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

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Abstract

How does income inequality and its structure affect credit? Based on various strands of the literature, we support that rising income inequality should bring higher household credit at the aggregate level, and that a substantial part of the positive impact of inequality on credit should be driven by the impoverishment of middle classes relatively to top incomes. These intuitions are empirically confirmed by a study based on a country-level dataset over the period 1970-2017. We identify exogenous variations of inequality through the total number of ratified ILO conventions and factor endowments at the country-level. Our results show that exogenous variations in inequality have a positive impact on household credit: a one standard-deviation increase in the Gini index generates a 5.5 to 8 percentage points expansion in the ratio of household credit over GDP. In addition, the impact is 1.4 to 2.6 times stronger when top incomes increase relatively to middle incomes, rather than at the expense of bottom incomes. Those results are robust to various instruments, databases, controls, and variable definitions. They also consistently disappear in countries where financial markets are insufficiently developed.

JEL classification: D31, E25, E44, G01

Keywords: Credit, Finance, Income Inequality, Inequality structure

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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.

However, the empirical literature on that matter has been rather 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 correlation between inequality and household indebtedness, in relation with 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 find a significant impact of the level of income inequality 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 not very different 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. Based on a very similar sample and estimation strategy, but restricting to the period 1995-2007, Gu et al. (2019) reach the same conclusion. These various, diverging outcomes emphasize the difficulties inherent in the identification of a causal relationship between inequality and finance, due to obvious endogeneity issues. Indeed, both variables are likely to be simultaneously determined by common shocks, and there is also an obvious reverse causality from finance to inequality.

The paper provides an empirical investigation of the existence and the characteristics of a causal relationship between income inequality and the expansion of credit. We identify several sources of exogenous variations in inequality, and estimate their effect on household credit over GDP, while controlling for many other time-varying, country-level relevant determinants of credit. In particular, we test different instrumentation strategies to ensure that our estimates are stable, regardless of the source of the exogenous shock to inequality.

Our empirical analysis relies on a country-level yearly dataset for 30 developed countries (and 19 emerging countries, for a key falsification test) over the period 1970-2017, based on two building blocks. We mainly rely on income inequality data coming from the World Income Inequality Database (WIID), but we also check at each key step that our results are unharmed when other databases such as the Standardized World Income Inequality Database and the World Inequality Database are used. Credit data come mainly from the Bank of International Settlements, completed by carefully checked and harmonized data from central banks. As our baseline instrument, we use the number of ratifications of International Labor Organization (ILO) conventions at the country-year level: since the second half of the 1970s, the ILO has autonomously implemented various strategies to promote common labor standards and decent work, characterized by an increasingly dynamic process of (country-level) ratifications over time which is mostly orthogonal to country-specific developments and other international economic policies. The exclusion restrictions are strengthened by the inclusion of several variables (GDP per capita, housing investment) controlling for standards of living, and therefore, ability to borrow, that may be impacted by higher wages, and consequently by ILO conventions. Alternatively, we consider additional variables reflecting factor endowments (land and capital endowments, and skill intensity/education level), which an extensive literature has shown to be strongly correlated with inequality (see Bourguignon and Morrisson, 1990, Spilimbergo et al., 1999 or Gourdon et al., 2008). To the best of our knowledge, this is the first time in the literature that such instruments are used to identify the causal impact of inequality on credit expansion.

We find that an exogenous increase in inequality triggers an expansion of household credit. Indeed, the latter is consistent with various theoretical environments, including the recent contribution by Kumhof et al. (2015) based on a DSGE model relying on inequalities between household groups, or relative income and consumption approaches (e.g., Duesenberry, 1949, Frank et al., 2014 or Bertrand and Morse, 2016), which all provide arguments in favor of a positive impact on household leverage of a permanently more unequal distribution of income. Doing so, we support that results by Bordo and Meissner (2012), Perugini et al. (2016) and Gu et al. (2019) on total credit may actually overlay household credit dynamics (Table E.10 in the Online Appendix (OA) provides evidence going into this direction). Therefore, we find that one standard-deviation increase in the Gini index (which can be understood as a synthetic measure of income inequality over the whole distribution) is associated with a significant 5 to 8 percentage points (pp) increase in the household credit to GDP ratio. When inequality is measured through the top incomes share, a rise by one standard deviation lifts credit to GDP ratio by 5 to 10.3 pp.

Beyond a reliable identification of the positive impact of inequality on household leverage, based upon credible instruments, a second contribution of this paper is to show that the size of this effect varies substantially with the structure of income inequality. Indeed, the existing literature tends to focus almost exclusively on the role of top incomes, which are opposed to a "bottom category" which actually mixes low and middle incomes. In this paper, we show that this effect is substantially higher when middle incomes are involved: a one standard-deviation increase in the Top incomes over Middle income share ratio (implying a relative impoverishment of middle classes compared to the Top 10%) brings an increase in household credit over GDP equivalent to 1.4 to 2.6 times the one stemming from a one-standard deviation rise in the ratio of Top 10% over Bottom incomes. Here again, simple intuitions stemming from Kumhof et al. (2015) or relative income frameworks bring that, for a comparable income loss relatively to top incomes, the middle class should contribute more to borrowing at the aggregate level.

A substantial part of the paper is devoted to exploring the sensitivity of our results to alternative empirical strategies. Our results hold with various combinations of alternative instruments, different databases, definitions of income groups and control variables. In particular, our results remain unaltered when data from the World Inequality Database or the Standardized World Income Inequality Database are used instead. We also check throughout the paper that our results are mostly unaltered by the dynamics arising from the financial crisis and the Great Recession of 2007-2008. Besides, we replicate our estimates on a sample exclusively based on developing/emerging countries, as a falsification test. Indeed, we do not expect our two key results to hold here, for two major reasons. Firstly, financial market imperfections and subsequent binding credit constraints in developing countries prevent low and middle incomes to borrow facing a loss of income (Kumhof et al., 2017). Secondly, middle classes are generally weakly developed in these countries: 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. As a consequence, we find that in almost all specifications, inequality indicators display an insignificant impact on household leverage. Note also that in additional results (Table E.3 to E.6 in the OA), 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.[1] 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.

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).[2] In order to avoid financial crises such as the one of 2007-2008, which triggered afterwards the Great Recession, one has therefore to prevent the creation

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

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

of household leverage bubbles. Another important implication of our results is that the relative impoverishment of middle classes compared to top incomes drives a significant part of the financial cycle.

The next section presents some stylized facts and theoretical underpinnings. Section 3 details 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. The last section concludes.

2 Stylized Facts and Theoretical Background

This section documents two key stylized facts characterizing income inequality and household leverage for various countries from our sample, over several decades belonging to the period under investigation. Each of these two stylized facts is then rationalized through various strands of the literature, all delivering the same theoretical conclusion.

2.1 Income inequality and aggregate household debt

Figure 1 below shows the evolutions of the share of total income owned by the top income decile, and the ratio of household credit over GDP for selected countries in our sample.[3]

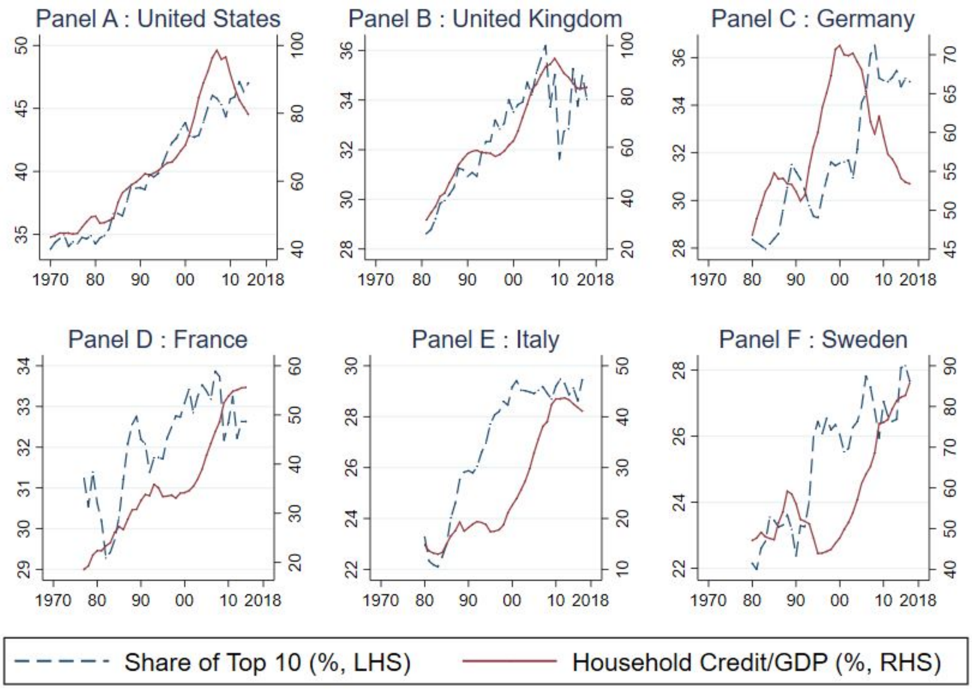
Over several decades, household leverage and top incomes seem to move mostly in the same direction, whatever the type of countries considered. This is especially true for Anglo-saxon countries, such as the US or the UK where the share of top 10% increased respectively by 12 and 7 percentage points (pp), while household leverage rose respectively by 40 to 60 pp. Interestingly, similar dynamics can be observed in countries with more redistributive welfare states, though to a consistently more limited extent. In this respect, the top 10% share increased from 2.5 pp in Sweden to 5-6 pp in France and Germany, and 8 pp in Italy, while household leverage moved up by 20 to 40 pp in these countries.[4]

How can we make some causal sense of these positive correlations? A burgeoning academic literature has pointed different potential theoretical channels through which a rise in income inequalities may endogenously trigger an expansion of credit. A critical point is that the underlying mechanisms will be very different depending on whether the rise in inequality is explained by a higher dispersion of transitory income (Krueger and Perri, 2006, Krueger and Perri, 2011 or Iacoviello, 2008) or by a shift of permanent income between social groups (Piketty and Saez, 2013). Following permanent income theory, leverage can be seen as a rational answer to a higher

[3]Figures for all other countries in the sample of developed countries are reported in Figure A.2 in the OA. For most countries, the same joint dynamics for the income share owned by the top 10% and household leverage appear. Figures A.3 and A.4 replicate the exercise, replacing the top incomes share by the middle incomes share. The overall pattern is less clear.

[4]There are of course interesting national specificities. For example, in Germany, household credit over GDP rose from 50 to 70 % between 1980 and 2000, before regressing almost completely to its initial level in 2018. Interestingly, the share of the top 10% stopped increasing and started stagnating around 2010.

Figure 1: Top 10% income share and household credit over GDP



Note: Years on the x-axis. Household credit over GDP comes from the Bank of International Settlements, the Top 10% income share comes from the World Inequality Database.

dispersion of transitory income. However, if the shift in income is permanent, the permanent income theory would predict a proportional adjustment of consumption, without permanent alteration of savings/indebtness. Evidence from various countries tends to show that the rise of inequalities is more likely to be explained by permanent shocks.[5] Therefore, it is necessary to depart from the permanent income theory to explain why households may decide to increase their borrowing in response to permanently stagnating incomes.[6]

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 approach within a DSGE model relying on inequalities between two household groups, top and bottom earners. Top earners display a preference for wealth related to their pleasure to hold financial wealth. The latter can represent different saving motives, such as, following e.g. Carroll (2000), agents deriving direct utility from the social status and power conferred by wealth.[7] For-

[5] 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, 2011) also find that the variance in transitory income declined or remained constant after 1980 unlike the variance in permanent income. Cappellari and Jenkins (2014) and Jenkins (2015a) report very similar evidence (lack of changes in social mobility over time, decrease in income volatility observed) for the UK. On a cross-country perspective, Andrews and Leigh (2009) confirm this negative link between income inequality and social mobility over a sample of 16 countries. Similar evidence of an increase in between-group inequality, reflecting permanent income shocks, has also been found in emerging countries (see Ferreira and Litchfield, 2008 on Brazil; Kanbur and Zhuang, 2014 on some Asian countries including China, and India).

[6] Detailed surveys on those issues can be found in van Treeck (2014) and Bazillier and Hericourt (2017).

[7] Kumhof et al. (2015) provide an extensive survey of the literature on preferences for wealth. The latter have

mally, preference for wealth enters top earners' utility function directly, which implies a positive marginal propensity to save out of permanent income shocks. Put differently, top earners will use most of their additional income to increase their financial wealth through loans to bottom earners, whose marginal propensity to save following a permanent income shock is assumed to be zero. This reflects in a growing income share of high-income households, together with higher leverage of bottom-income households allowing them to support their consumption level. 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.

