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

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Abstract

How does income inequality and its structure affect 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 the middle classes. Consistently, this impact should weaken in countries where financial markets are insufficiently developed. These theoretical predictions are empirically confirmed by a study based on a 41-country dataset over the period 1970-2014, where exogenous variations of inequality are identified with a new instrument variable, the total number of ILO conventions signed at the country-level.

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1 Introduction

It has only been recently that academic attention started focusing on the potential issues raised by 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. At the beginning of the 2010s, some academic economists started supporting a direct, causal relationship between those rising inequalities, the excess leverage of low- and middle-income households, and the financial crisis. Debate entered the public sphere based on the arguments of Rajan (2010) and Galbraith (2012) 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 subject of a burgeoning academic literature, focusing on different potential theoretical channels through which a rise in income inequalities[1] may endogenously trigger an expansion of credit.[2] An important issue relates to the type of income shock at stake, whether transitory (Krueger and Perri, 2006, Krueger and Perri, 2011 or Iacoviello, 2008) or permanent (Piketty and Saez, 2013). Evidence from various countries tends to show that the rise of inequalities is more likely to be explained 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

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

[2]Detailed surveys can be found in van Treeck (2014) and Bazillier and Hericourt (2017).

[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 larger 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).

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. (2016) 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.

These contradictory outcomes emphasize the difficulties inherent in the identification of a causal relationship between inequality and finance, due to the multiplicity of circular linkages and intertwined credit supply and demand mechanisms. Besides, the existing literature tends to focus almost only on the role of top incomes, which are opposed to a “bottom category” which actually mixes low and middle incomes. This paper aims at filling these different gaps. First, we include the potential role of middle-classes both at the empirical and theoretical levels. Second, we propose a new identification strategy based on International Labour Organization (ILO) ratifications’ behavior to allow a causal interpretation of our results.

Theoretically, we provide an extension of the framework of Kumhof et al. (2015), first by distinguishing explicitly between low and middle-class incomes, versus top incomes, and secondly, by identifying demand (in addition to supply) effects in the causal dynamics between inequality and credit. On the one hand, supply-side arguments emphasize the role of top incomes through the rise in global savings, which in turn triggered global excess demand for securities driving up the credit supply. On the other hand, demand-side arguments put an emphasis on the proactive will of low/middle-income households to maintain their consumption level relative to that of top income households ('keeping up with the Joneses' hypothesis).

The middle-class households are significantly richer than low-income ones. Even without any assumption on the intensity of the demand-side mechanism, it generates striking differences in terms of consumption per capita and of credit patterns. Consistently, our model delivers three testable predictions: (i) an increase in inequality leads to an expansion in household credit at the aggregate level, (ii) the bulk of the positive impact of inequality on household credit is driven by the middle classes and (iii) this positive causal link exists if and only if the country is sufficiently developed.

The model is then brought to the data to empirically investigate the existence and the determinants of a causal relationship between inequality and the expansion of credit. 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 ILO conventions 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. The organization expanded its technical cooperation at the end of the 1970s, and has adopted a strategy of active promotion of core labor standards and decent work in the 1990s (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 led 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 convention ratification allows us to identify the causal effect of inequalities on credit.

Our empirical analysis relies on a country-level yearly dataset for 41 countries over the period 1970-2014, based on two building blocks. Income inequality data come from the World Income Inequality Database (WIID). Credit data (household, aggregate, firm) come from various sources, such as the Bank of International Settlements, central banks, the OECD and Datastream.[4]

We find that an exogenous increase in inequality coming from ILO ratification shocks triggers an expansion of *household* credit. While Bordo and Meissner (2012) and Perugini et al. (2016) were focusing on total credit, we show that this dynamic is driven by household credit, which is consistent with theoretical intuitions. In addition, 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 one standard deviation increase is associated with a significant 7.3 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 top incomes share, an increase by one standard deviation lifts credit to GDP ratio by 8.5 to 10.3%. Besides, and maybe more importantly, we show that this effect is substantially higher when middle incomes are involved: when their share in total income increases by one standard deviation (meaning a *decrease* in the inequality of the distribution of income), credit to GDP decreases by 11.5 to 19.4% percentage points, whereas the same increase in low-income share cuts credit to GDP ratio by 6 percentage points.

A substantial part of the paper is devoted to exploring the sensitivity of our results to robustness and falsification tests. The quantitative prevalence of the middle classes in the positive link between inequality and credit is robust to various definitions of middle

[4] In both cases, data have been cleaned and harmonized through a transparent process which is detailed in the Data section and Appendix B. Besides, various robustness checks are implemented in order to ensure the stability of our estimates.

incomes. Besides, an important falsification test is to check that income inequality does not have any impact on credit granted to firms, which is indeed confirmed by the data. The positive impact of inequality is found again on ratios of total credit over GDP, which is consistent with Perugini et al.'s (2016) results; however, our own findings tend to show that this results on credit is driven by credit to household. Furthermore, when we split our sample between developed and developing/emerging countries, we find that our results hold only for advanced countries, with 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 finding 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 on 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. Those on poor and middle incomes cannot respond to lower incomes by borrowing (Kumhof et al., 2012). We find indeed that emerging countries displaying a sufficient level of openness to international capital flows do exhibit a positive impact of inequality on household credit.[5] Conversely, the Gini index has no impact on credit for countries with a low or limited level of openness. This goes again in the direction of a relaxation of credit constraints by incoming financial flows, allowing wider categories of population to access credit, and consequently, to react to variations in inequality. Finally, our results are mostly not impacted by the dynamics arising with the financial crisis and the Great Recession of 2007-2008.

Our work has important implications regarding financial crisis 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., 2015b; Jordá et al., 2015a; Mian and Sufi, 2010; Mian and Sufi, 2014).[6] In order to avoid financial

[5]Which is consistent with the idea that inequality has an impact on the current account as shown by Behringer and van Treeck (2018).

[6]Using the database by Schularick and Taylor (2012) on 14 developed countries from 1870 to 2008,

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 is an important prerequisite of such a policy, especially at the middle of the income distribution. Hence, an implication of our results is that the middle classes drive most of the financial cycle.

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 consists of two kind 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 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 a rise in top earners' income z^T, and/or a decrease in middle-class share z^M, and/or a decrease in low incomes z^L. As stressed by Atkinson and Morelli (2010), there is a potential heterogeneous role of income distribution changes. The model respects the following conditions:

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

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

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.

2.1 Middle-class earners

The representative middle class earner maximizes the intertemporal utility function:

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

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 in the spirit of Christen and Morgan (2005).[7] We ensure that, all things being equal, their share of output is positively linked to the utility function. A similar relationship holds for debt. The 'keeping up with the Joneses' hypothesis works through the utility generated by the debt when one suffers an increase of inequalities. In other words, the agent maintains his consumption despite the negative income shock relative to other groups proxied by a decrease of z^M. 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.

This intertemporal utility function is subject to the following budget constraint:

$$c_t^M = y_t \frac{z_t^M}{\chi^M} + b_t^M p_t^M - b_{t-1}^M \tag{4}$$

The first part is the per capita income of middle-class households while the second part refers to debt flows: household receives b_t^M and reimburses b_{t-1}^M 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.[8] Similarly, when

[7] Ahlquist and Ansell (2017) use a complementary approach, which is called positional good arguments. Bottom earners compare their consumption to the consumption of the rich, but only at the first period in their model.

[8] A key feature of Kumhof et al. (2015) is endogenous default decision. We omit this default because we look for comparative statistics and, as noted by Kumhof et al. (2015), *"default has negligible effect on the Euler equations in the neighborhood of the original steady state"*. It is beyond the scope of this

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 higher the implicit interest rate.

Middle-class earners maximize (3) subject to (4). Their optimal condition is as follows:

$$p_t^M = \beta_M \mathbb{E}_t \left[\left(\frac{c_{t+1}^M}{c_t^M} \right)^{-\frac{1}{\sigma}} \right] - \gamma \left(\frac{z_t^M}{\chi^M} \right)^{\frac{\theta-1}{\theta}} \left(b_t^M \right)^{-\frac{1}{\theta}} (c_t^M)^{\frac{1}{\sigma}} \tag{5}$$

This condition highlights a trade-off between the 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 latter holds only if $\theta < 1$. When z_t^M increases, indicating 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 a lower implicit interest rate. Symmetrically, an increase in inequalities implies a higher implicit interest rate and, consequently, higher demand for loans from middle-class earners. By comparison, Kumhof et al. (2015) provide 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 as the middle-class ones, but with one key difference: their share of output is significantly lower than the middle-class one, that is $z^M > z^L$. Their utility has the same functional form and the same elasticities σ and θ.[9]

Calculations, similar to the previous one, give this optimal condition:

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

paper, but we can expect a different penalty for defaults for low- and middle-income groups, which in turn affect trade-off about rational default decisions.

[9] As discussed below, other restrictive assumptions are feasible such as various discount factors or the strength of the demand-side mechanism. We do not use these assumptions to ensure the consistency of our testable predictions.

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 e.g. Carroll (2000) and Kumhof et al. (2015). The wealth preference alters the arbitrage between consumption and debt in favor of supplying loans to other types of households. By contrast with Kumhof et al. (2015), it is not additive with respect to the two amounts of debt, which is broadly consistent with Carroll (2002) and Goetzmann and Kumar (2008). They document the high-level of diversification in top income earners' portfolios and investigate various determinants such as age, education and financial sophistication.

Consequently, 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.

$$V_t^T = \mathbb{E}_t \sum_{k\geq 0}^{\infty} \beta_T^k \left[\frac{(c_{t+k}^T)^{1-\frac{1}{\sigma}}}{1-\frac{1}{\sigma}} + \varphi^L \frac{(1+\frac{\chi^L}{\chi^T}(b_{t+k}^L))^{1-\frac{1}{\eta}}}{1-\frac{1}{\eta}} + \varphi^M \frac{(1+\frac{\chi^M}{\chi^T}(b_{t+k}^M))^{1-\frac{1}{\eta}}}{1-\frac{1}{\eta}} \right] \tag{7}$$

We can write top earners' budget constraints as follows:

$$c_t^T = y_t \frac{z_t^T}{\chi^T} + \frac{\chi^L}{\chi^T}(b_{t-1}^L - b_t^L p_t^L) + \frac{\chi^M}{\chi^T}(b_{t-1}^M - b_t^M p_t^M) \tag{8}$$

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

$$p_t^L = \beta_T \mathbb{E}_t \left[(\frac{c_{t+1}^T}{c_t^T})^{-\frac{1}{\sigma}} \right] + \varphi^L \frac{(c_t^T)^{\frac{1}{\sigma}}}{(1+\frac{\chi^L}{\chi^T} b_t^L)^{\frac{1}{\eta}}} \tag{9}$$

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

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. In addition, we distinguish our supply-side argument: an increase in top earners' income share z_t^T in c_t^T leads to a decrease of implicit interest rate. They also suggest a no-arbitrage condition between loans to low-income earners and those to middle-class earners.

