2015).[19]

[19] However, both the limited number of countries and the weakness of our instrument on this specific subsample lead to interpret cautiously these results.

Table 14 – Baseline with only emerging economies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.			Household Credit over GDP				
Gini	0.00697	7.949					
	(0.409)	(8.249)					
Palma			0.490				
			(0.643)				
Top 10				29.98			
				(87.06)			
Top 30					12.67		
					(16.51)		
Middle 50-70						-18.58	
						(15.68)	
Bottom 10-40							-37.41
							(84.18)
GDP per capita	0.470***	1.741	2.247	4.622	2.346	1.435	4.210
	(0.0880)	(1.440)	(2.469)	(12.19)	(2.537)	(0.904)	(8.557)
M2 Ratio	0.147***	0.430	0.529	0.536	0.437	0.306*	0.694
	(0.0283)	(0.299)	(0.531)	(1.217)	(0.408)	(0.182)	(1.241)
Credit Deregulation	-0.00687*	-0.0283	0.0229	-0.00328	-0.0176	0.00156	-0.0513
	(0.00353)	(0.0262)	(0.0477)	(0.0553)	(0.0247)	(0.0183)	(0.102)
$KPF-stat$	14.248	0.810	0.511	0.093	0.510	1.364	0.160
$Obs.$	202	125	125	125	125	125	125
$Countries$	15	9	9	9	9	9	9
adj. R^2	0.569	-7.328	-11.818	-75.390	-12.892	-5.506	-37.184

Robust standard errors in parentheses.

Country and Year Fixed Effects.

*, ** and *** denote respectively significance at the 1, 5 and 10% levels.

6. Conclusion

This paper extended the DSGE framework by Kumhof et al. (2015) to provide the intuition that both inequality and its structure should matter on credit dynamics. Based on a 44 countries dataset over the period 1970-2012, we confirm the first theoretical prediction of the model: using various indicators of inequality, we show that household credit is positively impacted by inequality when the latter is predicted by exogenous shocks on the number of ILO conventions ratified. A second prediction of our theoretical setting is that this positive impact should be stronger when inequality hits more middle classes (i.e., when their share in total income decreases). This is once again confirmed by our empirical exercise. Those results are supported by various robustness and falsification tests, as well as alternative samples, which also show that our results hold exclusively for developed countries. For emerging economies, no such effects can be observed, possibly due to credit constraints and insufficiently important middle income categories.

Our work has important implications regarding financial crises prevention. In order to avoid financial crises such as the one of 2007-2009, which triggered afterwards the Great Recession, one has therefore to prevent the creation of household leverage bubbles. Our findings suggest that the reduction of inequality is an important prerequisite of such a policy, especially at the middle of of the income distribution.

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Appendix A: Data Appendix

Table A.1 – Data Sources

Variable	Description	Source
	Credit	
Household credit/GDP		BIS, CB, DATASTREAM
log(Household credit/price level)	GDP deflator from World Bank.	BIS, CB, DATASTREAM, WB
Firm credit/GDP	Linear intrapolation for some years for 5 countries.	BIS, CB, DATASTREAM
Domestic bank credit /GDP	Total non-financial credit from domestic bank.	BIS, WB, CB
Total domestic credit /GDP	Total non-financial credit from domestic financial system.	World Bank
Total credit/GDP	Total non-financial credit from domestic and international financial systems.	BIS
	Inequalities	
Gini		Wiid
Palma	Share in total income of the richest 10% with the one of the poorest 40%.	Wiid, Palma (2011)
	Control Variables	
GDPpercapita	Log-linearized.	World Bank
M2	Ratio divided by GDP or log-linearized.	World Bank, Datastream
Credit Deregulation	Index from 0 to 10 about financial deregulation. Summary index.	Fraser Institute
	Instrument	
ILO conventions	International Labour Organization conventions ratifications.	ILO

Table A.2 – List of Advanced Economies: Time Coverage and Main Sources

	Baseline Coverage	WIID Source	Household Cred.	Firm Cred.	Total BIS
Austria	1995-2011	Eurostat	BIS	BIS	BIS
Australia	1981-2010	LIS, National Source	BIS	BIS	BIS
Belgium	1985-2011	Eurostat, Other	BIS	BIS	BIS
Canada	1983-2008	OECD	BIS	BIS	BIS
Czech Republic	2001-2011	Eurostat	BIS	BIS	BIS
Denmark	1995-2011	Eurostat	BIS	BIS	BIS
Estonia	2000-2011	Eurostat	Datastream	Datastream	
Finland	1970-2003	National Source	BIS	BIS	BIS
France	1995-2011	Eurostat	BIS	BIS	BIS
Germany	1984-2004	Other	BIS	BIS	BIS
Greece	1995-2011	Eurostat	BIS	BIS	BIS
Iceland	2004-2011	Eurostat	CB	CB	
Ireland	2002-2010	Eurostat	BIS	BIS	BIS
Israel*	1992-2010	LIS	BIS	BIS	BIS
Italy	1986-2011	LIS, Eurostat	BIS	BIS	BIS
Japan	1985-2009	OECD	BIS	BIS	BIS
Korea*	1970-2011	OECD, Other	BIS	BIS	BIS
Malta	2003-2011	Eurostat	CB	CB	
Netherlands	1990-2011	Eurostat, Other	BIS	BIS	BIS
New Zealand	1990-2009	OECD	BIS	BIS	BIS
Norway	1986-2002	National Source	BIS	BIS	BIS
Poland	1995-2011	Transmonee, Eurostat	BIS	BIS	BIS
Portugal	1995-2011	Eurostat	BIS	BIS	BIS
Singapore*	2003-2011	National Source	BIS	BIS	BIS
Spain	1995-2011	Eurostat	BIS	BIS	BIS
Sweden	1981-2011	LIS, Eurostat	BIS	BIS	BIS
Switzerland	2007-2011	Eurostat	BIS	BIS	BIS
United Kingdom	1970-2011	Eurostat, Other	BIS	BIS	BIS
United States	1979-2010	LIS	BIS	BIS	BIS