It is also possible to imagine various types of preferences for bottom earners delivering similar outcomes, as long as they depart from the permanent income conclusion. For instance, the relative income hypothesis can also deliver a causal, positive impact of inequality on household debt following a permanent income shock. Going back to Duesenberry (1949), this approach suggests that household consumption is a function of the household's position in the income distribution, and its past levels of consumption. Frank et al. (2014) propose a theory of "expenditure cascade" where the reference group framing consumption standards is the one just above in the income scale. Any change at the top of the income distribution will affect the consumption of the group just below, and then lead to an expenditure cascade, impacting also the consumption of low- and middle-income households. Based on the US Consumer Expenditure Survey, Bertrand and Morse (2016) provide a strong case for this kind of 'trickle-down consumption' from top to bottom incomes. A similar argument is made by approaches presuming that the overall level of satisfaction derived from a given level of consumption depends not only on the actual current consumption level but also on how it compares with some benchmark levels: the individual's own past consumption levels ("habit-formation") or past consumption of some outside reference group ("keeping up with the Joneses", see e.g. Christen and Morgan, 2005). We now characterize the common testable prediction of these various setups regarding the link between aggregate household credit and income inequality.

Testable Relationship 1: An increase in inequality leads to an expansion in household credit at the aggregate level.

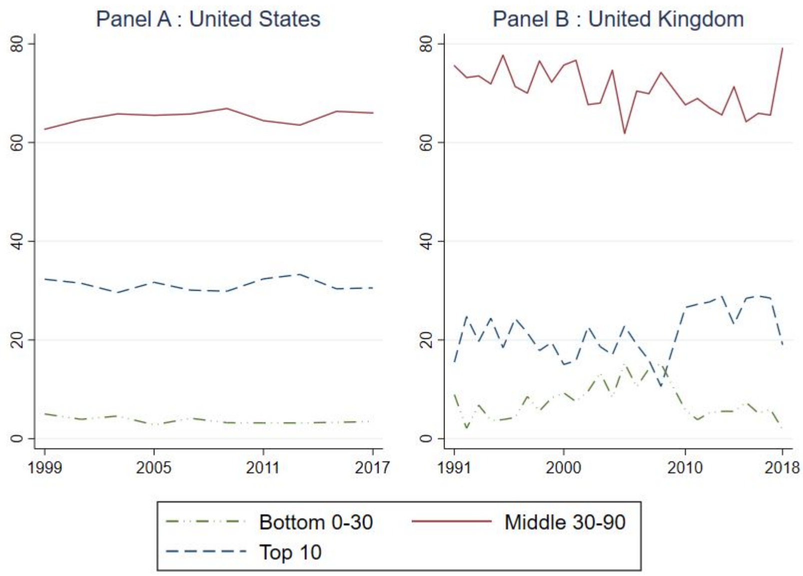
2.2 On the specific part of middle classes

Based on indebtedness data by deciles of incomes, Figure 2 below shows the shares of total credit originated by bottom (3 first deciles), middle (from the 3$^{\text{rd}}$ decile until, but not including, the 9$^{\text{th}}$ decile) and top (9$^{\text{th}}$ decile, or Top 10%) incomes for the United States (Panel A) and the United Kingdom (Panel B). On each panel, the time period has been constrained by data

been suggested as a way to address the difficulties by models with standard preferences to account for the saving behavior of the richest households. For example, Carroll (2000) shows that the permanent income hypothesis model can match the aggregate saving behavior only by over-predicting the saving behavior of median households and by underpredicting the saving behavior of the richest household.

availability: 1999-2017 for the US, 1991-2018 for the UK. In both countries, it is striking to see that, over several decades, the share of middle incomes in household credit ranges between 60 and 80%, 10 to 20 times more than bottom incomes, even though middle incomes deciles are roughly twice more numerous than bottom incomes. In both countries, middle incomes account for the bulk of household leverage.

Figure 2: Credit shares (in %) per income group, US and UK



Note: authors' calculations. Data source is US Panel Study of Income Dynamic for the US, and British Household Panel Survey/United Kingdom Longitudinal Study for the UK. US: mortgages and car loans. UK: all types of debts.

Table 1 reports similar information for Canada and New Zealand, but based on quintiles of incomes and for a few years, due to data availability. Bottom incomes represent now the first 40% of the income distribution, middle incomes the following 40%, and the last 20% are the top incomes. Table 1 delivers a message very similar to the one stemming from Figure 2: middle incomes represent between 60 and 70 % of total household debt, around 6 times more than bottom incomes.

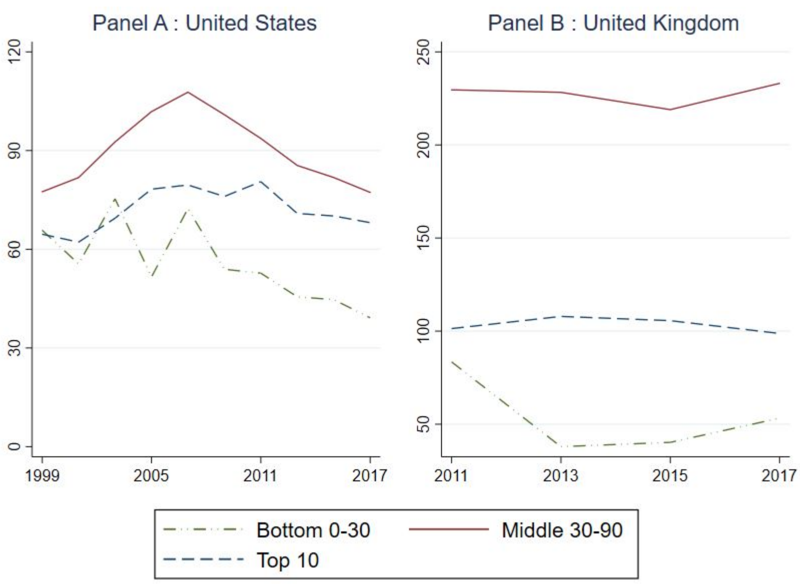
Table 1: CreditsShares (in %) per income group, Canada and New Zealand

Country	Year	Bottom 40%	Middle 40-80%	Top 20%
Canada	1999	12.3	62.0	25.7
Canada	2005	12.6	66.2	21.2
Canada	2012	13.4	60.0	26.6
Canada	2016	10.8	58.7	30.5
New Zealand	2015	15.0	60.0	25.0
New Zealand	2018	18.0	73.0	9.0

Note: authors' calculations. Data Source is Statistics New Zealand and Survey of Financial Security for Canada. Median values for debt.

Figure 3 and Table 2 provide some complementary perspective by showing the debt-to-income ratios along the same division between bottom, middle and top incomes. Figure 3 provide some long-run evidence for US and UK over the periods covered in Figure 2. Debt-to-income ratios appear systematically higher for middle incomes: it is, respectively, 1.5 to 2 times higher than bottom income's ratio in the US (where debt is restricted to mortgages and car loans due to data availability) and more than twice higher in the UK (where all kinds of debts are considered). Table 2 also provides debt-to-income ratios for 14 EU countries belonging to our sample, for the last available wave of the Household Finance and Consumption Survey (2017). For comparison purposes, we also report the debt-to-income ratios for the UK and the US. In a majority of cases, the debt-to-income ratio is 1.5 to 4 times higher for middle than for bottom incomes. They are equivalent for Estonia, Hungary and Portugal, it is only in 3 cases (Greece, Italy and Netherlands) that the debt-to-income ratio is lower for middle than for bottom incomes.[8]

Figure 3: Debt-to-Income Ratios by income group (in %), US and UK



Note: authors' calculations. Data source is Panel Study of Income Dynamics for the US, Office for National Statistics, Wealth and Assets Survey & Institute for Fiscal Studies for the UK. US: mortgages and car loans. UK: all types of debts.

All in all, Figures 2 and 3, as well as Tables 1 and 2 support that, across several recent decades and various countries, middle classes generate the bulk of aggregate household leverage and consistently tend to have higher debts compared to their income. Relying on the same strands of the literature than previously, we can point several mechanisms generating a key part for middle classes. In Kumhof et al. (2015), main results would be strengthened if marginal propensity to save of bottom earners was not assumed to be zero, since a nonzero marginal propensity to save creates a desire to dissave in response to a negative income shock. In addition,

[8]Tables A.1 and A.2 in the OA provide figures for the two other waves (2010-2011 and 2014-2015), with very similar patterns, even though some countries occasionally show some interesting differences, e.g., Portugal in 2014-2015 displays a higher debt-to-income ratio for middle incomes.

Table 2: Debt-to-Income Ratio (in %) per income group, 2017

Country	Bottom	Middle	Top
	Bottom 30%	*30-90%*	*Top 10%*
UK	53.3	233.1	98.7
US	39.2	77.3	68.1
	Bottom 40%	*40-90%*	*Top 10%*
European Union	58.2	72.28	78.7
Austria	13.4	43.9	49.6
Belgium	34.0	124.9	71.6
Estonia	23.9	21.4	52.2
Finland	50.5	83.7	95.9
France	32.4	74.6	96.2
Germany	26.7	46.7	66.5
Greece	281.2	51.6	68.9
Hungary	21.8	20.1	17.9
Ireland	22.4	78.7	79.5
Italy	56.6	35.9	64.3
Netherlands	454.1	253.8	152.4
Poland	12.7	18.9	31.4
Portugal	147.6	146.1	96.1
Spain	116.7	123.4	86.6

Source: Panel Study of Income Dynamics (US), Office for National Statistics, Wealth and Assets Survey (UK), Household Finance and Consumption Survey (European Union), authors calculations. Note: Average debt-to-income ratio in the US, median debt to income ratio in the UK and Euro Area. The debt-to-income ratio is the ratio of debt to gross household income. Euro and UK data include total debts: mortgages and non-mortgage loans - consumer credit loans, private loans - credit lines/bank overdrafts debt and credit card debt. For the US, it includes mortgages and car loans.

Kumhof et al. (2015) consider two kinds of agents, top and bottom earners, corresponding roughly to the top 5% and bottom 95% in the US case. Therefore, bottom earners involve *de facto* low and medium-income households. An explicit distinction between the former and the latter seems relevant, by assuming that middle classes have a higher marginal propensity to save. This is both consistent with the "fundamental psychological law" of consumption put forward by Keynes (1936) (p. 96)[9] and by empirical evidence. Based on US micro data, Dynan et al. (2004) and Kumhof et al. (2015) find savings rate steeply increasing with income: slightly above 2% for the first quintile, it revolves between 10.5 and 16.5% for the third and fourth quartiles (likely to embody middle classes), and between 30 and 40% for the top 5% income share. Based on those estimates, Dynan et al. (2004) compute the marginal propensity to save for the same income categories, with 8.9% for the first quintile, between 7.5% and 22.7% for the middle classes, and 50.5% for the top 5% income share.[10]

As a result, it seems natural and plausible that the middle class suffering the same income-

[9]Put simply, the marginal propensity to consume decreases with income, and symmetrically, the marginal propensity to save increases with income.

[10]Kumhof et al. (2015) find a marginal propensity to save of 40% for the top 5%, by excluding capital gains.

loss as the bottom earners would contribute more to the dissaving at the aggregate level, since it has higher marginal propensity to save. In addition, middle-class households are by definition higher in the income distribution, so that they have higher past levels of income and consumption, and their reference group is closer to top incomes. In other words, relative income and consumption approaches presented above would predict that middle classes have a higher level of consumption to support, requiring higher borrowing than bottom incomes. Therefore, we will bring to the data the following relationship.

Testable Relationship 2: When the share of top incomes increases relatively to bottom incomes, the bulk of the positive impact of this rising inequality on household credit is driven by the middle class, rather than lower incomes.

3 Data

Our empirical analysis relies primarily on a country-level yearly dataset for 30 developed countries over the period 1970-2017[11] based on two building blocks, income inequality and credit.

3.1 Inequality

The use of inequality data in cross-country studies raises several challenges. More specifically, the choice for a specific database is a crucial issue. Jenkins (2015b), among others, shows how it can have major implications on empirical results. We will rely primarily on the World Income Inequality Database (WIID), which offers the best compromise in terms of coverage and variety of income inequality indicators used. Jenkins (2015b) recommends the use of the WIID. The latter 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 all countries over the world between 1867 and 2018.

However, we will report at each key step robustness checks of our results based on the Standardized World Income Inequality Database (SWIID) and the World Inequality Database (WID) - among others, a contribution of this paper is to show that our main results do not vary according to the dataset used. The SWIID (Solt, 2009) has more systematic coverage than the WIID on recent decades, with a lower number of missing observations. But beyond the fact that the imputation procedure that is used to fill missing data raises potential issues[12], this database does not provide information on deciles of income distribution. As for the WID database, it

[11] The analysis will be extended to a sample of 19 developing and emerging countries in section 5.3 below.

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

contains information on income deciles based on administrative tax data, together with survey data. Bordo and Meissner (2012) and Perugini et al. (2016), among others, use top income shares from the WID database. This database built by Alvaredo et al. (2017) is available for 116 countries with high time coverage for some countries. However, their key income inequality indicators are based on pre-tax and not disposable income, i.e. they do not take into account the effect of fiscal redistribution on the disposable income.