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:

$$y_t = \chi^T c_t^T + \chi^M c_t^M + \chi^L c_t^L \tag{11}$$

Two properties appear in equilibrium. First, the Euler equations (5), (6), (9) and (10) can be interpreted as the price of demand and supply of these loans while keeping their consumption constant. The following condition holds:

$$b_{t-1}^i - b_t p_t = b^i(1 - p^i(b^i)) \tag{12}$$

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

$$\begin{aligned}
c^T &= \overline{y}\overline{z^T}\frac{1}{\chi^T} + \frac{\chi^L}{\chi^T}(b^L(1 - p^L(b^L))) + \frac{\chi^M}{\chi^T}(b^M(1 - p^M(b^M))) && (13)\\
c^M &= \overline{y}\overline{z^M}\frac{1}{\chi^M} + \frac{1}{\chi^M}b^M(p^M(b^M) - 1) && (14)\\
c^L &= \overline{y}\overline{z^L}\frac{1}{\chi^L} + \frac{1}{\chi^L}b^L(p^L(b^L) - 1) && (15)
\end{aligned}$$

Second, we look for the neighborhood of the steady-state. Therefore, we simplify these demands and supplies to yield:

$$p^M(b^M) = \beta_M - \gamma \left(\frac{z_t^M}{\chi^M}\right)^{\frac{\theta-1}{\theta}} \left(b_t^M\right)^{-\frac{1}{\theta}} (c_t^M)^{\frac{1}{\sigma}} \tag{16}$$

$$p^M(b^M) = \beta_T + \varphi^M \frac{(c^T)^{\frac{1}{\sigma}}}{(1+\frac{\chi^M}{\chi^T}b^M)^{\frac{1}{\eta}}} \tag{17}$$

$$p^L(b^L) = \beta_L - \gamma \left(\frac{z_t^L}{\chi^L}\right)^{\frac{\theta-1}{\theta}} \left(b_t^L\right)^{-\frac{1}{\theta}} (c_t^L)^{\frac{1}{\sigma}} \tag{18}$$

$$p^L(b^L) = \beta_T + \varphi^L \frac{(c^T)^{\frac{1}{\sigma}}}{(1+\frac{\chi^L}{\chi^T}b^L)^{\frac{1}{\eta}}} \tag{19}$$

We aim to obtain steady-state relationships similar to Kumhof et al. (2015) but we cannot simply drop the price because of supply-demand equality. By contrast, our extension gives two debt levels $(\overline{b^M}, \overline{b^L})$ with their prices $(\overline{p^M}, \overline{p^L})$. We combine equations (13) to (19)[10] and we differentiate these relationships to obtain a causal impact.

Demand-side effect. To highlight the demand-side argument, we can derive the effect of an increase in low- and middle-classes' income share $\overline{z^i}$ on the steady-state debt level $\overline{b^i}$ for $i \in (L, M)$ and $i \neq j$. As we show in Appendix A, it yields

$$\frac{\mathrm{d}log(\overline{b^i})}{\mathrm{d}log(\overline{z^i})} = \frac{\overbrace{\frac{\theta-1}{\theta}}^{Demand\ Side} + \overbrace{\frac{1}{\sigma}\frac{1}{\chi^i}\frac{\overline{y}}{\overline{c^i}}}^{KRW(2015)}}{\underbrace{\frac{1}{\theta}}_{Borrower\ pref.} + \underbrace{\frac{1}{\sigma}\frac{1}{\chi^i}\frac{1-\overline{p^i}}{\overline{c^i}}}_{quantity\ vs\ price} + \underbrace{\frac{1}{\eta}\frac{\chi^i}{\chi^T}\frac{1}{1+\frac{\chi^i}{\chi^T}\overline{b^i}}}_{Top\ income\ pref.} - \underbrace{\frac{1}{\sigma}\frac{\chi^i}{\chi^T}\frac{1-\overline{p^i}}{\overline{c^T}}}_{CRRA}} \tag{20}$$

This equation exhibits a negative effect if $\theta < 1$ (our previous assumption), the second term in the numerator is not too high and the denominator is globally positive. We disentangle this latter into four terms. The first directly depends on the borrower preference

[10] Because these equations are interlinked, we do not present direct steady-state relationship as equation (17) in Kumhof et al. (2015). But the balance of supply and demand of both kinds of credit suggests positive loans as long as these conditions $\beta_M > \beta_T$ and $\beta_L > \beta_T$ are satisfied. In addition, we implicitly assume that the endogenous amount of debt and consumption as well as interest rate do not change the sign of our testable predictions.

in equations (5) and (6). By contrast with Kumhof et al. (2015), the second part reflects the trade-off between price and quantity for loans. A decrease in inequality through the rising part of borrowers' income share could negatively affect interest rates, more than credit quantity. The two last parts are close to equation (18) of Kumhof et al. (2015) and respectively represent the top income households' preference on wealth and a specific CRRA function effect. To sum up, the denominator is positive if the implicit interest rate is not too high and/or the consumption of the top income household is high.

In addition, our model allows a definition of the cross-derivatives, which measure the responsiveness of the loans demanded by a borrower's group to a change in the income share of the other borrower's group. As described in Appendix A, the impact is positive if the demand-side argument works.

Supply-side effect. To show the supply-side argument, we proceed the same way with an increase in the top earners' income share $\overline{z^T}$,

$$\frac{\mathrm{d}log(\overline{b^i})}{\mathrm{d}log(\overline{z^T})} = \frac{\frac{1}{\sigma}\frac{\overline{y}}{\chi^T}\frac{1}{\overline{c^T}}}{\frac{1}{\theta}+\frac{1}{\sigma}\frac{1}{\chi^i}\frac{1-\overline{p^i}}{\overline{c^i}}+\frac{1}{\eta}\frac{\chi^i}{\chi^T}\frac{1}{1+\frac{\chi^i}{\chi^T}\overline{b^i}}-\frac{1}{\sigma}\frac{\chi^i}{\chi^T}\frac{1-\overline{p^i}}{\overline{c^T}}} \tag{21}$$

If the denominator is again positive, the supply-side argument holds.

Difference between middle-class and low-income households. We determine if the bulk of the positive impact of inequality on household credit is driven by the middle-class or by the low-income class. If the middle class is the key driver, so we should have

$$\frac{\mathrm{d}log(\overline{b^M})}{\mathrm{d}log(\overline{z^M})} < \frac{\mathrm{d}log(\overline{b^L})}{\mathrm{d}log(\overline{z^L})} < 0 \tag{22}$$

We show in Appendix A that equation 22 holds under three reasonable conditions: (i) middle-class consumption should be significantly higher than that of the low-income household, (ii) poor household should be more credit-constrained than the middle class, (iii) the pass-through to the implicit interest rate of an inequality shock should not be too high.

2.5 Testable Predictions

We can derive three main theoretical predictions, which we will subsequently bring to the data:

Testable Prediction 1: An increase in inequality leads to an expansion in household credit at the aggregate level. This is consistent with both Kumhof et al. (2015) and our own setting. Here, it is the combination of a demand-side effect (equation 20) and a supply-side effect (equation 21).

Testable Prediction 2: The bulk of the positive impact of inequality on household credit is driven by the middle class (equation 22).

Testable Prediction 3: The positive causal link from inequality to household credit exists if and only if the country is sufficiently developed. As proposed by Kumhof et al. (2012), the credit constraints are so high in the emerging world that potential borrowers have little access to domestic financial markets and no access to international ones. In these countries, top income households *"deploy their surplus funds abroad, leading to current account surpluses"*, which drop current wealth preference, i.e. the parameters φ^L and φ^M are equal to 0.

3 Data

Our empirical analysis relies on a country-level yearly dataset for 41 countries over the period 1970-2014, based on two building blocks, income inequality and credit.

3.1 Inequality

The use of inequality data in cross-country studies raises several challenges. The use of one specific index of inequality and one specific database is not neutral. Jenkins (2015b), among others, shows 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 parts of the income distribution. Furthermore, we implement a transparent 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. One serious limitation is that it is based on pre-tax and not disposable income. As we focus on the saving and borrowing behavior 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 focuses exclusively on top incomes. 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 on 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, income shares per decile, as well as ratios between those income shares. 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 tails dynamics. Afterwards, we go one step deeper by investigating the impact of different income shares categories: the top incomes, alternatively defined as the share of income owned by the Top 10% (corresponding to incomes after the 9$^{\text{th}}$ decile) and Top 30% (corresponding to incomes after the 7$^{\text{th}}$ decile); the middle class incomes, defined alternatively as Middle 30-70% (corresponding to incomes after the 3$^{\text{rd}}$ and up to the 7$^{\text{th}}$ decile) and Middle 30-90% (corresponding to incomes after the 3$^{\text{rd}}$ and up to the 9$^{\text{th}}$ decile); the bottom incomes, defined as the share of income owned by the Bottom 30% (corresponding to incomes up to the 3$^{\text{rd}}$). Finally, we complement this by using the ratios of these different shares, in order to assess the impact of relative variations, i.e. gain or impoverishment of one category versus another one. More precisely, we study the impact of the ratio of Top incomes over middle-class incomes (Top 10/Middle 30-90, and Top 30/Middle 30-70), and Top incomes over Bottom incomes (Top 10/Bottom 30, and Top 30/Bottom 30).[11] More generally, 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 some implications of the theoretical model. More specifically, if lower incomes are highly credit-constrained, i.e. if they have a more difficult access to credit, the income dynamics of the middle class is more likely to have an effect on credit dynamics.

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, 2016), the Luxembourg Income Study, OECD and EUROSTAT. It covers 161 countries between 1867 and 2015. 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.[12]

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

[11] Note that these ratios are intuitively closed to the Palma (Palma, 2011) index that combines the top 10% income share with the bottom 40% income share.