* meaning that divergent view according to UN and World Bank classifications.

Table A.3 – List of Emerging Economies: Time Coverage and Main Sources

	Baseline Coverage	WIID Source	Household Cred.	Firm Cred.	Total BIS
Argentina	1989-2011	SEDLAC 2012	CB	BIS	BIS
Brazil	1994-2009	SEDLAC 2012	BIS	BIS	BIS
Chile	1988-2009	SEDLAC 2012	CB	CB	
China	1995-2003	Other	OXFORD	BIS	BIS
Colombia	1994-2010	SEDLAC 2012	CB	CB	
Egypt	2008-2010	National Source	CB	CB	
Hungary*	1993-2006	Transmonee	BIS	BIS	BIS
India	1998-1999	World Bank	OXFORD	BIS	BIS
Indonesia	2001-2011	World Bank	BIS	BIS	BIS
Malaysia	1996-1999	Other	OXFORD	BIS	BIS
Mexico	1994-2010	SEDLAC 2012	BIS	BIS	BIS
Russian Fed.*	1998-2010	LIS	BIS	BIS	BIS
South Africa	1994-2009	World Bank, Other	OXFORD	BIS	BIS
Thailand	1991-2008	World Bank	BIS	BIS	BIS
Turkey	1987-2011	OECD, National Source	BIS	BIS	BIS

* meaning that divergent view according to UN and World Bank classifications.

Table A.4 – Sources of Inequality Measures after processing WIID

Source	Eurostat	OECD	LIS	National Offices	SEDLAC	Transmonee	WB	Other
Countries	20	4	6	10	6	2	4	6

Appendix B: Instrumental Variable, First Stage and Additional Tests

Table B.1 – First Stage Inequality Structure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Gini	Gini	Gini	Gini	Palma	Top 10	Middle	Bottom
Sample		Credit	<2008	Deciles	Deciles	Deciles	Deciles	Deciles
ILO Conv	-0.00168***	-0.00160***	-0.00150***	-0.00147***	-0.0178***	-0.000974***	0.000295*	0.00112***
	(0.000375)	(0.000404)	(0.000406)	(0.000479)	(0.00610)	(0.000343)	(0.000166)	(0.000199)
GDP per capita	-0.140***	-0.102**	-0.0950**	-0.112***	-1.321***	-0.120***	0.0601***	0.0560***
	(0.0383)	(0.0381)	(0.0436)	(0.0394)	(0.425)	(0.0293)	(0.0140)	(0.0191)
M2 Ratio	0.0109	0.0184	0.0206	0.0264**	0.0993	0.0103	-0.00237	-0.0126**
	(0.0102)	(0.0114)	(0.0145)	(0.0129)	(0.128)	(0.00876)	(0.00365)	(0.00594)
Credit Dereg.	-0.000531	0.00276	0.00442*	0.00233	-0.00216	-0.000810	0.000994	-0.00210*
	(0.00202)	(0.00205)	(0.00231)	(0.00235)	(0.0257)	(0.00167)	(0.000758)	(0.00120)
Cons	0.931***	0.760***	0.718***	0.791***	7.358***	0.767***	0.0180	-0.0407
	(0.146)	(0.145)	(0.176)	(0.145)	(1.828)	(0.113)	(0.0569)	(0.0668)
Obs.	959	774	650	571	571	571	571	571
Countries	45	44	43	35	35	35	35	35
adj. R^2	0.418	0.247	0.271	0.398	0.243	0.396	0.296	0.403

Robust standard errors in parentheses.

Country and Year Fixed Effects.

*, ** and *** denote respectively significance at the 1, 5 and 10% levels.