One of our aim in this paper is to focus on the potential heterogenous role of different shocks along the income distribution on the inequality-credit relationship. Indeed, 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). Any distributional change *within* the bottom 90% will not be captured by top income share indexes. Consequently, we will not focus exclusively on the Gini coefficient and top income shares usually studied in the literature, but we will also investigate ratios between income share deciles.

The use of the Gini index remains definitely useful, as it takes into account the whole distribution of income and not only tails dynamics. Afterwards, we go one step deeper by investigating the part of different income shares categories. We start with an indicator commonly used in the literature, the top incomes, alternatively defined as the share of income owned by the Top 10% (corresponding to incomes after the 9^{th} decile). We complement this top income share by using ratios of the latter to other income categories, 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, where "Middle 30-90" corresponds to incomes after the 3^{rd} and up to (but not including) the 9^{th} decile. Finally, we focus on the ratio of Top incomes over Bottom incomes, Top 10/Bottom 30, where "Bottom 30" is defined as the share of income owned by the Bottom 30% (corresponding to incomes up to the 3^{rd} decile).[13] These indicators will allow disentangling the specific effect of income shocks for the poorest and income shocks for the middle class, ad consequently to assess the empirical validity of our two testable relationships.[14]

Going into the details of data sources for each indicator, we use the Gini coefficient predominantly from the WIID, but also report estimates based on the Gini index from the SWIID. Furthermore, the ratios between income shares will come both from the WIID and the WID. The former provides the complete distribution of income per deciles, while the latter distinguishes

[13]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.

[14]Tables D.5 and D.6 in the OA report results based on alternative definitions of top and middle incomes, the former being defined as the Top 30% (corresponding to incomes after the 7^{th} decile) and the latter ("Middle 30-70") to incomes after the 3^{rd} and up to the 7^{th} decile, with no major qualitative change compared to our benchmark results.

the top 10%, the middle 50-90% and the bottom 50%.

Finally, we provide a transparent process to use WIID rigorously. The use of several data types (gross versus net income data, household versus individual income data and income versus expenditure data) may alter the comparability of the inequality measures (Atkinson and Brandolini, 2001, Jenkins, 2015b), so it is necessary to use comparable data across sources. Our rules of selection ensure high-quality data within and between countries. We keep only observations with specific characteristics: they are coded as high (or medium) quality, and they concern post-tax income. They are also consistent according to the income share unit, the unit of analysis, as well as 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. 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. To ensure consistency, we generally prefer to use only one dataset. We combine datasets if and only if the risk of structural break is very low.[15] Appendix A summarizes the primary sources used for each country. Only three countries (Finland, Sweden and United Kingdom) out of 30 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 straightforward theoretical mechanism, at least arising from the various frameworks surveyed in section 2, to explain the potential effect on other sources of private credit such as business credit.[17]. In this regard, Table E.10 in the OA show that the impact of inequality on firm credit and bank credit is unclear, and mostly insignificant.

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 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

[15]We use linear interpolation only if the time span between two observations is limited. For the use of multiple datasets, 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.

[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. Gu et al. (2019) alternate both indicators.

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

our results behave when we use the log of household credit.[18]

Our main datasource for household credit is the Bank for International Settlements (BIS): Over 76% (23 countries) of household credit directly comes from BIS. The remainder of household credit data comes from Central Banks, and has been carefully checked and harmonized (see Data Appendix A).

3.3 Other variables

The classical determinants of credit pointed by the literature are financial liberalization, monetary dynamics and the level of economic development. Regarding financial liberalization, we use indexes of credit market deregulation provided by the Fraser Institute, 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. We also include the now well-known Chinn and Ito's (2006) index measuring a country's degree of capital account openness.

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 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.

We also include two variables controlling for the dynamics of the real-estate market: real house prices, provided by the BIS and Cesa-bianchi et al. (2015), and the ratio of housing Gross Fixed Capital Formation to GDP (coming from OECD), representing households' investment in real-estate. These two latter variables will control for the dynamics of indebtedness specifically driven by households' housing investment, which proved to be increasingly important over a significant part of the studied period. As we write in section 4.2 below, these variables, together with GDP per capita, also play an important part in supporting the validity of our IV strategy.

Finally, we also include four variables representing common trends and shocks: world GDP (from the World Bank) and oil prices (from FRED Saint-Louis) control for common business cycle and inflation conditions, while the Fed Funds rate and the VIX index (both coming from FRED Saint Louis) represent the world financial cycle (see Miranda-Agrippino and Rey, 2015 and Rey, 2015).

[18]Reported on Tables C.7 and C.8 in Appendix C, results of these estimates are qualitatively and quantitatively very similar to our benchmark estimates, though with a generally lower significance.

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:

$$Credit_{i,t} = \beta Ineq_{i,t} + \Gamma X_{i,t} + \lambda Y_t + \mu_i + \epsilon_{i,t} \tag{1}$$

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 index, share of top incomes, ratios of 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 over GDP, the log of GDP per capita and the index of financial deregulation, as well as the real house prices and the ratio of housing Gross Fixed Capital Formation to GDP. λY_t is a vector of variables representing common trends and shocks, consisting alternatively of year dummies, or four variables including: world GDP, oil prices, the Fed Funds rate, and the VIX index. Finally, μ_i denotes country fixed effects, capturing all time-invariant country characteristics.

We are specifically interested in changes in credit driven by exogenous variations in inequality. Our coefficient of interest is β: the various strands of the literature surveyed in section 2 predict $\beta > 0$ when inequality rises, i.e. when the Gini index, the share of top incomes (top 10%) in the total income, or the ratio of top incomes to low or middle incomes increase.

Table 3 below shows the results obtained when equation 1 is estimated by OLS. Column (1) to (4) reports the estimated coefficients when inequality is proxied through the standard measures used in the literature, namely the Gini index (columns (1) and (3)) and the share of top incomes (represented by the top 10% in columns (2) and (4)). Columns (5) and (6) rely on ratios measuring relative variations in inequality, i.e. between the share of top incomes and middle or bottom incomes. More precisely, column (5) reports estimates for an inequality measure defined as the ratio of the top incomes share to the share of middle classes (corresponding to incomes after the 3^{rd} and up to the 9^{th} decile, denominated *Mid. 30-90*). Finally, column (6) provides estimates for the ratio of top incomes to bottom incomes (covering the 1^{st}, 2^{nd} and 3^{rd} deciles).

The correlation between inequality and credit is massively insignificant in all specifications - this is also the case in extensive additional OLS estimates reported in Tables B.1 and B.2 in the OA. 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. 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.

[19] As the deregulation wave occurs simultaneously in most developed countries, part of this effect is captured

Table 3: OLS estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Household Credit/GDP					
Ineq. measure	Gini	Top 10	Gini	Top 10	$\frac{Top10}{Mid.30-90}$	$\frac{Top10}{Bot.0-30}$
Ineq. measure	-0.361	-0.084	-0.327	-0.066	0.062	-0.007
	(0.554)	(0.681)	(0.555)	(0.688)	(0.349)	(0.048)
GDP per capita	-0.348	-0.355*	-0.340	-0.347	-0.353*	-0.347
	(0.208)	(0.207)	(0.207)	(0.206)	(0.207)	(0.206)
Broad Money Ratio	0.159*	0.152*	0.166*	0.160*	0.158*	0.161*
	(0.091)	(0.089)	(0.090)	(0.087)	(0.086)	(0.089)
Financial Openness	-0.074	-0.064	-0.057	-0.048	-0.043	-0.049
	(0.094)	(0.092)	(0.101)	(0.098)	(0.098)	(0.100)
Credit Deregulation	-0.002	-0.003	-0.002	-0.003	-0.003	-0.003
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Real House Prices	0.174**	0.172**	0.159**	0.157**	0.158**	0.157**
	(0.070)	(0.070)	(0.071)	(0.071)	(0.071)	(0.072)
Housing GFCF Ratio	0.015	0.045	0.009	0.037	0.053	0.038
	(0.306)	(0.295)	(0.308)	(0.296)	(0.289)	(0.299)
Obs.	726	726	698	698	698	698
Countries	30	30	29	29	29	29
adj. R^2	0.757	0.756	0.749	0.748	0.748	0.748

All estimations include country fixed effects and time dummies. Intercept not reported. Robust standard errors in parentheses, with *, ** and *** respectively denoting significance at the 10%, 5% and 1% levels. Sample in column (3) to (6) exclude New Zealand, for which detailed income data by decile is missing.

We reduce the bias by controlling for financial liberalization and capital account openness, 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. The idea that the latter should be negative has been widespread in the literature since Banerjee and Newman (1993) and Galor and Zeira (1993): since financial market imperfections are mainly binding on the poor, better access to credit markets, allowing more poor people to become entrepreneurs or to invest in human capital, will help reducing inequalities. This long-standing conventional wisdom about financial development and inequality is summarized in Levine (2005), p. 920: "the results indicate that finance exerts a disproportionately large, positive impact on the poor and hence reduces income inequality." In addition, Beck et al. (2007) find that the reduction in inequality allowed by increased access to finance is sizeable. Consequently, this negative bias is likely to offset the previously mentioned positive bias, bringing the noisy, non-statistically different from zero OLS estimates.

Finally, Table 4 below shows that credit is often much more volatile than inequality (whichever measure is considered): this creates an attenuation bias driving β towards zero.

through the time dummies. However, differences in the timing of financial deregulation may still bias our OLS estimates.

Table 4: Descriptive statistics: credit and inequality

	Mean	First quartile	Median	Third quartile	S.D.*within*	S.D.*overall*
Levels						
Gini	0.292	0.257	0.29	0.329	0.019	0.044
Top 10	0.231	0.212	0.232	0.25	0.014	0.026
Top 10/Middle 30-90	0.37	0.336	0.369	0.4	0.028	0.048
Top 10/Bottom 0-30	1.62	1.296	1.556	1.891	0.176	0.402
Household credit/GDP	0.557	0.342	0.521	0.723	0.161	0.279
log(real household credit)	5.94	4.89	6.23	7.09	0.533	1.67
Nbr. of ratified ILO Conv.	74.3	57	75	96	6.83	28.69

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 lags of inequality (due to strong persistence in the latter), but also indicators of labor market flexibility and institutions, such as the ones used in the two single papers, to the best of our knowledge, which identify causality through instrumental variable strategies, Perugini et al. (2016) and Gu et al. (2019).[20] 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). To a certain extent, the same issue arises for trade openness: the latter has increased in many countries following various trade liberalization waves, both at the world (GATT and WTO negotiations round) and regional (with the rise in regional trade agreements) levels. This process happened simultaneously with capital flows liberalization, and both phenomena have been driven by the same worldwide movement towards globalization. In other words, it is very likely that credit, labor, and product markets regulation levels and trade openness are driven by deeply related dynamics, casting strong doubts on the validity of exclusion restrictions in such a context.

Therefore, we propose to use ratifications of ILO conventions as an exogenous source of variation to assess the causal impact of inequality on credit. To the best of our knowledge, this is the first time in the literature that such an identification strategy is used. We argue that these ratifications are mostly explained by ILO's inner dynamics and were largely exogenous to specific country characteristics. We also argue that these dynamics were disconnected from other policy packages implemented during the same period, including financial liberalization.

Orthogonality condition: The autonomous dynamic of ILO conventions' ratifications. The International Labor Organisation (ILO) was created in 1919, as part of the Treaty

[20]Both articles use very similar identification strategies and samples, though Gu et al. (2019) restrict to a shorter period of time.

of Versailles that ended World War I. With 187 member states, the ILO 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.[21] 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.

It is important to highlight the uniqueness of the tripartite structure of the ILO and its consequences in terms of policy agenda. Governance differs drastically from other international organizations such as the IMF or the World Bank where voting power is determined by national quotas and each country represented by a governor nominated by the government only. Workers' representatives have therefore much more power than in any other international organizations. Beyond such institutional difference, the fundamental goals of the ILO also explained why its policy agenda is so specific. The 1919 preambule of ILO Constitution states that "*universal and lasting peace can be established only if it is based upon social justice*".[22] The 1944 constitutive Declaration of Philadelphia emphasizes as a central aim that "*all human beings, irrespective of race, creed or sex, have the right to pursue both their material well-being and their spiritual development in conditions of freedom and dignity, of economic security and equal opportunity*" and states that "*all national and international policies and measures, in particular those of an economic and financial character, should be judged in this light and accepted only in so far as they may be held to promote and not to hinder the achievement of this fundamental objective*".

Such differences may explain why the ILO policy agenda is largely autonomous from other international economic policies. For instance, the increasing influence of free-market economics in international economic policies had little effects on the ILO agenda, even during the 1980s when the ILO model of tripartite dialogue was contested. Figure 4 shows the evolution of the average number of ILO conventions ratified by country.[23] As we can see, there is an increasing trend of ratifications and we do not observe historical breakdowns such as the one characterizing the IMF or the World Bank policies - the Washington consensus, starting in the 1980s for instance.