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

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 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 employ similar equivalence scale. Our selection promotes the use of one unique dataset but also provides arguments in favor of some datasets mix. To ensure consistency, we generally prefer to use only one dataset.[13] In some cases, we face a trade-off between the use of one particular dataset with potential limited linear interpolations 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.[14] Appendix B summarizes the primary sources used for each country. A total of 19,5% (**8** countries[15] out of 41) of our sample use series mixing different primary sources.

3.2 Credit

By contrast with the existing works based on cross-country samples, we refer to household credit[16], which is much more relevant to analyze the potential effect of inequalities. There is no theoretical mechanism to explain the potential effect on other sources of private credit such as business credit.[17] Besides, we rely on the ratio of household credit over GDP, since recent literature (e.g. Atkinson and Morelli, 2015) emphasizes that it is the excessive level of credit compared to output that may lead to financial instability. Increasing levels of credit do not imply instability if productive investment is funded, triggering

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

[14]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.

[15]Austria, Belgium, Finland, Ireland, Portugal, Sweden. We also use different datasources for South Korea and United Kingdom for various decades but without any interpolation across years.

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

[17]In addition, Buyukkarabacak and Valev (2010) find that business credit is a much weaker predictor of financial crises.

an increase in the long-run output: In other words, we are not that much interested in the growth of credit *per se*, but in 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. However, we also check in additional estimates how our results behave when we use the log of household credit.

Our main datasource for household credit is the Bank for International Settlements (BIS): Over 87% (36 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 Data Appendix B). Note that aggregate private credit computed by the BIS involves loans from both the domestic and international financial sector. In robustness checks, we check how inequality affects total credit to the private sector, using the corresponding variable from the BIS database, and also two alternative indexes from the World Bank (WB), which are restricted, respectively, to private credit from the 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 affected by inequality.

3.3 Other variables

The classical determinants of credit pointed to 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[18], concerning private ownership of banks, 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 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 affects the depth of the domestic

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

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:

$$Credit_{i,t} = \beta Ineq_{i,t} + \Gamma X_{i,t} + \mu_i + \lambda_t + \epsilon_{i,t} \tag{23}$$

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 clarify 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-fixed effects, and λ_t represents year dummies. The former captures all time-invariant country characteristics and the latter common trends 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 and the share of top incomes (top 10%, top 30%) in the total income increases, or when the share of low and middle incomes decreases.

Table 1 below shows the results obtained when equation 23 is estimated by OLS. Column (1) reports the estimated coefficient when inequality is proxied through the Gini index. Columns (2) to (6) use alternatively different deciles of income, distinguishing between the rich (*Top 10* and *Top 30*), the middle classes (corresponding to either incomes after the 3^{rd} and up to the 9^{th} decile, denominated *Mid. 30-90%*, or to incomes after the

3rd and up to the 7th decile, *Mid. 30-70%*). Finally, columns (7) to (10) rely on the ratio between top incomes and middle and lower incomes.

The correlation between inequality and credit is correctly signed according to theoretical predictions (except for bottom incomes in column (6)), 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 1: OLS specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable: Household Credit/GDP									
Inequality Measure	Gini	Top 10	Top 30	Mid. 30-90	Mid. 30-70	Bottom	$\frac{Top10}{Mid.30-90}$	$\frac{Top10}{Bottom}$	$\frac{Top30}{Mid.30-70}$	$\frac{Top30}{Bottom}$
Inequality	0.221	0.465	0.329	-0.935	-0.909	0.0734	0.223	0.0290	0.0692	0.0189*
	(0.351)	(0.501)	(0.463)	(0.875)	(0.896)	(0.922)	(0.223)	(0.0177)	(0.0678)	(0.0109)
GDP per capita	0.0212	0.0242	0.0228	0.0304	0.0285	0.0216	0.0255	0.0254	0.0260	0.0238
	(0.0613)	(0.0639)	(0.0621)	(0.0688)	(0.0666)	(0.0606)	(0.0644)	(0.0616)	(0.0636)	(0.0605)
Broad Money Ratio	0.147*	0.144*	0.146*	0.146*	0.145*	0.156**	0.144*	0.145*	0.146*	0.144*
	(0.0748)	(0.0747)	(0.0747)	(0.0742)	(0.0745)	(0.0736)	(0.0746)	(0.0742)	(0.0745)	(0.0741)
Credit Dereg.	-0.00771	-0.00796	-0.00788	-0.00751	-0.00803	-0.00689	-0.00781	-0.00831	-0.00792	-0.00851
	(0.0102)	(0.0104)	(0.0103)	(0.0102)	(0.0104)	(0.00988)	(0.0104)	(0.0105)	(0.0104)	(0.0104)
Cons.	-0.191	-0.268	-0.308	0.348	0.113	-0.146	-0.261	-0.225	-0.282	-0.224
	(0.595)	(0.632)	(0.623)	(0.892)	(0.763)	(0.637)	(0.642)	(0.608)	(0.637)	(0.595)
Obs.	896	896	896	896	896	896	896	896	896	896
Countries	41	41	41	41	41	41	41	41	41	41
adj. R^2	0.661	0.663	0.662	0.666	0.664	0.661	0.664	0.668	0.664	0.667

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

However, for a number of reasons these OLS estimates may 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[19], which increased simultaneously the two variables; in that case, β is positively biased. We reduce the bias by controlling for financial liberalization, but other dimensions and shocks might still be at play. 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 questioned to some extent in the literature (see Bazillier and Hericourt, 2017), making the extent and sign of the bias on β uncertain. Finally, Table 2 below shows that credit is much more volatile than

[19] 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.

inequality (whichever measure is considered): 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.

Table 2: Descriptive Statistics: Credit and Inequality

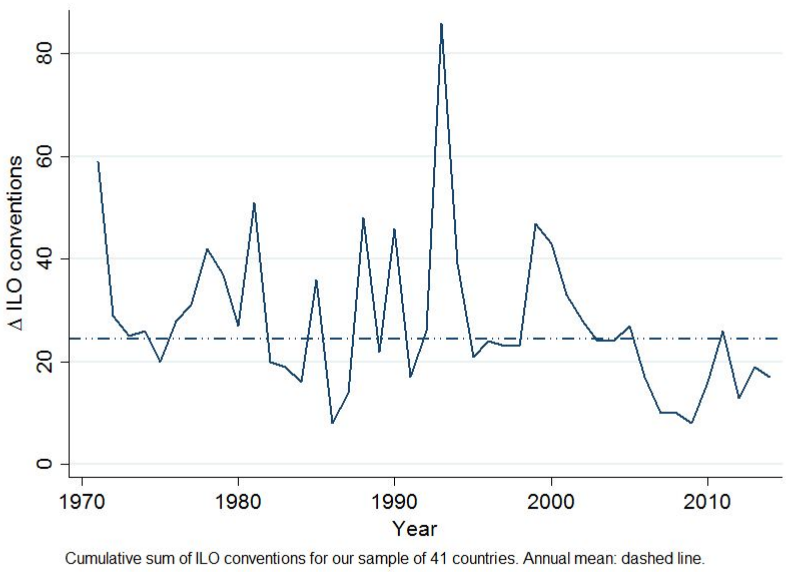
	Mean	First quartile	Median	Third quartile	S.D.*within*	S.D.*overall*
Levels						
Gini	0.340	0.267	0.317	0.374	0.020	0.099
Top 10	0.268	0.218	0.244	0.282	0.016	0.076
Top 30	0.537	0.481	0.517	0.563	0.015	0.079
Middle 30-90	0.60	0.594	0.617	0.629	0.011	0.046
Middle 30-70	0.332	0.322	0.347	0.361	0.009	0.046
Bottom 0-30	0.131	0.111	0.135	0.158	0.007	0.034
Top 10/Middle 30-90	0.461	0.350	0.394	0.473	0.039	0.187
Top 30/Middle 30-70	1.706	1.337	1.487	1.740	0.125	0.635
Top 10/Bottom 0-30	2.515	1.375	1.801	2.527	0.407	1.971
Top 30/Bottom 0-30	4.800	3.025	3.851	5.017	0.582	2.872
Household credit/GDP	0.421	0.178	0.397	0.580	0.138	0.279
log(real household credit)	6.579	5.181	6.475	7.419	0.739	2.379
ILO Conv.	64.68	41	69	87	6.547	31.85

4.2 Identification strategy

To identify how variations in inequality driven by exogenous shocks affect household credit over GDP, we need an instrument that affect inequality without influencing directly credit (exclusion restriction), and that is orthogonal to any country-specific characteristics which may drive 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 policies of the International Labor Organization. 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 country-level inequality. 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. However, we identify two waves of ratifications that are likely to be exogenous to these national characteristics. As we can see in Figure 1, the first wave of increase starts in the mid-1970s and the second one in the 1990s. We detail below the reasons why these two waves are very likely to be exogenous to countries' characteristics.

Figure 1: ILO's Conventions Ratifications



Source: ILO website, compilation by the authors.

The International Labor Organisation and waves of ratifications. The International Labor Organisation (ILO) 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 is based on social justice"* (ILO Website).[20] 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

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

a convention, it becomes binding. Ratifying countries commit themselves to applying the convention in national law and practice 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 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 (1973 - 1989), the ILO expanded 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 1980s 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. A debate started in the middle of the 1990s 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 donor countries (Rodgers et al., 2009, p. 73).

A careful look at the evolution of the ILO ratifications over time is consistent with the two different waves we identified analyzing the history of the ILO. On average over the period, there are 30 additional conventions that are ratified per year. But we observe some peaks. In 1971 (corresponding to the beginning of the first wave), we observed 62 additional conventions, and the number of ratifications between 1977 and 1981 (end of the first wave) is above average (from 36 in 1977 to 51 in 1981). The second wave starts in the mid-90s and we observe two peaks in 1999 and 2000 (with respectively 49 and 44 ratifications), right after the adoption of the Declaration on Fundamental Principles and Rights at Work. This is consistent with our hypothesis that it is possible to identify dynamics of ratifications that depend on the international policies and strategies of the ILO, and not on national circumstances. We believe it is a strong argument supporting the orthogonality condition of our instrument.

ILO ratifications and credit market liberalisation. One particular threat to identification is that ILO conventions might be correlated with other variables that should also have an impact on inequalities. If governments aiming at strengthening labor regulations are also ratifying ILO conventions, our instrument would be correlated with broader labor market regulations. It would be a matter of concern if labor market *deregulation* and financial deregulation are correlated, as the latter is likely to have a direct effect on our dependent variable: household credit. It is the main argument of Tridico (2012) who shows that these two policies are often part of the same policy package of deregulation. It is why we do not use indexes of labor market regulations as instrument. We therefore check the dynamics of both the instrument (ILO ratification) and credit market liberalisation.