Table B.2 – First Stage Inequality Structure, Lagged Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Gini	Gini	Gini	Gini	Palma	Top 10	Middle	Bottom
L.ILO Conv	-0.00173***	-0.00148***	-0.00124***	-0.00121***	-0.0167**	-0.000814**	0.000236	0.000966***
	(0.000381)	(0.000413)	(0.000400)	(0.000439)	(0.00653)	(0.000348)	(0.000173)	(0.000192)
L.GDP per capita	-0.144***	-0.112***	-0.104**	-0.121***	-1.288***	-0.125***	0.0624***	0.0591***
	(0.0367)	(0.0361)	(0.0412)	(0.0369)	(0.389)	(0.0274)	(0.0135)	(0.0178)
L.M2 Ratio	0.00946	0.0199*	0.0218	0.0305**	0.181	0.0155*	-0.00449	-0.0145**
	(0.0102)	(0.0113)	(0.0143)	(0.0121)	(0.123)	(0.00886)	(0.00393)	(0.00534)
L.Credit Deregulation	-0.0000191	0.00323	0.00526**	0.00322	0.0124	-0.000148	0.000500	-0.00239**
	(0.00200)	(0.00207)	(0.00227)	(0.00212)	(0.0221)	(0.00162)	(0.000763)	(0.00113)
Cons	1.094***	0.894***	0.720***	0.897***	8.180***	0.869***	-0.0246	-0.101
	(0.160)	(0.161)	(0.152)	(0.169)	(2.076)	(0.136)	(0.0685)	(0.0790)
Obs.	955	774	647	569	570	570	570	570
adj. R^2	0.424	0.248	0.275	0.415	0.239	0.403	0.295	0.407

Standard errors in parentheses

*, ** and *** denote respectively significance at the 1, 5 and 10% levels.

Table B.3 – Testing for Exclusion Restriction

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Household Credit/GDP			Log(Household Credit)		
Inequality measure	Gini	Palma	Top 10	Gini	Palma	Top 10
Inequality	-0.144	0.0526	0.775	-0.890	-0.0147	-0.418
	(0.546)	(0.0493)	(0.723)	(0.940)	(0.0606)	(0.728)
ILO Conv	-0.00478**	-0.00279	-0.00297	0.00913	0.000290	0.000140
	(0.00236)	(0.00263)	(0.00267)	(0.00898)	(0.00236)	(0.00222)
GDP per capita	0.172*	0.330***	0.354**	1.746***	1.895***	1.859***
	(0.0862)	(0.116)	(0.137)	(0.332)	(0.293)	(0.310)
M2	0.157**	0.215***	0.212***	0.327*	0.288**	0.292**
	(0.0586)	(0.0672)	(0.0671)	(0.172)	(0.115)	(0.114)
Credit Deregulation	-0.0175*	-0.0122	-0.0117	0.0320*	0.0157	0.0153
	(0.00907)	(0.00981)	(0.00949)	(0.0161)	(0.0145)	(0.0147)
Cons	-0.240	-1.088*	-1.295*	0.0419	0.0889	0.272
	(0.501)	(0.573)	(0.749)	(2.607)	(1.190)	(1.244)
Obs.	774	572	571	774	572	571
Countries	44	35	35	44	35	35
adj. R^2	0.679	0.687	0.687	0.798	0.873	0.874

The variable M2 is a ratio for the columns (1)-(3). It is log-linearized for the columns (4)-(6).

Robust standard errors in parentheses.

Country and Year Fixed Effects.

*, ** and *** denote respectively significance at the 1, 5 and 10% levels.

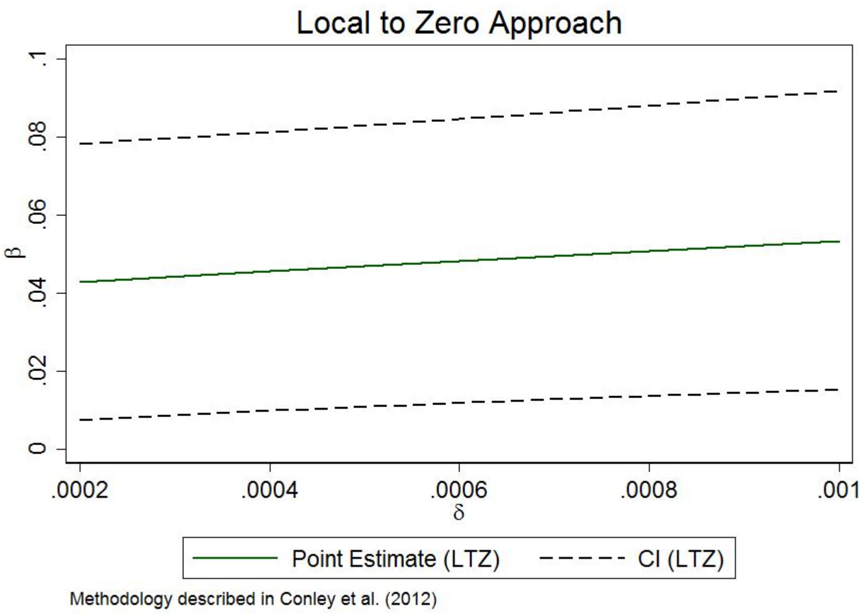

Figure B.1 – Conley-Hansen-Rossi bounds test for instrument validity
Coefficient of Gini according to potential violation of the exclusion restriction