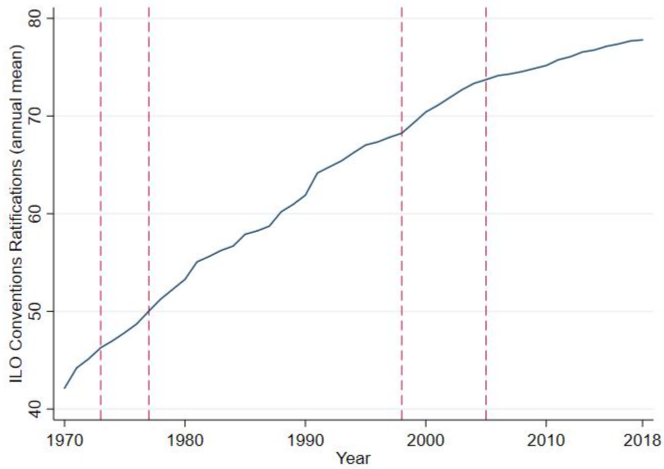
This increasing trend in the number of ILO conventions' ratifications is indeed mainly explained by the evolution of the ILO strategy over time (see Rodgers et al., 2009, for a global overview of ILO history). The launching of the World Employment Programme in 1969 "*marked*

[21] The ratification of conventions is voluntary. Once one country has ratified a convention, it becomes binding. Ratifying countries commit themselves to applying the convention in national law and practice, and to reporting on its implementation at regular intervals.

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

[23] Figure A.1 in the OA also shows the cumulative number of ratifications per year.

Figure 4: ILO's Conventions Ratifications



Source: ILO website, compilation by the authors. Main sample of advanced countries, excluding Czech Republic, Estonia, Slovenia and Slovakia. Vertical lines indicate two specific waves of ratifications (1973-1977 and 1995-2008).

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 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. Clearly, these ratifications became possible because of the ILO policy and were not related to policy changes within countries.

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, starting in 1992, targeting more than 90 countries.

Potential threat to identification: ILO ratifications and credit market liberalization. One particular threat to identification is that ILO conventions might be correlated with other country-level variables that would impact household credit. For example, if governments aiming at strengthening labor regulations are also ratifying ILO conventions, our instrument would be correlated with broader, country-level labor market regulations. It may 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. This is why we do not use indexes of labor market regulations as instruments. We therefore check the dynamics of both the instrument (ILO ratification) and credit market liberalization.

We find that the evolution of ILO ratifications is poorly correlated with the evolution of both labor market[24] and credit market deregulation.[25] The correlation between the evolution of ILO ratifications and the evolution of the credit market (respectively, labor market) regulation is only 0.06 (respectively, -0.03). 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 regarding the average evolution of the index of credit market deregulation, depending on the number of additional ILO conventions ratified.[26] 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.[27] This is consistent with the idea that ILO policies are independent from other international economic policies, due to the specific structure and goals of the ILO. The low correlation between ILO conventions ratifications and labor market regulation index can be explained by the wideness of topics covered by ILO conventions, which goes far beyond minimum wage, employment protection or mandated benefits, usually targeted by national labor market deregulation policies.

We therefore argue that dynamics of ratification depend mainly on the international policies and strategies of the ILO, and are largely orthogonal to other international (deregulation) policy packages and national circumstances. We believe it is a strong argument supporting the orthog-

[24] We use the labor market regulations index provided by the Fraser Institute (`https://www.fraserinstitute.org/economic-freedom/approach` It measures six dimensions: (1) hiring regulations and minimum wage, (ii) hiring and firing regulations, (iii) centralized collective bargaining, (iv) hours regulations, (v) mandated cost of worker dismissal, (vi) conscription.

[25] Index of Credit market regulations provided by the Fraser Institute. See Table A.1 in the Data Appendix.

[26] Average change in credit market deregulation index is respectively 0.05, 0.07 and 0.10 when there is no change, one additional ILO convention and more than one additional ILO convention. The confidence intervals for each mean cross each other.

[27] The average change in ILO convention ratification is 0.61, 0.42 and 0.72 when there is less, no change or more credit deregulation respectively.

onality condition of our instrument. Based on the history of ILO policies, we also identify two waves of ratifications that are driven by specific ILO internal changes. The first one is the period 1973-1977, with the new leadership of ILO Director-General Francis Blanchard and the start of the International Programme for the Improvement of Working Conditions and Environment. The second one is the period 1995-2008, starting with the Social Summit of Copenhagen and the Declaration on Fundamental Principles and Rights at work, which boosted a new dynamic of ratifications, under the leadership of ILO Director-General Juan Somavia. We argue that the argument supporting the orthogonality condition is even stronger during these periods as additional ratifications are strongly explained by new drives specific to the ILO. Note that these waves are obviously not related to the massive liberalization packages that occurred mainly in the 1980s and in the first half of the 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.

Other threat to identification: ILO ratifications and household debt. One additional threat to identification would come from a direct effect of ILO conventions on household debt, that would not go through a change in income distribution. If ILO conventions have a positive effect on *total* wages and income, it might also increase the ability to refund loans and consequently, to access credit. We argue that our main specification includes country-year variables controlling for this channel through which ILO conventions may affect directly household leverage. GDP per capita controls for the *average* level of wages. In addition, we also control for the ratio of housing Gross Fixed Capital Formation to GDP representing households' investment in real-estate, jointly with real house prices. It is indeed acknowledged that a very significant part of the increase in household leverage over the past decades has been devoted to housing investment: therefore, the latter should be able to capture the additional indebtedness capacity allowed by better wages/labor incomes, based on the idea that a better income improves the ability to refund bigger loans, which are typical of housing investments. We are therefore confident that the effect we capture through our identification strategy is the effect of ILO conventions on income *distribution* rather than a direct effect on household leverage.[28]

Strength of the instrument: 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. ILO conventions cover a wide range of topics related to wages, working conditions and labor relations; with an explicit goal of improving workers' well-being (as described in

[28] In Table B.6, we include ILO ratification variables in an OLS regression similar to table 3. The estimated coefficient is always negative, which goes against the argument that ILO conventions might have a direct and *positive* effect on household leverage, through an easier access to credit. Furthermore, estimated coefficients are not significant or very weakly significant, which gives an additional argument the exclusion restriction. Significance is even lower for ratifications during the two waves.

the 1919 ILO Constitution and the 1944 Declaration of Philadelphia). Beyond the diversity of such conventions and their potential heterogeneous effects on different labor market outcomes, one common characteristic of these conventions is to contribute to increase workers' bargaining power by providing them a more protective regulatory framework. Such increase in workers' bargaining power is associated with an increase in wage compression and therefore a decrease in inequalities. The overall distributional effect of labor market institutions has been consensual in the literature. As summarized by Betcherman (2012), *"by disproportionately raising earnings of workers with less market power, these institutions narrow wage differentials based on skill, gender, and age"* (Betcherman, 2012, p.42). This assumption is confirmed by Calderón and Chong (2009) in a cross-country study on the effect of labor regulations on inequality where they use the number of ILO conventions specifically. 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, and by Koeniger et al. (2007) who show that *"changes in labor market institutions can account for much of the change in the wage inequality between 1973 and 1998"*.

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, $ILO_{i,t}$) on the ratio of household credit to GDP:

$$Ineq_{i,t} = \alpha ILO_{i,t} + \delta X_{i,t} + \Phi Y_t + \mu_i + \nu_{i,t} \tag{2}$$

$$Credit_{i,t} = \beta \widehat{Ineq}_{i,t} + \Gamma X_{i,t} + \Psi Y_t + \mu_i + \epsilon_{i,t} \tag{3}$$

where $\widehat{Ineq}_{i,t}$ is the predicted value of the inequality index from Equation 2. Given that they give higher protection and bargaining power to workers, we expect a negative association between this variable and inequality.

We also propose a modified specification of equation 2 to measure the specific effects of ILO ratifications during the two waves 1973-1977 and 1995-2008 (equation 4).[29] The goal is to rely on a "quasi-natural experiment" environment provided by the strategy of the International Labor Organization. During these two periods, the increase in ratifications has been largely explained by new ILO policies impulsed by their Directors-General at that time.

[29] For this specification, Y_t includes 73-77 and 95-08 period dummies (in addition to the vector of variables representing common trends and shocks) when year dummies are not included.

$$Ineq_{i,t} = \alpha_1 ILO_{i,t} + \alpha_2 ILO_{i,t} \times Year_{73-77} + \alpha_3 ILO_{i,t} \times Year_{95-08} + \delta X_{i,t} + \Phi Y_t + \mu_i + \nu_{i,t} \quad (4)$$

Alternative instruments. While we are confident in the validity of our identification strategy, it is worth assessing if our results are robust to alternative types of exogenous inequality shocks. This also allows us to test for overidentifying restrictions and to show that the precise type of exogenous inequality shocks considered does not matter for the results. In this respect, trade openness is also a potential source of inequality, though obviously it cannot be used directly as an instrument: trade openness is likely to be jointly determined with credit dynamics, e. g., because trade and financial liberalization have gone hand-in-hand in most countries. That said, the *determinants* of trade openness, or factor endowments, are much more exogenous to these joint dynamics, while an extensive literature has shown they are strongly correlated with inequality (see e.g. Spilimbergo et al., 1999, Bourguignon and Morrisson, 1990, or Gourdon et al., 2008). These determinants are usually the land and capital endowments, and skill intensity/education level. They will therefore correspond to three alternative instruments, which definition and source are provided in full details in Table A.1: the agricultural land share as a percentage of total territory, the ratio of net capital stock over total hours worked, and the average number of years of total schooling.[30] Using alternative instruments allows us to perform Hansen's J-test of overidentifying restrictions. As shown later, almost all test statistics are insignificant, indicating that the orthogonality of the overidentifying instruments and the error term cannot be rejected; thus, our choice of instruments is appropriate on that ground.

We perform the Durbin–Wu–Hausman test for exogeneity of regressors. Unsurprisingly, the null hypothesis of exogeneity is rejected in almost all cases, which confirms the need to use instrumental variables.[31] 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 robust version of the Cragg-Donald statistic suggested by Stock and Yogo (2005) as a test for weak instruments. In most cases, statistics are comfortably above the critical values, confirming that our instrument is a strong predictor of inequality.

5 Results

5.1 Impact of income inequality on household leverage

In this section, we focus on the empirical assessment of our first testable relationship, namely the positive impact of an exogenous variation in income inequality on the ratio of household

[30] Unfortunately, we could not retrieve sufficiently numerous and comparable measures of skilled labor intensity for our sample.

[31] All statistics and corrsponding p-values available upon request to the authors.

credit over GDP.

Baseline estimates. Table 5 reports our baseline results for equation 3, focusing on two indicators of income inequality widely used in the literature, the Gini index (which gives an idea of the "average" inequality of the income distribution, columns (1) to (4)) and the share of income going to the Top 10% ((columns (5) to (8)). Both 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. As previously mentioned in Section 4.1, we check how our results behave when common time dynamics are included through a set of control variables (columns (1), (3), (5) and (7)) or alternatively year dummies (columns (2), (4), (6) and (8)). In this respect, we devote specific attention to the 2007-2008 financial crisis, which may have impacted the relationship we are interested in: this is why we report in columns (3), (4), (7) and (8) estimates over a period restricted to years before 2008.[32]

The first testable relationship 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 specification is estimated, though significance appears slightly weaker in columns (1) and (4). As expected, this is likely to be a consequence of the post-financial crisis years: significance of the Gini index and Top 10% income is very strong in all other columns, where post-financial crisis years are either controlled in a more exhaustive way through year dummies (columns (2) and (5)), or removed from estimations (columns (3)/(4) and (7)/(8)). In all cases, the strength of our instruments is confirmed: the Kleibergen-Paap statistic is above, or at least very close to the threshold value pointed by Stock and Yogo (2005), and in any case, above the value of 10 prescribed by Staiger and Stock (1997). Given the first stage coefficients (Table 6, column (1)), the ratification of one additional ILO convention is found to generate a decrease in the Gini (on a [0-1] scale) ranging from -0.001 to -0.0013 (until the 2008 financial cris), which in turn implies a 0.35 to 0.6 (until the 2008 financial crisis) percentage point decrease in credit over GDP.

Regarding control variables, GDP per capita and Broad Money Ratio are significant only over the whole period. Broad Money Ratio is positively associated with household leverage, consistently with the well-known idea that a higher money supply brings additional credit. GDP per capita displays a negative impact[33]; as for the two proxies for financial liberalization, while financial openness is largely insignificant, financial deregulation exhibits a negative impact on household credit over GDP whatever the considered period.

[32]Three countries are excluded from these pre-2008 estimates due to data availability: Romania, Switzerland and Slovenia - see Table A.2 in the Data Appendix. Table B.1 in OA presents the OLS results with the same specifications.