We find that the evolution of ILO ratifications is poorly correlated with the evolution of both labor market regulation and credit market regulation. The correlation between ILO ratifications and the evolution of the credit market (respectively, labor market) deregulation is only 0.08 (respectively, 0.04). We also compute what is the average change in the credit market deregulation index, when there is no change in the number of ILO ratifications, when there is one additional ILO ratified conventions, and when there is more than one ratified ILO convention. We do not observe significant differences between the average evolution of the index of credit market deregulation, depending on the number of additional ILO conventions ratified.[21] We also test the opposite relation: the average change in ILO convention ratification when there is respectively more credit market regulation, no change, or less credit market regulation. The average change in ILO convention ratification is not statistically different depending on the change in credit market regulation.

Beyond this analysis of correlation, we identified two main waves of ratifications: mid 70s to the beginning of the 1980s and the end of the 1990s. These waves are not related to the massive liberalization packages that occurred mainly in the 1980s and early to mid-1990s. This is an additional argument showing that these waves of ratifications are uncorrelated with the dynamics of liberalization. We therefore conclude that the change in inequalities explained by our instrument is not likely to be driven by other policy changes.

For all these reasons, we argue that the main 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.

[21] Average change in credit market deregulation index is respectively 0.05, 0.06 and 0.09 when there is no change, one addition ILO convention and more than one additional ILO convention. The confidence intervals for each mean cross each other.

ILO conventions and inequalities. On the other side, the ratification of ILO 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 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 Labor 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.

Therefore, we 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 the number of ILO conventions ratified) on the ratio of household credit to GDP:

$$Ineq_{i,t} = \alpha ILO_{i,t} + \delta X_{i,t} + \lambda_i + \lambda_t + \mu_{i,t} \tag{24}$$

$$Credit_{i,t} = \beta \widehat{Ineq}_{i,t} + \Gamma X_{i,t} + \lambda_i + \lambda_t + \epsilon_{i,t} \tag{25}$$

where $\widehat{Ineq}_{i,t}$ is the predicted value of the inequality index from Equation 24. 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 3: Inequality decreases when the number of ILO conventions ratified increases. Put differently a higher number of signed ILO conventions decreases the Gini index and the share of Top incomes, and increases the shares of bottom and middle incomes. This result also holds when we include instead lagged values of the number of ILO conventions (see Table C.2 in Appendix C). In Appendix C, we also provide evidence that $ILO_{i,t}$ is not likely to violate exclusion restrictions seriously. Table C.3 reports estimates of a modified Equation 23, including the number of ILO conventions ratified ($ILO_{i,t}$). Results largely support that the exclusion restrictions are respected, whatever the indicator of inequality used or the considered countries (developed or emerging): the number of ILO conventions appears consistently insignificant in most cases, or weakly significant in a couple of specifications.

Table 3: First stage, Inequality structure

Dep. Var.	(1) Gini	(2) Top 10	(3) Top 30	(4) Middle 30 90	(5) Middle 30 70	(6) Bottom	(7) $\frac{Top10}{Mid.30-90}$	(8) $\frac{Top10}{Bottom}$	(9) $\frac{Top30}{Mid.30-70}$	(10) $\frac{Top30}{Bottom}$
# ILO Conv.	-0.00108***	-0.000613***	-0.000697***	0.000224*	0.000308***	0.000445***	-0.00135***	-0.0187***	-0.00499***	-0.0296***
	(0.000220)	(0.000181)	(0.000176)	(0.000132)	(0.000108)	(0.0000860)	(0.000425)	(0.00412)	(0.00126)	(0.00601)
GDP per capita	-0.00289	-0.00831	-0.00680	0.0105**	0.00896**	-0.00205	-0.0234	-0.205	-0.0839*	-0.234
	(0.00727)	(0.00627)	(0.00617)	(0.00477)	(0.00429)	(0.00256)	(0.0144)	(0.136)	(0.0451)	(0.202)
Broad Money	0.0311***	0.0218***	0.0230***	-0.00894***	-0.0100***	-0.0129***	0.0431***	0.270**	0.103***	0.428***
	(0.00572)	(0.00452)	(0.00449)	(0.00298)	(0.00269)	(0.00214)	(0.0104)	(0.107)	(0.0328)	(0.158)
Credit Dereg.	0.00390***	0.00246***	0.00311***	-0.000688	-0.00133***	-0.00179***	0.00448***	0.0570***	0.0164***	0.0987***
	(0.000862)	(0.000697)	(0.000693)	(0.000520)	(0.000441)	(0.000347)	(0.00166)	(0.0168)	(0.00524)	(0.0249)
Obs.	896	896	896	896	896	896	896	896	896	896
Countries	41	41	41	41	41	41	41	41	41	41
adj. R^2	0.173	0.104	0.130	0.024	0.055	0.196	0.033	0.008	-0.003	0.023

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

Finally, we performed the Durbin–Wu–Hausman test for exogeneity of regressors ("Durbin-Wu" statistics, together with p-values, are reported at the bottom of our main results Table 4[22]). Unsurprisingly, the null hypothesis of exogeneity is rejected in all cases, which confirms the need to use an instrumental variable. 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.

[22]Statistics for other specifications/tables available upon request to the authors.

5 Results

5.1 Baseline Results

Table 4: Baseline

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep. Var.					Household Credit/GDP					
Inequality Measure	Gini	Top 10	Top 30	Mid. 30-90	Mid. 30-70	Bottom	$\frac{Top10}{Mid.30-90}$	$\frac{Top10}{Bottom}$	$\frac{Top30}{Mid.30-70}$	$\frac{Top30}{Bottom}$
Inequality	3.645***	6.428***	5.654***	-17.59*	-12.79***	-8.851***	2.923***	0.211***	0.789***	0.133***
	(0.942)	(2.086)	(1.677)	(10.20)	(4.791)	(2.283)	(0.967)	(0.0510)	(0.219)	(0.0312)
GDP per capita	0.0183	0.0612	0.0462	0.192	0.122	-0.0104	0.0762	0.0510	0.0740	0.0390
	(0.0353)	(0.0518)	(0.0451)	(0.147)	(0.0801)	(0.0312)	(0.0539)	(0.0344)	(0.0461)	(0.0325)
Broad Money Ratio	0.0225	-0.00446	0.00616	-0.0212	0.00738	0.0214	0.00989	0.0789**	0.0543	0.0789**
	(0.0459)	(0.0632)	(0.0556)	(0.118)	(0.0702)	(0.0454)	(0.0616)	(0.0381)	(0.0452)	(0.0373)
Credit Deregulation	-0.0187***	-0.0204***	-0.0221***	-0.0167	-0.0216**	-0.0204***	-0.0176**	-0.0166***	-0.0175***	-0.0177***
	(0.00577)	(0.00723)	(0.00705)	(0.0113)	(0.00883)	(0.00598)	(0.00692)	(0.00578)	(0.00633)	(0.00578)
Quantification										
$\beta_{Ineq} * SD_{within}$	0.0729	0.1028	0.0848	-0.1935	-0.1151	-0.0619	0.1140	0.0859	0.0986	0.0774
$DurbinWu-stat$	27.871	26.793	27.603	27.919	26.649	31.681	26.998	24.932	26.620	24.733
$P-value$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$KPF-stat$	24.089	11.440	15.775	2.867	8.083	26.802	10.08	20.579	15.705	24.209
Obs.	896	896	896	896	896	896	896	896	896	896
Countries	41	41	41	41	41	41	41	41	41	41
adj. R^2	0.438	0.211	0.331	-1.117	0.040	0.440	0.068	0.362	0.217	0.417

Robust standard errors in parentheses. Country- and Year-Fixed Effects. The critical value for the weak instruments test is based on a 10% 2SLS bias at the 5% significance level, which is 16.4 in all estimations. *, ** and *** denote respectively significance at the 10, 5 and 1% levels.

We present in Table 4 our baseline results for equation 25, in which various indicators of income distribution are instrumented by the number of ILO conventions ratified at the country-level. In order to make meaningful comparisons, we report in the "Quantification" row the product between the estimated parameter for each inequality indicator and its within standard deviation.[23] Column (1) relies on the Gini, which gives an idea of the "average" inequality of the income distribution. Columns (2) to (6) go into more details of the structure of inequality, first by focusing on top incomes (Top 10 in column (2) and Top 30 in column (3)), then on middle incomes (either incomes from the 3rd to the 9th decile in column (4), or those from the 3rd to the 7th decile in column (5)) and low incomes (up to the 3rd decile, in column (6)). Columns (7) to (10) go one step further by studying the impact of relative variations of these different shares, through ratios between top incomes and middle and lower incomes.

[23] As an alternative, we also report standardized coefficients (based on variables rescaled so as to have 0 mean and a variance equal to 1) in Table C.1 in Appendix C.

The first theoretical prediction is validated: positive changes in inequality, as predicted by changes in the number of ILO conventions ratified, are positively related to 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 3, 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 0.6 percentage point decrease in credit over GDP.

Regarding control variables, GDP per capita and M2 over GDP have the expected positive signs, but are mostly insignificant. Conversely, financial deregulation exhibits a negative impact on credit, which seems at first sight at odds 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 Tables 10 and 11, where the financial liberalization indicator shows the expected positive impact on the log of household credit.

Regarding the size of the effects, a one standard deviation in the Gini index is associated with a 7.3 percentage point increase in the household credit to GDP ratio. Interestingly, when we investigate specific parts of the income distribution, effects display some quantitative heterogeneity: when inequality is measured through the top incomes share, an increase by one standard deviation lifts the credit to GDP ratio by 10.3 (Top 10) and 8.5% (Top 30). Besides, as indicated by the second prediction of our model, this effect is substantially higher where the share of middle-class incomes is concerned: when the share of Middle30-90 (respectively, Middle30-70) in total income increases by one standard deviation (meaning a *decrease* in the inequality of the distribution of income), credit to GDP decreases by 19.4 (respectively, -11.5) percentage points, whereas the same one standard deviation increase in low-income share only cuts credit to GDP ratio by 6.2 percentage points. A similar effect can be found with income shares ratios: credit over GDP rises by 11.4% (respectively, 9.9%) following a one standard deviation increase in the ratio of Top 10 (respectively Top 30) over Middle 30-90 (respectively Middle 30-70), and by 8.6% (respectively 7.7%) following same increase for the ratio of Top 10 (respectively Top 30) over Bottom.

All these results are consistent with the fact that the 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 Advanced versus Emerging Economies

The third and last implication of our theoretical approach predicts that the positive causal link from inequality to household credit exists if and only if the country is sufficiently developed. In a few words, the underlying intuitions are the following: 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 that the mechanism related 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 share of middle incomes to explain the aggregate dynamics of credit. Since our sample includes a majority of developed countries, but also a significant number of emerging countries, we can bring this intuition to the data by estimating again our empirical model on two subsamples: the first one is restricted to developed countries (estimates reported in Table 5), and the second one, to emerging economies (results in Table 6).

Table 5: Baseline with only advanced economies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep. Var.					Household Credit/GDP					
Inequality Measure	Gini	Top 10	Top 30	Mid. 30-90	Mid. 30-70	Bottom	$\frac{Top10}{Mid.30-90}$	$\frac{Top10}{Bottom}$	$\frac{Top30}{Mid.30-70}$	$\frac{Top30}{Bottom}$
Inequality	3.442***	5.139***	4.614***	-9.947***	-8.150***	-8.304***	1.097***	0.262***	0.772***	0.167***
	(1.260)	(1.893)	(1.700)	(3.816)	(2.861)	(3.073)	(0.366)	(0.0800)	(0.255)	(0.0519)
GDP per capita	-0.0416	-0.0668	-0.0418	-0.113	-0.0603	-0.0273	-0.0628	-0.0447	-0.0502	-0.0353
	(0.0802)	(0.0821)	(0.0827)	(0.0905)	(0.0802)	(0.0830)	(0.0769)	(0.0723)	(0.0771)	(0.0743)
Broad Money Ratio	0.124**	0.140***	0.131**	0.205***	0.177***	0.106*	0.159***	0.157***	0.160***	0.148***
	(0.0540)	(0.0496)	(0.0517)	(0.0348)	(0.0374)	(0.0607)	(0.0416)	(0.0415)	(0.0408)	(0.0443)
Credit Deregulation	-0.00800	-0.00238	-0.00633	0.0102	0.000923	-0.0128*	-0.00119	-0.00367	-0.00256	-0.00581
	(0.00585)	(0.00568)	(0.00592)	(0.00755)	(0.00587)	(0.00655)	(0.00543)	(0.00520)	(0.00551)	(0.00543)
$KPF-stat$	18.90	16.693	18.800	11.130	20.593	18.839	18.576	44.738	30.133	43.625
Obs.	611	611	611	611	611	611	611	611	611	611
Countries	25	25	25	25	25	25	25	25	25	25
adj. R^2	0.599	0.581	0.600	0.500	0.621	0.574	0.595	0.665	0.650	0.656

Robust standard errors in parentheses. Country and Year Fixed Effects. The critical value for the weak instruments test is based on a 10% 2SLS bias at the 5% significance level, which is 16.4 in all estimations. *, ** and *** denote respectively significance at the 10, 5 and 1% levels.

Table 6: Baseline with only emerging economies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep. Var.					Household Credit/GDP					
Inequality Measure	Gini	Top 10	Top 30	Mid. 30-90	Mid. 30-70	Bottom	$\frac{Top10}{Mid.30-90}$	$\frac{Top10}{Bottom}$	$\frac{Top30}{Mid.30-70}$	$\frac{Top30}{Bottom}$
Inequality	-0.793	-1.358	-1.340	2.101	2.058	3.656	-0.199	-0.0478	-0.143	-0.0324
	(0.517)	(0.923)	(0.876)	(1.537)	(1.359)	(2.497)	(0.149)	(0.0398)	(0.104)	(0.0265)
GDP per capita	0.201***	0.224***	0.217***	0.231***	0.220***	0.207***	0.211***	0.203***	0.207***	0.198***
	(0.0292)	(0.0451)	(0.0387)	(0.0536)	(0.0408)	(0.0354)	(0.0393)	(0.0372)	(0.0352)	(0.0329)
Broad Money Ratio	0.0951***	0.107***	0.0933***	0.111***	0.0898***	0.0996***	0.0980***	0.0856***	0.0894***	0.0805***
	(0.0225)	(0.0291)	(0.0246)	(0.0314)	(0.0240)	(0.0279)	(0.0271)	(0.0244)	(0.0247)	(0.0240)
Credit Deregulation	-0.00284	-0.00206	0.000471	-0.00682	-0.00283	0.00594	-0.00553	-0.00228	-0.00458	-0.000604
	(0.00624)	(0.00705)	(0.00814)	(0.00510)	(0.00651)	(0.0116)	(0.00584)	(0.00866)	(0.00616)	(0.00967)
$KPF-stat$	10.977	5.623	5.48	5.415	7.208	3.187	4.172	2.963	4.956	2.923
Obs.	285	285	285	285	285	285	285	285	285	285
Countries	16	16	16	16	16	16	16	16	16	16
adj. R^2	0.802	0.735	0.756	0.695	0.754	0.741	0.643	0.636	0.678	0.661

Robust standard errors in parentheses. Country and Year Fixed Effects. The critical value for the weak instruments test is based on a 10% 2SLS bias at the 5% significance level, which is 16.4 in all estimations. *, ** and *** denote respectively significance at the 10, 5 and 1% levels.

As expected, our results, concerning both 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, 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).It is all the most striking that all inequality measures deliver the same message. Interestingly, credit deregulation does not seem to have any impact on either subsample, and GDP per capita emerges as a significant determinant only for developing economies. This would tend to suggest that, at an early stage of economic development, credit constraints ar so binding that only an increase in average wealth per capita can ease access to credit; after a certain threshold of development however, credit constraints become less binding (as suggested by the insignifcant coefficient on GDP per capita), and the inequality mechanism driving up household credit (over GDP) suggested by our theoretical framework starts working.

Finally, we investigate further the role of credit constraints in emerging economies, by examining the heterogenous response of household credit to inequality according to the openness to international financial flows. Here we use the Chinn and Ito index measuring a country's degree of capital account openness. Table 7 shows how the causal relationship between household credit over GDP (columns (1) to (3)) and the log of real household credit (columns (4) to (6)) is altered around a threshold of 0.65 for the index, above which countries have a capital account considered as fully open. Interestingly, the result show that emerging countries displaying a sufficient level of openness to international capital flows (columns (2) and (5)) do exhibit a positive impact of inequality on household credit. Conversely, there is not any impact of the Gini index on credit for countries with a low or limited level of openness (i.e. below this threshold, see columns (3) and (6)). This goes again in the direction of a relaxation of credit constraints by incoming financial flows, allowing wider categories of the population to access credit, and consequently, to react to variations in inequality.

Table 7: Level of financial openness of emerging economies

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Household Credit/GDP			log(Real Household Credit)		
Kaopen		>0.65	<0.65		>0.65	<0.65
Gini	-0.800	1.054*	0.902	-37.63***	6.862**	-99.42*
	(0.504)	(0.629)	(6.908)	(12.58)	(3.073)	(54.85)
GDP per capita	0.198***	-0.0222	-0.00461	4.821***	0.0164	6.340*
	(0.0344)	(0.133)	(0.499)	(0.974)	(0.771)	(3.340)
Broad Money Ratio	0.0885***	-0.115**	0.164			
	(0.0282)	(0.0450)	(0.377)			
Log(Real Broad Money)				1.069**	-0.614***	5.965**
				(0.520)	(0.213)	(2.571)
$KPF-stat$	10.821	5.329	0.136	14.298	5.820	3.323
Obs.	285	68	214	285	68	214
Countries	16	6	10	16	6	10
adj. R^2	0.801	-0.017	0.850	0.108	0.666	-1.144

Robust standard errors in parentheses. Country and Year Fixed Effects. The critical value for the weak instruments test is based on a 10% 2SLS bias at the 5% significance level, which is 16.4 in all estimations. *, ** and *** denote respectively significance at the 10, 5 and 1% levels.

5.3 Robustness and Falsification Tests

Definition of the Middle Classes. A key result reported above is the quantitative prevalence of the middle classes in the positive causal impact of inequalities on household credit over/GDP. However, it could be argued that this is due mainly to the two specific definitions of the middle classes we use, i.e. the share of income held by incomes after the 3rd and up to the 9th decile, or the share held by incomes after the 3rd and up to the 7th.

Therefore, Table 8 reports the results of estimates testing the validity of this definition, based on two strategies. First, columns (1) and (4) substitute for our preferred definitions of the middle classes on the right-hand side two alternatives : the share of income owned by the 3rd to the 8th decile (the definition proposed by Easterly, 2001) in column (1), and the share of income owned by the 4th to the 7th decile in column (4). While slightly lower, corresponding quantifications are still around twice higher than the one found for low incomes in Table 4. Second, columns (3) and (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 (2nd and 3rd decile) and middle incomes. As expected, the estimated coefficients (still negative and significant) are getting closer to the one reported in column (6) in Table 4. Finally, columns (2) and (5) display estimates which are compromises between these two strategies, by putting the lower bound on the 2nd 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 is restricted to consistent definitions of the midd classes. All in all, Table 8 does confirm the importance of the middle classes in the positive dynamics linking inequality to credit.

Table 8: Baseline with various definitions of the middle classes

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.			Household Credit/GDP			
Middle Classes	30-80	20-80	10-80	40-70	20-70	10-70
Middle	-13.30**	-9.016***	-6.563***	-19.21**	-8.779***	-6.437***
	(5.803)	(3.324)	(2.104)	(7.780)	(2.938)	(1.939)
GDP per capita	0.150	0.109	0.0683	0.117	0.0914	0.0560
	(0.101)	(0.0739)	(0.0546)	(0.0843)	(0.0633)	(0.0490)
Broad Money Ratio	-0.0128	0.000793	0.0161	0.0157	0.0143	0.0257
	(0.0883)	(0.0706)	(0.0574)	(0.0718)	(0.0608)	(0.0519)
Credit Deregulation	-0.0210**	-0.0215**	-0.0211***	-0.0172**	-0.0219***	-0.0214***
	(0.0100)	(0.00859)	(0.00744)	(0.00858)	(0.00793)	(0.00709)
Quantification						
$\beta_{Mid} * SD_{within}$	-0.1444	-0.1169	-0.0978	-0.1332	-0.1015	-0.0879
$KPF - stat$	5.508	8.369	12.174	6.594	10.996	14.895
Obs.	896	896	896	896	896	896
Countries	41	41	41	41	41	41
adj. R^2	-0.281	0.055	0.246	-0.139	0.210	0.327

Robust standard errors in parentheses. Country and Year Fixed Effects. The critical value for the weak instruments test is based on a 10% 2SLS bias at the 5% significance level, which is 16.4 in all estimations. *, ** and *** denote respectively significance at the 10, 5 and 1% 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 9 replicates estimates from Table 4 but excluding all years after 2007. Reported results are basically identical to those presented in Table 4, indicating that no impact of the Great Recession on our key mechanism can be detected.