[33]Interestingly, the sign on GDP per capita is reverted when we run our estimation on a sample of emerging and developing countries, see Table 13 in section 5.3.

Table 5: TR 1: Baseline estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.				Household Credit/GDP				
Sample	All	All	Bef. 2008	Bef. 2008	All	All	Bef. 2008	Bef. 2008
Gini	2.861*	3.686***	3.869***	4.143***				
	(1.541)	(1.350)	(1.339)	(1.246)				
Top 10					3.962*	5.172***	6.016***	6.739***
					(2.061)	(1.855)	(2.186)	(2.227)
GDP per capita	-0.394***	-0.455***	-0.0984	-0.233	-0.445***	-0.490***	-0.168	-0.353*
	(0.0936)	(0.0998)	(0.151)	(0.157)	(0.108)	(0.105)	(0.164)	(0.185)
Broad Money Ratio	0.0958**	0.0734*	-0.0385	-0.0469	0.116***	0.0924**	-0.000252	-0.0116
	(0.0443)	(0.0412)	(0.0841)	(0.0780)	(0.0361)	(0.0362)	(0.0767)	(0.0766)
Financial Openness	0.00832	0.0599	-0.0895*	-0.0313	0.0202	0.0773	-0.0653	-0.00457
	(0.0509)	(0.0634)	(0.0466)	(0.0556)	(0.0533)	(0.0656)	(0.0523)	(0.0647)
Credit Deregulation	-0.0168*	-0.0191**	-0.0367**	-0.0340**	-0.0134*	-0.0131*	-0.0373**	-0.0314**
	(0.00937)	(0.00898)	(0.0152)	(0.0143)	(0.00789)	(0.00759)	(0.0160)	(0.0154)
Real House Prices	0.183***	0.154***	0.192***	0.178***	0.196***	0.179***	0.242***	0.245***
	(0.0253)	(0.0290)	(0.0389)	(0.0423)	(0.0249)	(0.0281)	(0.0499)	(0.0515)
Housing GFCF Ratio	0.116	0.432**	0.167**	0.712***	0.122	0.471**	0.147**	0.840***
	(0.0851)	(0.181)	(0.0767)	(0.176)	(0.0809)	(0.188)	(0.0739)	(0.230)
World GDP	0.569***		0.495**		0.572***		0.335	
	(0.132)		(0.241)		(0.131)		(0.262)	
Oil Price	0.0918***		0.0909***		0.0918***		0.0903***	
	(0.0147)		(0.0204)		(0.0145)		(0.0212)	
VIX	0.0105		0.00358		0.00787		0.00361	
	(0.00886)		(0.0129)		(0.00905)		(0.0132)	
FED Rate	-0.833***		-0.448*		-0.929***		-0.576**	
	(0.198)		(0.250)		(0.190)		(0.274)	
Quantification								
$\beta_{Ineq} * SD_{within}$	0.053	0.068	0.075	0.08	0.055	0.072	0.086	0.097
$KPF-stat$	13.753	18.359	19.237	20.899	13.305	18.112	15.46	14.803
Year Dummies	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	726	726	467	467	726	726	467	467
Countries	30	30	27	27	30	30	27	27

Robust standard errors in parentheses. All specifications includes country fixed effects. The critical value for the weak instruments test is based on a 10% (resp. 15%) 2SLS size at the 5% significance level, which is 16.4 (8.96) in all estimations. *, ** and *** denote respectively significance at the 10, 5 and 1% levels.

Interestingly, Table C.7 in appendix C shows that, when the dependent variable is simply the log of household credit, GDP per capita and the financial openness indicator display the expected positive sign, while financial deregulation turns simply insignificant. Regarding credit deregulation, this means that a positive deviation from the mean across countries does not bring additional household credit, decreasing its share over GDP. Besides, Tables E.1 and E.2 in the OA show that, without country fixed effects, estimated parameters on GDP per capita and financial openness are always positive and highly significant, as well as financial deregulation. This suggests that higher levels of development and financial openness do bring an increase in household credit, but that the latter does not move faster than GDP. Though it is beyond the scope of this paper to deliver some definite explanations for these estimates, there may be a common rationale underlying them. Beyond a certain (average over countries) level of development (GDP per capita) and financial liberalization, the latter variables keep supporting the growth of household credit, but at a slower path than GDP. In this regard, it is interesting to see in Table E.10 from the OA that financial openness has a positive impact on the ratio of private credit to GDP (at least, until the 2007-2008 financial crisis), and that credit deregulation has also a positive impact on bank credit over GDP for the whole period. These two credit aggregates also encompass corporate credit, suggesting that, beyond a certain level of development and/or financial liberalization, the expansion of credit as a share of GDP benefits firms in priority, rather than households.

In addition, Tables E.3 and E.4 (columns (1) to (4)) in the OA report estimates for a specification in which the Gini index and the Top 10% are interacted alternatively with financial deregulation and financial openness. If the interactions with the former bring mostly insignificant results, those with the latter tend to show a positive impact. This result is consistent with a supply-side effect: if additional inequality triggers more demand for credit through the various channels surveyed in section 2.2, financial openness magnifies this effect by bringing capital in the country, allowing to increase credit supply.

As expected, real-estate controls (house prices and housing GFCF) are both positively associated with household leverage. Finally, the latter moves in the same direction than the world business cycle (world GDP and oil prices) and financial cycle (a decrease in the Fed rate brings additional country-year household credit, the VIX index appearing insignificant in all estimates).

Regarding the size of the effects, a one standard deviation in the Gini index is associated with a 5.3-6.8 (all period) to a 7.5-8 (pre-financial crisis) percentage point increase in the household credit to GDP ratio. Interestingly, when inequality is measured through the top incomes share, we find that an increase by one standard deviation lifts the credit to GDP ratio by almost identical figures over the whole period (+5.3 to +7.2 pp), but slightly higher ones for the pre-2008 financial crisis period (+8.6 to +9.7 pp).

Table 6 confirms the theoretical intuitions presented in section 4.2 regarding the negative association between the number of ILO conventions ratified and inequality, due to the higher protection and bargaining power they grant to workers. Put differently a higher number of signed ILO conventions decreases the Gini index (columns (1) to (4)) and the share of Top incomes (columns (5) to (8)). As explained earlier, our overall exclusion restriction relies on the fact it is very likely the overall ratification process of OIT conventions is supported by an international organization acting independently from country governments.

In addition, Table 7 reports estimates where inequality is instrumented not only with number of ratified OIT conventions, but also with interactions between the later and time dummies for specific time periods (1973-1977, 1995-2008) corresponding to particular waves of ratifications that are specifically explained by ILO's internal dynamics (see section 4.2). The first-stage results (columns (1) to (4)) confirm that the latter bring their own, specific reduction in inequality, especially the 1973-1977 wave, the 1995-2008 displaying a much more modest impact. In any case, this specification including explicitly the impact of ratifications waves do not bring any significant alterations to our 2nd stage results (columns (5) to (8) report those for the Gini, those for the Top 10% are reported in Table C.2 in the OA).

Table 6: TR 1: First stage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Gini				Top 10			
Sample	All	All	Bef. 2008	Bef. 2008	All	All	Bef. 2008	Bef. 2008
ILO conv.	-0.000797***	-0.000927***	-0.00123***	-0.00134***	-0.000576***	-0.000661***	-0.000792***	-0.000826***
	(0.000215)	(0.000216)	(0.000281)	(0.000294)	(0.000158)	(0.000155)	(0.000201)	(0.000215)
GDP per capita	0.0420***	0.0356**	0.0500**	0.0677***	0.0432***	0.0322***	0.0438**	0.0594***
	(0.0134)	(0.0139)	(0.0250)	(0.0242)	(0.0105)	(0.0104)	(0.0172)	(0.0170)
Broad Money Ratio	0.0180***	0.0154**	0.0447***	0.0387***	0.00786	0.00730	0.0224***	0.0185***
	(0.00668)	(0.00605)	(0.00964)	(0.00948)	(0.00482)	(0.00451)	(0.00692)	(0.00714)
Financial Openness	-0.0203***	-0.0317***	-0.0133*	-0.0258***	-0.0177***	-0.0260***	-0.0126**	-0.0198***
	(0.00656)	(0.00618)	(0.00752)	(0.00753)	(0.00458)	(0.00444)	(0.00523)	(0.00557)
Credit Deregulation	0.00462***	0.00434***	0.00893***	0.00835***	0.00248***	0.00194**	0.00585***	0.00475***
	(0.00119)	(0.00125)	(0.00207)	(0.00202)	(0.000880)	(0.000903)	(0.00141)	(0.00155)
Real House Prices	0.00125	0.00360	-0.0113**	-0.00625	-0.00219	-0.00237	-0.0156***	-0.0137***
	(0.00354)	(0.00362)	(0.00566)	(0.00586)	(0.00275)	(0.00269)	(0.00432)	(0.00412)
Housing GFCF Ratio	-0.0378***	-0.100***	-0.0310**	-0.108***	-0.0287***	-0.0792***	-0.0166*	-0.0851***
	(0.0128)	(0.0194)	(0.0127)	(0.0204)	(0.00855)	(0.0142)	(0.00862)	(0.0165)
World GDP	0.0518**		0.0727*		0.0366**		0.0734**	
	(0.0233)		(0.0417)		(0.0175)		(0.0295)	
Oil Price	-0.00722***		-0.0105***		-0.00519***		-0.00662***	
	(0.00165)		(0.00268)		(0.00123)		(0.00189)	
VIX	-0.000282		-0.00375*		0.000460		-0.00242*	
	(0.00141)		(0.00201)		(0.00110)		(0.00142)	
FED Rate	-0.0333		0.0122		0.000319		0.0291	
	(0.0367)		(0.0452)		(0.0276)		(0.0337)	
Year Dummies	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	726	726	467	467	726	726	467	467
Countries	30	30	27	27	30	30	27	27

Robust standard errors in parentheses. All specifications includes country fixed effects.

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

Table 7: TR 1: The specific part of waves

Dep. Var.	First stage: Gini				Second stage: Household Credit/GDP			
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	All	All	Bef. 2008	Bef. 2008	All	All	Bef. 2008	Bef. 2008
Gini					1.282**	1.684***	2.492***	2.524***
					(0.647)	(0.637)	(0.723)	(0.614)
ILO conv.	-0.000653***	-0.000553**	-0.000680*	-0.000667*				
	(0.000252)	(0.000241)	(0.000348)	(0.000346)				
ILO conv. *7377	-0.00338***	-0.00348***	-0.00276***	-0.00300***				
	(0.000687)	(0.000708)	(0.000722)	(0.000742)				
ILO conv. *9508	-0.0000659*	-0.0000814**	-0.000180***	-0.000180***				
	(0.0000398)	(0.0000408)	(0.0000629)	(0.0000628)				
GDP per capita	0.0226*	0.0400***	0.0456**	0.0685***	-0.325***	-0.402***	-0.0847	-0.175
	(0.0134)	(0.0141)	(0.0230)	(0.0251)	(0.0785)	(0.0809)	(0.115)	(0.118)
Broad Money Ratio	0.0164**	0.0121**	0.0429***	0.0388***	0.125***	0.116***	0.0260	0.0357
	(0.00650)	(0.00612)	(0.00977)	(0.00975)	(0.0350)	(0.0328)	(0.0514)	(0.0463)
Financial Openness	-0.0262***	-0.0327***	-0.0140*	-0.0178**	-0.0257	-0.00641	-0.0875**	-0.0723*
	(0.00622)	(0.00638)	(0.00840)	(0.00881)	(0.0341)	(0.0381)	(0.0383)	(0.0397)
Credit Deregulation	0.00342***	0.00386***	0.00867***	0.00690***	-0.00874	-0.0107	-0.0258**	-0.0206**
	(0.00112)	(0.00120)	(0.00204)	(0.00199)	(0.00630)	(0.00652)	(0.0105)	(0.0103)
Real House Prices	0.000251	0.00231	-0.00588	-0.00726	0.190***	0.164***	0.167***	0.175***
	(0.00341)	(0.00364)	(0.00530)	(0.00594)	(0.0225)	(0.0253)	(0.0317)	(0.0354)
Housing GFCF Ratio	-0.0330**	-0.110***	-0.0391***	-0.120***	0.0791	0.225*	0.234***	0.552***
	(0.0136)	(0.0195)	(0.0131)	(0.0198)	(0.0563)	(0.120)	(0.0624)	(0.107)
1973-1977 Wave	0.186***		0.153***		-0.0123		0.0167	
	(0.0449)		(0.0467)		(0.0291)		(0.0328)	
1995-2008 Wave	0.0143***		0.0319***		-0.00989		-0.0798***	
	(0.00296)		(0.00529)		(0.0119)		(0.0233)	
World GDP	0.0420*		-0.0640		0.616***		1.038***	
	(0.0228)		(0.0439)		(0.116)		(0.226)	
Oil Price	-0.00316**		-0.00470*		0.0766***		0.0590***	
	(0.00160)		(0.00255)		(0.00931)		(0.0125)	
VIX	-0.00220		-0.00486**		0.0128		0.00771	
	(0.00136)		(0.00194)		(0.00796)		(0.0110)	
FED Rate	-0.122***		-0.0822**		-0.822***		-0.158	
	(0.0374)		(0.0415)		(0.200)		(0.224)	
$KPF-stat$					28.951	25.992	24.425	25.527
Year Dummies	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	726	726	467	467	726	726	467	467
Countries	30	30	27	27	30	30	27	27

Robust standard errors in parentheses. All specifications includes country fixed effects. The critical value for the weak instruments test is based on a 10% 2SLS size at the 5% significance level, which is 22.3 in all estimations. For the 5% 2SLS bias at the 5% significance level, it is 13.9.
*, ** and *** denote respectively significance at the 10, 5 and 1% levels.