Table 9: Baseline without the Great Recession (years after 2007 excluded)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep. Var.					Household Credit/GDP					
Inequality Measure	Gini	Top 10	Top 30	Mid. 30-90	Mid. 30-70	Bottom	$\frac{Top10}{Mid.30-90}$	$\frac{Top10}{Bottom}$	$\frac{Top30}{Mid.30-70}$	$\frac{Top30}{Bottom}$
Inequality	3.685***	6.847***	5.651***	-28.18	-15.06**	-8.341***	3.428***	0.255***	0.955***	0.156***
	(1.007)	(2.376)	(1.715)	(25.12)	(6.135)	(2.233)	(1.274)	(0.0627)	(0.281)	(0.0371)
GDP per capita	0.147***	0.256***	0.207***	0.817	0.427***	0.0767**	0.283***	0.150***	0.252***	0.123***
	(0.0443)	(0.0764)	(0.0599)	(0.643)	(0.153)	(0.0390)	(0.0848)	(0.0415)	(0.0639)	(0.0409)
Broad Money Ratio	0.0304	0.0194	0.0215	0.0361	0.0338	0.0300	0.0279	0.118***	0.0696	0.115***
	(0.0528)	(0.0685)	(0.0592)	(0.165)	(0.0760)	(0.0523)	(0.0740)	(0.0433)	(0.0541)	(0.0419)
Credit Deregulation	-0.0257***	-0.0319***	-0.0322***	-0.0523	-0.0434***	-0.0245***	-0.0312***	-0.0249***	-0.0318***	-0.0252***
	(0.00723)	(0.0105)	(0.00947)	(0.0423)	(0.0167)	(0.00697)	(0.0108)	(0.00675)	(0.00916)	(0.00668)
$KPF-stat$	21.362	9.840	15.354	1.169	6.626	25.204	7.776	20.882	13.857	25.190
Obs.	666	666	666	666	666	666	666	666	666	666
Countries	39	39	39	39	39	39	39	39	39	39
adj. R^2	0.319	-0.037	0.220	-5.490	-0.357	0.337	-0.445	0.170	-0.118	0.290

Robust standard errors in parentheses. Country and Year Fixed Effects. The critical value for the weak instruments test is based on a 10% 2SLS bias at the 5% significance level, which is 16.4 in all estimations. *, ** and *** denote respectively significance at the 10, 5 and 1% levels.

Dependent Variable. We provided several arguments in the data section supporting the ratio of household credit over GDP as a dependent variable. To sum it up, our focus is on the part of the rise in credit which is not matched by a corresponding increase in output. Still, we check how estimates change when we use instead the log of household credit to its ratio over GDP as a dependent variable in equation 25. The results of this modification are reported in Tables 10 and 11, which replicates the structure of Table 4, respectively for developed and emerging countries. Regarding developed countries, it is striking to see that our first prediction still holds: estimates keep supporting a positive impact of inequality on the log of household credit, whatever the variable used to proxy inequality. However, there does not seem to be any difference between middle-class and bottom incomes anymore.

Concerning emerging economies, the picture is less clear: our key result on the positive relationship between inequality and credit seems to be reverted in most specifications: an exogenous increase in inequality seems to raise the log of household credit. However, the negative R^2 is clearly an invitation not to overinterpret these results: they indicate that with the log of household credit as a dependent variable, on average over the sample of emerging countries, our empirical model fits the data quite badly. Besides, column (5) in Table 7 presented previously suggested that above a sufficient threshold of openness to international capital flows, the positive impact of inequality on the log of household credit was restored also for emerging economies, in an estimated specification with correct statistical properties (high and positive R^2, sufficient predictive power of the instrumental variable).

Table 10: Log with only advanced economies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep. Var.	log(Real Household Credit)									
Inequality Measure	Gini	Top 10	Top 30	Mid. 30-90	Mid. 30-70	Bottom	$\frac{Top10}{Mid.30-90}$	$\frac{Top10}{Bottom}$	$\frac{Top30}{Mid.30-70}$	$\frac{Top30}{Bottom}$
Inequality	9.652**	13.93**	12.90**	-25.13**	-21.96***	-24.05**	6.794**	0.741***	2.139***	0.481***
	(4.019)	(5.710)	(5.393)	(9.783)	(8.363)	(10.36)	(2.666)	(0.259)	(0.791)	(0.173)
GDP per capita	2.519***	2.397***	2.504***	2.129***	2.345***	2.621***	2.349***	2.455***	2.419***	2.513***
	(0.337)	(0.321)	(0.341)	(0.301)	(0.311)	(0.363)	(0.311)	(0.308)	(0.315)	(0.320)
log(Real Broad Money)	-0.0641	-0.00994	-0.0486	0.147**	0.0614	-0.124	0.0167	-0.00764	0.0138	-0.0378
	(0.117)	(0.102)	(0.111)	(0.0710)	(0.0745)	(0.140)	(0.0925)	(0.0890)	(0.0843)	(0.0975)
Credit Deregulation	0.0526**	0.0690***	0.0574***	0.102***	0.0779***	0.0377	0.0742***	0.0644***	0.0680***	0.0578***
	(0.0215)	(0.0215)	(0.0217)	(0.0245)	(0.0211)	(0.0236)	(0.0212)	(0.0200)	(0.0205)	(0.0204)
Quantification										
$\beta_{Ineq} * SD_{within}$	0.1783	0.1972	0.1774	-0.2384	-0.1724	-0.1780	0.1902	0.1281	0.1465	0.1291
$KPF-stat$	18.011	17.342	18.120	13.630	22.134	16.491	19.678	40.864	30.056	37.872
Obs.	611	611	611	611	611	611	611	611	611	611
Countries	25	25	25	25	25	25	25	25	25	25
adj. R^2	0.730	0.721	0.730	0.707	0.759	0.709	0.735	0.782	0.772	0.774

Robust standard errors in parentheses. Country and Year Fixed Effects. The critical value for the weak instruments test is based on a 10% 2SLS bias at the 5% significance level, which is 16.4 in all estimations. *, ** and *** denote respectively significance at the 10, 5 and 1% levels.

Table 11: Log with only emerging economies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep. Var.	log(Real Household Credit)									
Inequality Measure	Gini	Top 10	Top 30	Mid. 30-90	Mid. 30-70	Bottom	$\frac{Top10}{Mid.30-90}$	$\frac{Top10}{Bottom}$	$\frac{Top30}{Mid.30-70}$	$\frac{Top30}{Bottom}$
Gini	-46.83***	-70.47**	-78.04**	100.1***	116.0**	223.3*	-29.39**	-3.244	-8.619**	-2.312
	(16.88)	(28.30)	(35.45)	(36.87)	(46.13)	(132.4)	(13.40)	(2.260)	(4.322)	(1.694)
GDP per capita	5.146***	5.566***	5.908***	5.232***	5.687***	5.968**	5.610***	6.333**	5.513***	6.303**
	(1.126)	(1.444)	(1.724)	(1.242)	(1.415)	(2.339)	(1.667)	(2.901)	(1.698)	(3.017)
log (Real Broad Money)	0.170	0.947	0.327	1.493**	0.660	-0.215	0.973	-0.811	0.139	-1.163
	(0.620)	(0.721)	(0.803)	(0.685)	(0.714)	(1.055)	(0.793)	(1.444)	(0.853)	(1.673)
Credit Deregulation	0.612***	0.576**	0.781**	0.282*	0.540**	1.207*	0.454*	0.751	0.499*	0.903
	(0.232)	(0.248)	(0.366)	(0.149)	(0.241)	(0.702)	(0.240)	(0.556)	(0.289)	(0.684)
Quantification										
$\beta_{Ineq} * SD_{within}$	-1.0518	-1.3713	-1.4443	1.4091	1.3673	1.8159	-1.6652	-2.1919	-1.7029	-2.2084
$KPF-stat$	11.880	7.699	6.29	8.323	8.842	3.218	5.603	2.299	4.997	2.079
Obs.	285	285	285	285	285	285	285	285	285	285
Countries	16	16	16	16	16	16	16	16	16	16
adj. R^2	-0.108	-0.681	-0.947	-0.630	-0.660	-1.800	-1.701	-3.761	-2.120	-3.796

Robust standard errors in parentheses. Country and Year Fixed Effects. The critical value for the weak instruments test is based on a 10% 2SLS bias at the 5% significance level, which is 16.4 in all estimations. *, ** and *** denote respectively significance at the 10, 5 and 1% levels.

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 12 reports estimates of equation 25 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 credit from the BIS (column (2)), total bank credit form the BIS (column (3)), firm credit (column (4)) and household credit (column (5)) - all regressions reported in Table 12 were rerun on a common sample to make sure that the sample alteration cannot be responsible for some differences. Columns (6) to (10) replicate columns (1) to (5) for 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 (4) and (9)), or on bank credit (columns (3) and (8)). Besides, columns (1)/(2) and (6)/(7) show that the way total credit is measured may be non-neutral on the result. When the measure by the World Bank is used, the impact of inequality remains positive (as in Perugini et al., 2016). When the measure by the BIS (the most legitimate for us since household and firm credit also come from the BIS) is used instead, the impact of the predicted Gini coefficient becomes insignificant over the whole period of estimation. A possible explanation comes from the fact that the World Bank aggregate excludes credit from the international financial sector, which may create a bias in the results. In any case, this "falsification evidence" indicates that the positive causal impact of inequality is mainly concentrated on household credit.