Alternative datasets. As explained in Section 3, we believe the WIID database offers the best compromise in terms of country coverage and income inequality indicators available. However, it is a useful and interesting robustness to check how estimates behave with alternative datasets, such as the SWIID database (for which we can retrieve Gini indexes, but no income deciles) and the WID database, which contains information on income deciles based on administrative tax data (rather than the survey data used in WIID). The latter will be especially useful to investigate our second testable relationship that the relative impoverishment of middle classes compared to top incomes matters quantitatively more for the evolution of the household leverage than the relative impoverishment of low incomes relatively to top incomes (see section 5.2 below).

Therefore, Table 8 reports estimates relying on the Gini index from SWIID (columns (1) to (4)), and the top 10% from WID (columns (5) to (8)). Both are instrumented either with the number of OIT conventions ratified (columns (1), (2), (5), and (6)), or with the latter and its interactions with the previously mentioned waves of ratifications (columns (3), (4), (7), and (8)). Common time dynamics are still alternatively controlled for with dedicated variables (columns (1), (3), (5) and (7)) or year dummies (columns (2), (4), (6) and (8)). Qualitatively, our results are basically unchanged compared to those stemming from our baseline estimates: positive variations in the SWIID-Gini and the WID-Top 10% income share driven by changes in the number of ratified ILO conventions keep impacting positively household leverage, though with a weaker significance in column (1).[34] Quantitatively, the impacts of one standard-deviation increases on the household credit over GDP ratio are very much in line with those reported in Table 5: if those for the SWIID-Gini (between +3.5 and +6.6 pp) are slightly smaller compared to the WIID-Gini, quantifications for the WID-Top 10% income share (between +6.5 and +10.3 pp) are almost identical to the ones arising from the WIID-Top 10% income share.

Alternative instruments. In this section, we check the robustness of our results with alternative instruments which are even less likely to be correlated with globalization trends or country-level policy packages. As detailed in section 4.2 above, we use three variables proxying for factor endowments: the agricultural land share, the ratio of net capital stock over total hours worked, and the average number or years of total schooling[35] - see table A.1 in the Data appendix for more details.

Table 9 reports estimates of Equation 3 where the Gini (columns (1) to (4)) and the Top 10 (columns (5) to (8)) are instrumented with these alternative instruments, as well as combinations of the latter with our preferred instrument, the number of ratified ILO conventions. Getting into details, we start with the agricultural land share as a single instrument (columns (1) and (5)). In columns (2) and (6), inequality measures are instrumented using a combination of the ratio of capital over total hours worked and the average number of years of total schooling. Columns (3) and (7) include all three variables (agricultural land share, capital/hours worked, years of schooling) in the set of instruments, and finally columns (4) and (8) add the number of ratified ILO conventions.

In all estimations, the coefficients on inequality measures are positive and significant, and, in specifications relying on more than one instrument, the Hansen test cannot reject our overi-

[34]We also check results before 2008 (table C.4 in OA); and results with one additional country (Japan) for which data were not available in WIID (table C.5 in OA). Results are unchanged.

[35]Unfortunately, we could not retrieve sufficiently numerous and comparable measures of skilled labor intensity for our sample.

Table 8: TR 1: Alternative datasets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Household Credit/GDP							
Other source	SWID				WID			
First stage: ILO waves	No	No	Yes	Yes	No	No	Yes	Yes
Gini index SWIID	2.359	3.220*	4.025***	4.465***				
	(1.824)	(1.733)	(0.888)	(0.896)				
Top 10% WID					3.062*	4.112***	4.190***	4.905***
					(1.700)	(1.551)	(0.954)	(0.942)
GDP per capita	-0.291***	-0.266***	-0.257***	-0.252***	-0.472***	-0.496***	-0.497***	-0.531***
	(0.0641)	(0.0817)	(0.0758)	(0.0842)	(0.134)	(0.117)	(0.105)	(0.114)
Broad Money Ratio	0.108**	0.0744	0.0571	0.0417	0.199***	0.176***	0.197***	0.179***
	(0.0502)	(0.0550)	(0.0369)	(0.0377)	(0.0373)	(0.0396)	(0.0387)	(0.0417)
Financial Openness	0.0193	0.0301	0.0243	0.0361	0.0458	0.0445	0.0534	0.0479
	(0.0282)	(0.0309)	(0.0310)	(0.0320)	(0.0372)	(0.0396)	(0.0403)	(0.0417)
Credit Deregulation	-0.00712	-0.0106	-0.00884	-0.0128*	-0.00910	-0.0118	-0.00961	-0.0127*
	(0.00732)	(0.00689)	(0.00635)	(0.00652)	(0.00740)	(0.00744)	(0.00728)	(0.00762)
Real House Prices	0.166***	0.137***	0.169***	0.133***	0.223***	0.220***	0.244***	0.234***
	(0.0214)	(0.0262)	(0.0236)	(0.0276)	(0.0421)	(0.0424)	(0.0350)	(0.0368)
Housing GFCF Ratio	0.0657	0.0168	0.0354	-0.00926	-0.0467	-0.300*	-0.0741	-0.329*
	(0.0411)	(0.0403)	(0.0301)	(0.0316)	(0.0996)	(0.165)	(0.108)	(0.169)
1973-1977 Wave			-0.0162				-0.0140	
			(0.0193)				(0.0240)	
1995-2008 Wave			-0.0218*				-0.0186	
			(0.0116)				(0.0125)	
World GDP	0.548***		0.426***		0.327		0.182	
	(0.151)		(0.133)		(0.241)		(0.190)	
Oil Price	0.0731***		0.0745***		0.0762***		0.0761***	
	(0.0114)		(0.00997)		(0.0129)		(0.0122)	
VIX	0.0199**		0.0254***		0.0190*		0.0236**	
	(0.00813)		(0.00879)		(0.00979)		(0.0109)	
FED Rate	-0.702***		-0.624***		-0.884***		-0.856***	
	(0.160)		(0.202)		(0.239)		(0.241)	
Quantification								
$\beta_{Ineq} * SD_{within}$	0.035	0.048	0.060	0.066	0.065	0.087	0.088	0.103
$KPF-stat$	9.153	11.288	22.745	23.829	15.753	20.713	17.048	19.34
Year Dummies	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	848	848	848	848	764	764	764	764
Countries	30	30	30	30	30	30	30	30

Robust standard errors in parentheses. All specifications includes country fixed effects. First stage is based on our preferred IV in columns (1), (2), (5), and (6), and our preferred IV plus interactions with waves periods in columns (3), (4), (7) and (8). The critical value for the weak instruments test is based on a 10% 2SLS size at the 5% significance level, which is 16.4 in columns (1), (2), (5) and (6), and 22.3 in columns (3), (4), (7) and (8). Here 5% 2SLS bias at the 5% significance level, it is 13.9. See Table C.3 of the OA for first stage results.

dentifying restrictions (except in column (8), but the latter reports estimates which are almost identical to those in columns (6) and (7)). This indicates that in almost all cases, the orthogonality of the overidentifying instruments and the error term cannot be rejected; thus, these various sets of instruments are appropriate on that ground. These results suggest that, regardless of the (exogenous) shock causing them, variations of inequality are positively related to the variation of household leverage. The coefficients and resulting quantifications are found to be quantitatively larger in the estimations using the agricultural land share as a single instrument, but our estimates are also less accurate - this instrument is arguably more exogenous, but also weaker as time variations are limited. In all other estimations (columns (2) to (4), and (6) to (8)), estimated parameters and quantifications are interestingly very similar to those found in Table 5: a one standard-deviation increase in the Gini index or the Top 10% lifts the household credit over GDP up by 5 to 7.5 percentage points. Finally, note that these alternative instruments have the expected effects on inequality indicators, as shown in Table C.6 in the OA, which reports first stage coefficients.

Table 9: TR 1: Alternative instrument sets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.				Household Credit/GDP				
Gini	9.561**	3.249***	3.555***	3.728***				
	(3.821)	(0.949)	(0.768)	(0.788)				
Top 10					17.691**	3.391***	3.919***	3.765***
					(8.295)	(0.923)	(0.857)	(0.846)
GDP per capita	-0.935**	-0.415***	-0.440***	-0.455***	-1.347**	-0.377***	-0.413***	-0.403***
	(0.400)	(0.149)	(0.147)	(0.151)	(0.611)	(0.126)	(0.128)	(0.126)
Broad Money Ratio	-0.252	0.020	0.007	-0.001	-0.253	0.080*	0.068	0.072*
	(0.176)	(0.057)	(0.051)	(0.052)	(0.205)	(0.045)	(0.044)	(0.044)
Financial Openness	0.162	-0.020	-0.011	-0.006	0.288	-0.036	-0.024	-0.028
	(0.131)	(0.049)	(0.049)	(0.050)	(0.208)	(0.042)	(0.043)	(0.042)
Credit Deregulation	-0.118***	-0.057***	-0.060***	-0.061***	-0.121***	-0.044***	-0.046***	-0.046***
	(0.039)	(0.014)	(0.013)	(0.013)	(0.047)	(0.011)	(0.010)	(0.010)
Real House Prices	0.302***	0.236***	0.239***	0.241***	0.483***	0.256***	0.264***	0.261***
	(0.072)	(0.040)	(0.040)	(0.041)	(0.148)	(0.037)	(0.037)	(0.037)
Housing GFCF Ratio	1.164***	0.502***	0.534***	0.553***	1.718**	0.460***	0.506***	0.493***
	(0.451)	(0.138)	(0.131)	(0.134)	(0.791)	(0.113)	(0.115)	(0.114)
Quantification								
$\beta_{Ineq} * SD_{within}$	0.189	0.064	0.070	0.074	0.260	0.050	0.058	0.055
Instruments	Agri	$\frac{K}{L}$+ School	Agri+$\frac{K}{L}$ + School	Agri+$\frac{K}{L}$ + School+ILO	Agri	$\frac{K}{L}$+ School	Agri+$\frac{K}{L}$ + School	Agri+$\frac{K}{L}$ + School+ILO
$KPF-stat$	9.562	27.068	27.639	20.662	5.374	49.355	40.534	32.714
$KPF\ size\ -crit.value$	16.38	19.93	22.3	24.58	16.38	19.93	22.3	24.58
$KPF\ bias\ -crit.value$			13.91	16.85			13.91	16.85
$Hansen-stat$		0.050	0.422	5.264		0.171	3.686	11.081
$Hansen-p-value$		0.823	0.810	0.153		0.679	0.158	0.011
Obs.	483	483	483	483	483	483	483	483
Countries	20	20	20	20	20	20	20	20

Robust standard errors in parentheses. All estimations include country fixed effects and year dummies. The critical values for the weak instruments test are based on a 10% 2SLS size and a 5% IV bias at the 5% significance level. See Table C.6 of the OA for first stage results. *, ** and *** denote respectively significance at the 10, 5 and 1% levels.

Lastly, we propose two additional robustness checks in this area. First, we add Real House Prices and Housing GFCF ratio to the set of instrumented variables, together with the inequality indicators. In table C.7 in the OA, we show that it does not affect our results in any way. Note that the significance of real house prices coefficient is lower when instrumented.[36] Second, we propose alternative control variables: alternative proxies for financial openness such as *De*

[36]We choose ILO convention, the capital/labor intensity and the number of years of schooling as instruments for our three instrumented variables. We do not use arable land which appears to be a very weak predictor of real-estate variables.

facto Financial Openness, i.e. the ratio (External Assets + External Liabilities)/GDP, or gross portfolio investments over GDP ; the short-term real interest rate as an additional control, together with money supply, for monetary policy stance ; and the long-term real interest rate to control for term premium (see table E.7 in OA for data sources). Again, our results remain unchanged (see table E.8 in OA).