Table 12: Falsification Tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			Whole Sample					Before 2008		
Dep. Var: Credit/GDP	TotalWB	TotalBIS	Bank	Firm	Household	TotalWB	TotalBIS	Bank	Firm	Household
Gini	15.44***	1.260	-2.089	-2.362	5.650***	17.67***	5.250**	2.184	0.809	6.727***
	(5.004)	(2.301)	(2.029)	(1.824)	(1.966)	(6.097)	(2.616)	(1.635)	(1.368)	(2.379)
GDP per capita	-0.111	-0.0205	0.0952**	-0.0745	0.0423	0.170	0.311***	0.305***	0.0932*	0.223***
	(0.110)	(0.0604)	(0.0449)	(0.0466)	(0.0496)	(0.164)	(0.0927)	(0.0657)	(0.0533)	(0.0718)
Broad Money Ratio	-0.136	0.254***	0.357***	0.210***	-0.0360	-0.263	0.130	0.250***	0.0944	-0.0725
	(0.199)	(0.0980)	(0.0874)	(0.0742)	(0.0787)	(0.254)	(0.122)	(0.0873)	(0.0655)	(0.0992)
Credit Deregulation	-0.0458**	0.00543	0.0317**	0.0250**	-0.0271***	-0.0900***	-0.00732	0.00374	0.0226**	-0.0416***
	(0.0226)	(0.0138)	(0.0142)	(0.0110)	(0.00911)	(0.0326)	(0.0160)	(0.0118)	(0.00980)	(0.0132)
$KPF-stat$	9.913	9.913	9.913	9.913	9.913	8.723	8.723	8.723	8.723	8.723
Obs.	867	867	867	867	867	653	653	653	653	653
Countries	39	39	39	39	39	37	37	37	37	37
adj. R^2	-0.393	0.573	0.274	0.246	0.134	-0.732	0.447	0.324	0.376	-0.294

Robust standard errors in parentheses. Country and Year Fixed Effects. The critical value for the weak instruments test is based on a 10% 2SLS bias at the 5% significance level, which is 16.4 in all estimations. *, ** and *** denote respectively significance at the 10, 5 and 1% levels.

6 Conclusion

This paper extends 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 41-country dataset over the period 1970-2014, 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 of total income decreases, either in absolute or relative terms). 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 mostly for developed countries, consistently with the third implication of the theoretical approach. For emerging economies, no such effects can be observed on average, possibly due to credit constraints and insufficiently important middle income categories. Consistently, it appears that the positive impact of inequality on household credit is restored on a sample of emerging countries with sufficient openness of the capital account: by relaxing financial constraints, capital inflows allow middle and low income individuals to access credit more easily.

Our work has important implications regarding financial crises prevention. In order to avoid financial crises such as the one of 2007-2009, which triggered 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 the income distribution.

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A Appendix A: Additional Proofs and Discussions

A.1 Proof of the equation (20)

We combine equation (16) and (17) and we reinject the level of consumption from equations (13) and (14). We log-linearize the sum to simplify the results. Then we generate the following function $f(log(\overline{b^M}), log(\overline{z^M})) = 0$. By assuming that price variables $(\overline{p^M}, \overline{p^L})$ and low-income households' variables $(\overline{b^L}, \overline{z^L})$ are fixed, the total derivative of f is given by

$$\mathrm{d}f = 0 = \frac{\partial f}{\partial log(b^M)} \mathrm{d}log(b^M) + \frac{\partial f}{\partial log(z^M)} \mathrm{d}log(z^M) \tag{26}$$

This yields

$$\frac{\mathrm{d}log(\overline{b^M})}{\mathrm{d}log(\overline{z^M})} = -\frac{\partial f / \partial log(\overline{z^M})}{\partial f / \partial log(\overline{b^M})} \tag{27}$$

We derive and find the equation (20). The same process holds for low-income households with equations (18) and (19).

A.2 Redistribution between middle-income and low-income households

We derive the effect of an increase in low- and middle classes' income share $\overline{z^i}$ on the steady-state debt level $\overline{b^j}$ for $i \in (L, M)$ and $i \neq j$,

$$\frac{\mathrm{d}log(\overline{b^i})}{\mathrm{d}log(\overline{z^j})} = \frac{\frac{\theta-1}{\theta} + \frac{1}{\sigma}\frac{1}{\chi^i}\frac{\overline{y}}{\overline{c^j}}}{\frac{1}{\theta} + \frac{1}{\sigma}\frac{1}{\chi^i}\frac{1-\overline{p^i}}{\overline{c^i}} + \frac{1}{\eta}\frac{\chi^i}{\chi^T}\frac{1}{1+\frac{\chi^i}{\chi^T}\overline{b^i}} - \frac{1}{\sigma}\frac{\chi^i}{\chi^T}\frac{1-\overline{p^i}}{\overline{c^T}}} \tag{28}$$

Following our assumption on the demand-side argument, this cross derivative exercise provides a positive impact of this redistribution in favor of the group j on the level of the debt chosen by the group j.

A.3 Proof of the 2^{nd} Testable Prediction

The proof is obtained by using the demand-side argument developed in equation (20) and by distinguishing the numerator and denominator of each part of the inequation (22).

About the *numerator*, we refer to our demand-side mechanism, that holds with $\theta < 1$. To obtain the inequation (22) with the assumption that denominators are positive, the numerators should respect the following condition

$$\frac{\theta-1}{\theta} + \frac{1}{\sigma}\frac{1}{\chi^M}\frac{\overline{y}}{\overline{c^M}} < \frac{\theta-1}{\theta} + \frac{1}{\sigma}\frac{1}{\chi^L}\frac{\overline{y}}{\overline{c^L}} < 0 \tag{29}$$

This condition is reasonably satisfied if we suppose that the second term relative to the consumption-output share is not higher than the first term. At the steady-state, the consumption per capita for middle-class earners should be higher than that of the poorest households. By definition of the three groups of households as defined in Table A.1, we have $\chi^L\overline{c^L} < \chi^M\overline{c^M}$, which supports the inequation (29).

In addition, Bertrand and Morse (2016) highlight that U.S. income inequality is positively correlated with the consumption share of the non-rich classes, but the quantitative result is stronger for the middle classes. It means that the demand-side mechanism is lower for low-income households than middle-class ones. Put differently, the curvature parameter θ of the utility function could be different between borrowers, but this assumption is not required for the inequation (29).

Table A.1: Quantitative Results - 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	Literature.
χ^L	Population Share of Low-Income Class Households	0.40	Literature.
$\overline{z^T}$	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

The steady-state output is normalized to one. The decomposition of bottom earners into low and middle-class incomes follows Palma (2011) and our empirical strategy. We use our inequality data from WIID in a similar fashion to determine steady-state output shares for the three classes.

Given the inequation (29), the result obtained in inequation (22) also depends on their *denominators* and yields the following condition

$$0 < \frac{1}{\sigma}\left[\frac{1}{\chi^M}\frac{1-\overline{p^M}}{\overline{c^M}} - \frac{\chi^M}{\chi^T}\frac{1-\overline{p^M}}{\overline{c^T}}\right] + \frac{1}{\eta}\frac{\chi^M}{\chi^T}\frac{1}{1+\frac{\chi^M}{\chi^T}\overline{b^M}}$$
$$< \frac{1}{\sigma}\left[\frac{1}{\chi^L}\frac{1-\overline{p^L}}{\overline{c^L}} - \frac{\chi^L}{\chi^T}\frac{1-\overline{p^L}}{\overline{c^T}}\right] + \frac{1}{\eta}\frac{\chi^L}{\chi^T}\frac{1}{1+\frac{\chi^L}{\chi^T}\overline{b^L}} \quad (30)$$

The first term on both sides of the inequation (30) reflects the trade-off between price and quantity for both loans to middle-class and low-income households. Based on the financial exclusion frontier in (French et al., 2013) and segregation (Ouazad and Rancière, 2016), we could easily assume that the market power of low-income household is lower than those of middle-class. Again, the smaller the amount p_t, the more expensive the implicit interest rate. So we anticipate that $\overline{p^M} \geq \overline{p^L}$. If the top income households' consumption is quite high, the first term on both sides fits the inequation (30).

The last term in both sides of the inequation (30) also depends on the steady-state debt levels $\overline{b^M}$ and $\overline{b^L}$. We reasonably expect that the steady-state debt level to middle class $\overline{b^M}$ is sufficiently higher than those to low-income class $\overline{b^L}$, which supports the testable prediction. An additional, though not crucial, argument can be found on Carroll (2002) and Goetzmann and Kumar (2008): the curvature parameter η of the utility function with respect to wealth could be potentially different between borrowers. We could imagine that top income households could prefer lending to middle-class ones, which again holds for inequation (30).

It is clear from this inequation (30) that middle-class are the key driver of this positive impact of inequality on household credit if (i) the middle classes consumption is sufficiently higher than the low-income household one, (ii) there is some discrimination against the poorer ones and (iii) the pass-through to implicit interest rate of an inequality shock is not too high.

B Appendix B: Data Appendix

Household credit is our key dependent variable, 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.

Table B.1: Data Sources

Variable	Description	Source
	Credit	
Household credit/GDP		BIS, CB, Oxford Economics
log(Household credit/price level)	GDP deflator from World Bank.	BIS, CB, Oxford Economics, WB
Firm credit/GDP	Linear intrapolation for some years for 5 countries.	BIS, CB, Oxford Economics
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 3.4
Palma, deciles	Share in total income of the richest 10% with the one of the poorest 40%.	Wiid 3.4, Palma (2011)
	Control Variables	
GDP per capita	Log-linearized and relative to the price level.	World Bank
M2	Ratio divided by GDP or log-linearized and relative to the price level.	World Bank, CB
Credit Deregulation	Index from 0 to 10 about financial deregulation. Summary index.	Fraser Institute
	Instrument	
ILO conventions	International Labor Organization conventions ratifications.	ILO

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

	Baseline Coverage	WIID Source	Household Cred.	Firm Cred.	Total BIS
Australia	1981-2010	LIS	BIS	BIS	BIS
Austria	1995-2014	Eurostat, European Comm.	BIS	BIS	BIS
Belgium	1995-2014	Eurostat, European Comm.	BIS	BIS	BIS
Canada	1981-2010	LIS	BIS	BIS	BIS
Czech Republic	1995-2013	LIS	BIS	BIS	BIS
Denmark	1994-2010	LIS	BIS	BIS	BIS
Estonia	2004-2014	Eurostat	CB	CB	
Finland	1970-2014	Eurostat, National Source	BIS	BIS	BIS
France	1980-2010	LIS	BIS	BIS	BIS
Germany	1978-2013	LIS	BIS	BIS	BIS
Greece	1995-2014	Eurostat	BIS	BIS	BIS
Hungary*	1991-2012	LIS	BIS	BIS	BIS
Iceland	2004-2014	Eurostat	CB	CB	
Ireland	2002-2014	Eurostat, European Comm.	BIS	BIS	BIS
Italy	1986-2010	LIS	BIS	BIS	BIS
Malta	2005-2014	Eurostat	CB	CB	
Netherlands	1990-2013	LIS	BIS	BIS	BIS
Norway	1979-2013	LIS	BIS	BIS	BIS
Poland	1995-2013	LIS	BIS	BIS	BIS
Portugal	1995-2014	Eurostat, European Comm.	BIS	BIS	BIS
Spain	1980-2013	LIS	BIS	BIS	BIS
Sweden	1981-2014	LIS, Eurostat	BIS	BIS	BIS
Switzerland	2007-2014	Eurostat	BIS	BIS	BIS
United Kingdom	1970-2014	IFS, Eurostat	BIS	BIS	BIS
United States	1979-2013	LIS	BIS	BIS	BIS

(*) defined as emerging country for World Bank classification. We follow UN classification.

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

	Baseline Coverage	WIID Source	Household Cred.	Firm Cred.	Total BIS
Argentina	1994-2014	SEDLAC 2016	CB	BIS	BIS
Brazil	1994-2014	SEDLAC 2016	BIS	BIS	BIS
Chile*	1987-2013	SEDLAC 2016	CB	CB	
China	1992-2013	World Bank	OXFORD	BIS	BIS
Colombia	1996-2013	EDLAC	BIS	BIS	BIS
India	2004-2011	World Bank	OXFORD	BIS	BIS
Indonesia	2001-2014	World Bank	BIS	BIS	BIS
Israel*	1992-2012	LIS	BIS	BIS	BIS
Korea*	1970-2012	OECD, Other	BIS	BIS	BIS
Malaysia	2006-2009	World Bank	OXFORD	BIS	BIS
Mexico	1994-2014	SEDLAC 2016	BIS	BIS	BIS
Russian Fed.*	1998-2012	World Bank	BIS	BIS	BIS
Singapore*	2003-2012	National Source	BIS	BIS	BIS
South Africa	1994-2011	World Bank	OXFORD	BIS/OXFORD	BIS
Thailand	1991-2013	World Bank	BIS	BIS	BIS
Turkey	1987-2013	World Bank	BIS	BIS	BIS

(*) defined as emerging country for World Bank classification. We follow UN classification.

Table B.4: Sources of Inequality Measures after processing WIID

Source	Countries
LIS	15
Eurostat	11
European Commission	2
OECD	1
World Bank	8
SEDLAC, EDLAC	5
National Sources, Other	4

C Appendix C: Instrumental Variable, First Stage and Additional Tests

Table C.1: Baseline, Standardized Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep. Var.					Household Credit/GDP					
Inequality Measure	Gini	Top 10	Top 30	Mid. 30-90	Mid. 30-70	Bottom	$\frac{Top10}{Mid.30-90}$	$\frac{Top10}{Bottom}$	$\frac{Top30}{Mid.30-70}$	$\frac{Top30}{Bottom}$
Inequality	1.288***	1.779***	1.621***	-2.882*	-2.141***	-1.109***	1.967***	1.525***	1.793***	1.408***
	(0.333)	(0.577)	(0.481)	(1.672)	(0.802)	(0.286)	(0.650)	(0.369)	(0.498)	(0.330)
GDP per capita	0.0653	0.218	0.165	0.684	0.436	-0.0370	0.272	0.182	0.264	0.139
	(0.126)	(0.185)	(0.161)	(0.526)	(0.285)	(0.111)	(0.192)	(0.123)	(0.164)	(0.116)
Broad Money Ratio	0.0340	-0.00673	0.00930	-0.0321	0.0111	0.0324	0.0149	0.119**	0.0820	0.119**
	(0.0693)	(0.0954)	(0.0839)	(0.179)	(0.106)	(0.0686)	(0.0930)	(0.0574)	(0.0682)	(0.0563)
Credit Deregulation	-0.164***	-0.179***	-0.194***	-0.146	-0.189**	-0.179***	-0.155**	-0.145***	-0.153***	-0.155***
	(0.0506)	(0.0634)	(0.0618)	(0.0992)	(0.0774)	(0.0524)	(0.0606)	(0.0506)	(0.0554)	(0.0506)
$DurbinWu-stat$	27.871	26.793	27.603	27.919	26.649	31.681	26.998	24.932	26.620	24.733
$P-value$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$KPF-stat$	24.089	11.440	15.775	2.867	8.083	26.802	10.08	20.579	15.705	24.209
Obs.	896	896	896	896	896	896	896	896	896	896
Countries	41	41	41	41	41	41	41	41	41	41
adj. R^2	0.438	0.211	0.331	-1.117	0.040	0.440	0.068	0.362	0.217	0.417

All variables are standardized, except the log(real GDP per capita). Robust standard errors in parentheses. Country and Year Fixed Effects.
The critical value for the weak instruments test is based on a 10% 2SLS bias at the 5% significance level, which is 16.4 in all estimations.
*, ** and *** denote respectively significance at the 10, 5 and 1% levels.

Table C.2: First Stage Inequality Structure, Lagged Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep. Var.	Gini	Top 10	Top30	Middle 30 90	Middle 30 70	Bottom	$\frac{Top10}{Mid.30-90}$	$\frac{Top10}{Bottom}$	$\frac{Top30}{Mid.30-70}$	$\frac{Top30}{Bottom}$
# ILO Conv$_{t-1}$	-0.000939***	-0.000529***	-0.000588***	0.000194	0.000253**	0.000387***	-0.00116***	-0.0178***	-0.00434***	-0.0282***
	(0.0620)	(0.0664)	(0.0616)	(0.0831)	(0.0669)	(0.0669)	(0.0645)	(0.0588)	(0.0574)	(0.0585)
GDP per capita	-0.00569	-0.0105*	-0.00920	0.0115**	0.0102**	-0.000772	-0.0263*	-0.186	-0.0886*	-0.213
	(0.00751)	(0.00639)	(0.00632)	(0.00486)	(0.00432)	(0.00274)	(0.0146)	(0.137)	(0.0455)	(0.205)
Broad Money R.	0.0301***	0.0220***	0.0222***	-0.0101***	-0.0103***	-0.0117***	0.0455***	0.307***	0.110***	0.458***
	(0.00578)	(0.00458)	(0.00455)	(0.00304)	(0.00275)	(0.00215)	(0.0107)	(0.117)	(0.0345)	(0.171)
Credit Dereg.	0.00441***	0.00305***	0.00363***	-0.00123**	-0.00182***	-0.00193***	0.00569***	0.0594***	0.0196***	0.101***
	(0.000834)	(0.000679)	(0.000667)	(0.000499)	(0.000419)	(0.000338)	(0.00162)	(0.0163)	(0.00505)	(0.0241)
Obs.	900	900	900	900	900	900	900	900	900	900
Countries	41	41	41	41	41	41	41	41	41	41
adj. R^2	0.186	0.117	0.142	0.033	0.067	0.203	0.041	0.014	0.002	0.029

Robust standard errors in parentheses. Country and Year Fixed Effects. The critical value for the weak instruments test is based on a 10% 2SLS bias at the 5% significance level, which is 16.4 in all estimations. *, ** and *** denote respectively significance at the 10, 5 and 1% levels.

Table C.3: Testing for Exclusion Restriction

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Advanced economies					Emerging economies				
Inequality measure	Gini	$\frac{Top10}{Mid30-90}$	$\frac{Top10}{Bottom}$	$\frac{Top30}{Mid30-70}$	$\frac{Top30}{Bottom}$	Gini	$\frac{Top10}{Mid30-90}$	$\frac{Top10}{Bottom}$	$\frac{Top30}{Mid30-70}$	$\frac{Top30}{Bottom}$
Inequality	-0.587	-0.0905	-0.0493	-0.0830	-0.0458	-0.0224	0.0233	0.00245	0.00681	0.00131
	(0.495)	(0.401)	(0.0512)	(0.151)	(0.0335)	(0.200)	(0.0458)	(0.00461)	(0.0148)	(0.00365)
# ILO Conv.	-0.00428*	-0.00379	-0.00435	-0.00405	-0.00466*	0.00109	0.00117	0.00118	0.00117	0.00117
	(0.00244)	(0.00256)	(0.00255)	(0.00259)	(0.00248)	(0.00151)	(0.00144)	(0.00141)	(0.00144)	(0.00142)
GDP per capita	0.0524	0.0428	0.0545	0.0483	0.0590	0.160***	0.156***	0.156***	0.156***	0.157***
	(0.163)	(0.166)	(0.162)	(0.165)	(0.161)	(0.0296)	(0.0278)	(0.0292)	(0.0283)	(0.0293)
Broad Money Ratio	0.225**	0.213**	0.221**	0.216**	0.228**	0.0853	0.0840	0.0850	0.0848	0.0852
	(0.0989)	(0.0962)	(0.0970)	(0.0972)	(0.0972)	(0.0572)	(0.0578)	(0.0593)	(0.0585)	(0.0595)
Credit Dereg.	-0.000451	-0.00159	-0.00115	-0.00144	-0.000381	-0.0102***	-0.0107***	-0.0108***	-0.0107***	-0.0108***
	(0.0102)	(0.00978)	(0.0101)	(0.00998)	(0.0102)	(0.00346)	(0.00347)	(0.00347)	(0.00344)	(0.00348)
Cons.	-0.00954	-0.0356	-0.101	-0.00659	-0.0704	-1.727***	-1.701***	-1.701***	-1.708***	-1.709***
	(1.639)	(1.632)	(1.636)	(1.620)	(1.645)	(0.309)	(0.314)	(0.330)	(0.318)	(0.328)
Obs.	611	611	611	611	611	285	285	285	285	285
Countries	25	25	25	25	25	16	16	16	16	16
adj. R^2	0.752	0.749	0.751	0.750	0.753	0.857	0.857	0.857	0.857	0.857

Robust standard errors in parentheses. Country and Year Fixed Effects. The critical value for the weak instruments test is based on a 10% 2SLS bias at the 5% significance level, which is 16.4 in all estimations. *, ** and *** denote respectively significance at the 10, 5 and 1% levels.