5.2 On the specific part of middle incomes

An important insight from the various strands of the literature surveyed in section 2 is that, for a given inequality shock increasing the share of top incomes relatively to incomes below, middle incomes should contribute more to the variation of household leverage than low incomes. This is what we assess in this section (note that the sample under study is identical to the one used in section 5.1 but for New Zealand, which had to be excluded for lack of required data on income deciles.[37])

Baseline estimates. Table 10 replicates the structure of Table 5, with columns (1) to (4) relying on the ratio of Top 10% incomes to Middle ones (share of the 3$^{\text{rd}}$ to the 9$^{\text{th}}$ decile) as inequality indicator, while columns (5) to (8) are dedicated to the ratio of Top 10% incomes to Bottom ones (share of incomes up to the 3$^{\text{rd}}$). Qualitatively, we still find strong support for the positive impact of exogenous variations of inequality on household leverage, though with weaker significance in columns (1) and (5).[38] Once again, the years following the 2008 financial crisis seems to explain most of the latter: once they are accounted for with time dummies, or removed from the estimation, all estimates are back to 1% significance.[39]

On the quantitative ground, quantifications confirm the intuitions wrapped in our 2$^{\text{nd}}$ Testable Relationship: a one standard-deviation increase in the Top incomes over Middle incomes ratio (implying a relative impoverishment of middle classes compared to the Top 10%) brings an increase in household credit over GDP equivalent to 1.4-1.5 times the one stemming from an increase in the ratio of Top 10% over Bottom incomes - see the row "Quantif. $Middle/Bottom$" at the bottom of the Table.[40] Interestingly, this order of magnitude of 1.5 for the additional impact of an inequality shock hitting the middle classes corresponds to the lower bound found for the gap regarding the debt-to-income ratios reported in section 2.2, found to be 1.5 to 4

[37] We check that this slight change of the sample does not affect results from Table 5. Table C.1 in OA shows the results using this new sample without New Zealand. Results are unchanged.

[38] As we did previously, we report in Tables E.5 and E.6 (columns (1) to (4)) in the OA estimates including interactions between financial deregulation and financial openness on the one hand, and our income inequality indicators on the other hand. Estimates are on the whole very noisy, though they remain consistent with the idea of positive impacts of inequality magnified by financial openness, i.e., by the relaxation of credit constraints.

[39] Table D.2 in the OA reports estimates where interactions between the number of ILO conventions ratified and the two waves are included in the set of instruments, with very similar results. Table E.2 in the OA presents results without country fixed effects. Our main result holds.

[40] These multipliers come from the ratio of quantifications in strictly comparable specifications, e. g. for columns (1) and (5), 0.040/0.028 gives 1.429, for columns (2) and (6), 0.057/0.039 gives 1.462...

times higher for middle incomes than for low incomes in a vast majority of countries.[41]

Table 10: TR 2: Baseline estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.				Household Credit/GDP				
Sample	All	All	Bef. 2008	Bef. 2008	All	All	Bef. 2008	Bef. 2008
$\frac{Top\ 10}{Mid.\ 30-90}$	1.444	2.039***	2.597***	2.945***				
	(0.905)	(0.782)	(0.949)	(0.940)				
$\frac{Top\ 10}{Bot.\ 0-30}$					0.159*	0.222***	0.296***	0.321***
					(0.0956)	(0.0772)	(0.0900)	(0.0823)
GDP per capita	-0.421***	-0.466***	-0.159	-0.330**	-0.362***	-0.414***	-0.0626	-0.164
	(0.103)	(0.0954)	(0.148)	(0.165)	(0.0778)	(0.0830)	(0.119)	(0.118)
Broad Money Ratio	0.144***	0.119***	0.0548	0.0429	0.137***	0.111***	0.0476	0.0395
	(0.0321)	(0.0326)	(0.0618)	(0.0611)	(0.0351)	(0.0337)	(0.0555)	(0.0514)
Financial Openness	0.0115	0.0637	-0.0650	-0.00931	-0.00716	0.0297	-0.0905**	-0.0322
	(0.0477)	(0.0576)	(0.0470)	(0.0576)	(0.0386)	(0.0456)	(0.0381)	(0.0462)
Credit Deregulation	-0.00982	-0.00960	-0.0275**	-0.0207	-0.00845	-0.0109*	-0.0167*	-0.0198*
	(0.00710)	(0.00669)	(0.0133)	(0.0129)	(0.00661)	(0.00658)	(0.00995)	(0.0111)
Real House Prices	0.187***	0.174***	0.224***	0.228***	0.180***	0.151***	0.175***	0.157***
	(0.0240)	(0.0268)	(0.0466)	(0.0478)	(0.0226)	(0.0252)	(0.0321)	(0.0361)
Housing GFCF Ratio	0.0958	0.376**	0.133**	0.766***	0.0666	0.180	0.143**	0.485***
	(0.0710)	(0.162)	(0.0649)	(0.196)	(0.0582)	(0.116)	(0.0574)	(0.113)
World GDP	0.592***		0.358		0.580***		0.454**	
	(0.120)		(0.232)		(0.117)		(0.205)	
Oil Price	0.0840***		0.0785***		0.0814***		0.0777***	
	(0.0125)		(0.0177)		(0.0111)		(0.0157)	
VIX	0.00754		0.0000736		0.0101		-0.0000382	
	(0.00855)		(0.0123)		(0.00808)		(0.0111)	
FED Rate	-0.984***		-0.567**		-0.954***		-0.503**	
	(0.175)		(0.250)		(0.166)		(0.209)	
Quantification								
$\beta_{Ineq} * SD_{within}$	0.040	0.057	0.074	0.084	0.028	0.039	0.053	0.0574
Quantif. *Middle/Bottom*	1.429	1.462	1.396	1.474				
$KPF-stat$	14.453	20.275	16.838	16.789	33.299	44.453	32.355	35.718
Year Dummies	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	698	698	449	449	698	698	449	449
Countries	29	29	26	26	29	29	26	26

Robust standard errors in parentheses. All specifications include country fixed effects. The critical value for the weak instruments test is based on a 10% 2SLS size at the 5% significance level, which is 16.4 in all estimations. See Table D.1 of the OA for first stage results.
*, ** and *** denote respectively significance at the 10, 5 and 1% levels.

Alternative dataset. As we did in the previous section for our 1st Testable Relationship, we check how our results behave with alternative data. Therefore, Table 11 replicates the structure of Table 10 using data from the WID (the SWIID does not provide information on income deciles). Note that the WID provides information on three categories of incomes which bounds slightly differ from ours: bottom incomes are defined as incomes up to the 5th decile, middle incomes go from the 5th to the 9th decile, while Top 10% has obviously the same definition than in our benchmark estimates.

[41] Table C.9 in Appendix C also reports estimates of a specification including the ratio of middle to bottom incomes.

Table 11: TR 2: Alternative dataset

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.				Household Credit/GDP				
Sample	All	All	Bef. 2008	Bef. 2008	All	All	Bef. 2008	Bef. 2008
$\frac{Top\ 10}{Mid.\ 50-90}$ WID	0.660*	0.758***	1.132**	1.114***				
	(0.337)	(0.289)	(0.483)	(0.368)				
$\frac{Top\ 10}{Bot.\ 0-50}$ WID					0.0987**	0.140***	0.136***	0.188***
					(0.0479)	(0.0509)	(0.0463)	(0.0496)
GDP per capita	-0.461***	-0.455***	-0.230	-0.244	-0.404***	-0.419***	-0.0448	-0.0302
	(0.103)	(0.0957)	(0.211)	(0.198)	(0.0812)	(0.0867)	(0.131)	(0.132)
Broad Money Ratio	0.164***	0.145***	0.166***	0.182***	0.164***	0.147***	0.188***	0.176***
	(0.0361)	(0.0372)	(0.0583)	(0.0596)	(0.0339)	(0.0349)	(0.0484)	(0.0495)
Financial Openness	0.126***	0.154***	-0.00235	0.0389	0.131***	0.156***	0.01000	0.0429
	(0.0378)	(0.0381)	(0.0393)	(0.0414)	(0.0362)	(0.0359)	(0.0340)	(0.0360)
Credit Deregulation	-0.0106*	-0.0133**	0.0136	0.00924	-0.00855	-0.0128**	0.00710	-0.00526
	(0.00622)	(0.00619)	(0.0134)	(0.0153)	(0.00584)	(0.00583)	(0.0103)	(0.0120)
Real House Prices	0.160***	0.139***	0.162***	0.148***	0.157***	0.137***	0.128***	0.110***
	(0.0299)	(0.0308)	(0.0538)	(0.0533)	(0.0273)	(0.0281)	(0.0379)	(0.0416)
Housing GFCF Ratio	-0.0341	-0.115	0.337***	0.435***	-0.0701	-0.228	0.310***	0.147
	(0.102)	(0.141)	(0.108)	(0.152)	(0.0984)	(0.147)	(0.0850)	(0.124)
World GDP	0.448***		0.231		0.529***		0.383*	
	(0.168)		(0.288)		(0.140)		(0.225)	
Oil Price	0.0754***		0.0508***		0.0700***		0.0461***	
	(0.0106)		(0.0164)		(0.00980)		(0.0141)	
VIX	0.0162*		-0.00176		0.0171*		0.00225	
	(0.00971)		(0.0134)		(0.00889)		(0.0107)	
FED Rate	-0.835***		-0.658**		-0.728***		-0.533**	
	(0.245)		(0.272)		(0.207)		(0.207)	
Quantification								
$\beta_{Ineq} * SD_{within}$	0.041	0.047	0.069	0.068	0.021	0.030	0.0266	0.037
Quantif. *Middle/Bottom*	1.952	1.584	2.594	1.838				
$KPF-stat$	33.39	39.452	17.325	22.719	83.027	53.563	104.722	61.625
Year Dummies	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	656	656	418	418	656	656	418	418
Countries	27	27	25	25	27	27	25	25

Robust standard errors in parentheses. All specifications include country fixed effects. The critical value for the weak instruments test is based on a 10% 2SLS size at the 5% significance level, which is 16.4 in all estimations. See Table D.3 of the OA for first stage results.
*, ** and *** denote respectively significance at the 10, 5 and 1% levels.

Results are qualitatively very similar to those reported in Table 10 - if anything, significance is improved in columns (1) and (5). As for quantifications, they provide additional support to our 2$^{\text{nd}}$ Testable Relationship: the row "Quantif. *Middle/Bottom*" reports that a one standard-deviation increase in the Top incomes over Middle incomes ratio (meaning a relative impoverishment of middle classes compared to the Top 10%) delivers an increase in household credit over GDP ranging from 1.6 to 2.6 times the one stemming from an increase in the ratio of Top 10% over Bottom incomes.[42] Interestingly, this order of magnitude of 1.6-2.6 for the additional impact of an inequality shock hitting the middle classes covers roughly the first half

[42] Again, these multipliers come from the ratio of quantifications in strictly comparable specifications, e. g., for columns (1) and (5), 0.041/0.021 gives 1.95, for columns (2) and (6), 0.0472/0.0298 gives 1.58...

of the interval regarding the debt-to-income ratios reported in section 2.2, found to be 1.5 to 4 times higher for middle incomes than for low incomes in a vast majority of countries. This clearly strengthens our point regarding the stronger impact of income inequality shocks hitting middle classes (compared to bottom incomes).

Alternative instruments. We keep following the strategy implemented in Section 5.1, and assess if our results are robust to alternative types of exogenous inequality sources. We rely on two of the variables proxying factor endowments used previously, agricultural land share and net capital/hours worked - we had to remove the average number of years of schooling in order to preserve the validity of overidentifying restrictions. More precisely, the first four columns of Table 12 are devoted to the ratio of Top 10% over Middle Incomes, while the following four focus on the ratio of Top 10% over Bottom Incomes. Columns (1) and (5) rely again on the agricultural land share as single instrument. Columns (2) and (6) add to the previous variable the ratio of capital over total hours worked. In columns (3) and (6), we rely on a combination the ratio of capital over total hours worked and the number of ratified ILO conventions. Finally, columns (4) and (8) add to the previous set of instruments the agricultural land share.

On the whole, even though instruments are a bit weaker in a couple of specification, estimates are completely consistent with those reported in Tables 9 and 10. The coefficients on both inequality measures are positive and significant, and once again, in specifications featuring more than one instrument, Hansen's J-test statistics of overidentifying restrictions are insignificant in all cases but in column (6), for which the null hypothesis that the over-identifying restrictions are valid cannot be rejected at the 5% threshold, though. More importantly, when the number of ratified ILO conventions is included in the set of instruments, Hansen's J-test statistics tend to be even more insignificant, supporting the orthogonality of this specific instrument with the error term.

Again, the estimated coefficients and quantifications are a bit noisier in the specifications relying only on the agricultural land share as single instrument. This is also the case, to as lesser extent, for those relying on the combination between agricultural land share and the ratio of capital stock over hours worked. But in general, all estimates, and more importantly, resulting quantifications, are very similar to those shown Table 10: a one standard-deviation increase in the Top incomes over Middle incomes ratio (implying a relative impoverishment of middle classes compared to the Top 10%) brings an increase in household credit over GDP equivalent to 1.2-1.45 times the one stemming from an increase in the ratio of Top 10% over Bottom incomes - see the row "Quantif. Middle/Bottom" at the bottom of the Table. This order of magnitude is very close, though slightly lower, than the one found in our benchmark estimates (1.4-1.5, see Table 10 above and related comments). This brings additional support to our point regarding the stronger impact of income inequality shocks hitting middle classes (compared to a similar shock hitting bottom incomes).[43]

Table 12: TR 2: Alternative instrument sets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.				Household Credit/GDP				
$\frac{Top\ 10}{Mid.\ 30-90}$	6.325**	4.592**	2.751***	3.228***				
	(2.757)	(2.013)	(0.769)	(0.869)				
$\frac{Top\ 10}{Bot.\ 0-30}$					0.857**	0.537**	0.315***	0.357***
					(0.433)	(0.259)	(0.076)	(0.083)
GDP per capita	-1.014**	-0.771**	-0.513***	-0.580***	-0.711**	-0.493**	-0.341***	-0.370***
	(0.417)	(0.312)	(0.164)	(0.179)	(0.347)	(0.217)	(0.121)	(0.127)
Broad Money Ratio	-0.085	-0.015	0.060	0.040	-0.152	-0.031	0.052	0.037
	(0.128)	(0.098)	(0.050)	(0.055)	(0.180)	(0.114)	(0.049)	(0.052)
Financial Openness	0.183	0.106	0.025	0.046	0.196	0.087	0.012	0.026
	(0.142)	(0.107)	(0.057)	(0.062)	(0.159)	(0.104)	(0.052)	(0.055)
Credit Deregulation	-0.081***	-0.065***	-0.049***	-0.053***	-0.094**	-0.068***	-0.049***	-0.053***
	(0.028)	(0.021)	(0.011)	(0.012)	(0.039)	(0.025)	(0.012)	(0.012)
Real House Prices	0.404***	0.343***	0.278***	0.295***	0.245***	0.221***	0.205***	0.208***
	(0.111)	(0.084)	(0.045)	(0.048)	(0.057)	(0.043)	(0.036)	(0.037)
Housing GFCF Ratio	1.270**	0.965**	0.641***	0.725***	0.678**	0.484**	0.349***	0.374***
	(0.534)	(0.401)	(0.182)	(0.201)	(0.305)	(0.203)	(0.116)	(0.120)
Quantification								
$\beta_{Ineq} * SD_{within}$	0.185	0.134	0.080	0.094	0.157	0.099	0.058	0.066
Quantif. *Middle/Bottom*	1.174	1.359	1.389	1.438				
Instruments	Agri	$\frac{K}{L}$+ Agri	$\frac{K}{L}$+ ILO	Agri+$\frac{K}{L}$ +ILO	Agri	$\frac{K}{L}$+ Agri	$\frac{K}{L}$+ ILO	Agri+$\frac{K}{L}$ +ILO
$KPF-stat$	7.048	4.201	12.912	8.925	6.296	4.634	27.482	18.641
$KPF\ size\ -crit.value$	16.38	19.93	19.93	22.3	16.38	19.93	19.93	22.3
$KPF\ bias\ -crit.value$				13.91				13.91
$Hansen-stat$		2.525	1.285	3.996		3.203	1.583	4.324
$Hansen-p-value$		0.112	0.257	0.136		0.074	0.208	0.115
Obs.	462	462	462	462	462	462	462	462
Countries	19	19	19	19	19	19	19	19

Robust standard errors in parentheses. All estimations include country fixed effects and year dummies. The critical values for the weak instruments test are based on a 10% 2SLS size and a 5% IV bias at the 5% significance level. See Table D.4 of the OA for first stage results. *, ** and *** denote respectively significance at the 10, 5 and 1% levels

5.3 Falsification Test: Emerging and Developing Economies

Kumhof et al. (2017) highlight that the credit constraints are so high in the emerging world that potential borrowers have little access to (too narrow or even non-existent) domestic financial markets, and no access to international ones. In these countries, domestic top income households cannot lend to those at the bottom, and are constrained to *"deploy all their additional savings abroad"*, leading to current account surpluses. In our context, this entails that, on the supply side, the financial system is on average less developed in emerging countries, implying less available credit.

On the demand side, it is also plausible that the various theoretical mechanisms put forward in section 2 are less at play in economies where bottom incomes represent a more homogenous

[43] Lastly, we also show that our results are not affected (1) when instrumenting real house prices and housing GFCF ratio (table D.7 in OA) (2) when alternative control variables are included (table E.9 in OA).

category, and are much too far below the Top income group for relative consumption approaches to apply. Put differently, since the middle class in emerging and developing economies is not developed as it is in the advanced countries (see Kochhar, 2015), the quantitative importance of the ratio of Top incomes to Middle incomes to explain the aggregate dynamics of credit should not materialize, or at least be seriously dampened. This is important since a key result of this paper is the part played by the relative impoverishment of middle incomes compared to top incomes in boosting household leverage.

Therefore, we propose, as a falsification test, to check that the positive causal link from inequality to household credit, and consequently the major part of middles classes in the latter, exists if and only if the country is sufficiently developed. We can bring this intuition to the data by estimating again our empirical model on an alternative sample focusing exclusively on emerging economies (full details about the composition of this sample to be found in Table A.3 in the Appendix A). Note that due to data limitations, we cannot include the ratio of housing GFCF over GDP in the estimations). Tables 13 and 14 report the results of these exercises.

Table 13: Falsification test: Emerging countries (1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.				Household Credit/GDP				
Sample	All	All	Bef. 2008	Bef. 2008	All	All	Bef. 2008	Bef. 2008
Gini	2.479	1.849**	1.889	0.844				
	(1.618)	(0.893)	(1.798)	(0.873)				
Top 10					6.298	3.155*	3.355	1.234
					(6.441)	(1.751)	(4.193)	(1.346)
GDP per capita	0.293***	0.162***	0.437**	-0.0185	0.337**	0.185***	0.476*	-0.0383
	(0.0806)	(0.0515)	(0.187)	(0.0764)	(0.167)	(0.0670)	(0.271)	(0.0861)
Broad Money Ratio	0.403***	0.359***	0.0847	-0.0126	0.532	0.371***	0.123	-0.00476
	(0.143)	(0.0857)	(0.0681)	(0.0672)	(0.348)	(0.103)	(0.0917)	(0.0616)
Financial Openness	-0.0507**	-0.0495**	-0.0127	0.0228	-0.0835	-0.0660**	-0.0312	0.0180
	(0.0252)	(0.0226)	(0.0253)	(0.0148)	(0.0633)	(0.0322)	(0.0479)	(0.0155)
Credit Deregulation	-0.0176	-0.00994	-0.0202	-0.0123	-0.0303	-0.00979	-0.0235	-0.0117
	(0.0147)	(0.00846)	(0.0250)	(0.0136)	(0.0355)	(0.00954)	(0.0369)	(0.0137)
Real House Prices	0.121*	0.0938*	0.0690	0.0925	0.223	0.132*	0.110	0.105
	(0.0703)	(0.0481)	(0.0931)	(0.0655)	(0.212)	(0.0755)	(0.173)	(0.0812)
World GDP	-0.00340		0.568		0.205		0.842	
	(0.147)		(0.561)		(0.302)		(0.947)	
Oil Price	0.000575		-0.0970*		0.0337		-0.103	
	(0.0174)		(0.0574)		(0.0563)		(0.0759)	
VIX	-0.00971		-0.0263		-0.0171		-0.0350	
	(0.00996)		(0.0210)		(0.0212)		(0.0358)	
FED Rate	0.0418		0.464		0.310		0.546	
	(0.218)		(0.403)		(0.533)		(0.513)	
$KPF-stat$	4.79	8.562	2.036	3.039	1.164	4.915	0.878	1.985
Year Dummies	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	260	260	110	110	260	260	110	110
Countries	19	19	15	15	19	19	15	15

Robust standard errors in parentheses. All specifications includes country fixed effects. The critical value for the weak instruments test is based on a 10% (resp. 15%) 2SLS size at the 5% significance level, which is 16.4 (8.96) in all estimations. *, ** and *** denote respectively significance at the 10, 5 and 1% levels.

Table 14: Falsification test: Emerging countries (2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.				Household Credit/GDP				
Sample	All	All	Bef. 2008	Bef. 2008	All	All	Bef. 2008	Bef. 2008
$\frac{Top\ 10}{Mid.\ 30-90}$	5.304	1.617	1.358	0.463				
	(10.226)	(1.020)	(1.830)	(0.518)				
$\frac{Top\ 10}{Bot.\ 0-30}$					0.243	0.167	0.083	0.034
					(0.266)	(0.123)	(0.091)	(0.036)
GDP per capita	0.384	0.183**	0.445*	-0.059	0.358*	0.175**	0.389**	-0.061
	(0.392)	(0.074)	(0.256)	(0.094)	(0.189)	(0.079)	(0.174)	(0.086)
Broad Money Ratio	0.805	0.386***	0.120	-0.010	0.504	0.443**	0.059	-0.017
	(1.166)	(0.124)	(0.097)	(0.066)	(0.321)	(0.172)	(0.076)	(0.071)
Financial Openness	-0.103	-0.064*	-0.020	0.024	-0.003	-0.025	0.038	0.047
	(0.151)	(0.036)	(0.039)	(0.015)	(0.060)	(0.028)	(0.048)	(0.031)
Credit Deregulation	-0.066	-0.013	-0.025	-0.012	-0.047	-0.027	-0.025	-0.014
	(0.134)	(0.013)	(0.041)	(0.014)	(0.056)	(0.025)	(0.033)	(0.015)
Real House Prices	0.437	0.166	0.096	0.097	0.304	0.216	0.075	0.089
	(0.812)	(0.107)	(0.169)	(0.076)	(0.322)	(0.164)	(0.110)	(0.065)
World GDP	0.799		1.012		0.025		0.593	
	(1.588)		(1.184)		(0.242)		(0.585)	
Oil Price	0.103		-0.104		0.030		-0.084	
	(0.232)		(0.080)		(0.054)		(0.054)	
VIX	-0.041		-0.037		-0.035		-0.029	
	(0.081)		(0.041)		(0.039)		(0.026)	
FED Rate	0.790		0.657		-0.159		0.391	
	(1.840)		(0.550)		(0.393)		(0.473)	
$KPF-stat$	0.272	3.185	0.747	1.971	0.980	2.028	1.574	2.735
Year Dummies	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	260	260	110	110	260	260	110	110
Countries	19	19	15	15	19	19	15	15

Robust standard errors in parentheses. All specifications includes country fixed effects. The critical value for the weak instruments test is based on a 10% (resp. 15%) 2SLS size at the 5% significance level, which is 16.4 (8.96) in all estimations. *, ** and *** denote respectively significance at the 10, 5 and 1% levels.

In both Tables, estimated parameters on the different income inequality indicators are correctly signed (positive), but turn to be massively insignificant in almost all specifications, with an IV appearing very weak. Conversely, GDP per capita emerges as a positive and significant determinant in a majority of specifications. This would tend to suggest that, at an early stage of economic development, credit constraints are 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 sing reversion on GDP per capita on our main sample, see e.g. Table 5), and the inequality mechanisms driving up household credit over GDP suggested by the various theoretical frameworks surveyed in section 2 start working. Finally, most other controls appear insignificant or weakly significant.

We also investigate further the role of credit constraints in emerging economies, by examining the heterogenous response of household credit to inequality according to the degree of financial deregulation and international financial openness. Columns (5) to (8) in Tables E.3 to E.6 in the

OA replicate the exercise already implemented on our main sample of developed countries. As for the latter, the results are quite noisy and insignificant regarding interactions with financial deregulation. Conversely, estimates tend to show in several specifications that emerging countries displaying a sufficient level of openness to international capital flows do exhibit a positive impact of inequality on household credit. 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.

6 Conclusion

Based on a country-level yearly dataset combining household credit and detailed information on income distribution from the WIID database over the period 1970-2017, this paper shows that rises in various indicators of income inequality driven by different exogenous sources trigger expansions of household credit, and that this effect is substantially higher when top incomes grow richer at the expense of middle classes, rather than at the expense of low incomes.

Our empirical strategy first identifies country-level variations in income inequality driven by exogenous changes in the number of ratified ILO conventions at the country-year level. We show that such exogenous rises in income inequality deliver additional household leverage, in a setup accounting for many other relevant determinants of credit, including some controlling directly for improvement in standards of living and ability to borrow, such as housing investment and GDP per capita. We also support the impact is magnified when middle incomes, rather than low incomes, impoverish compared to top incomes. We confirm these results using a set of alternative instruments reflecting country-level factor endowments (agricultural land share, capital intensity, mean years of schooling), different databases (SWIID and WID), definitions of income groups and control variables. We also check throughout the paper that our results are not importantly altered by the period following the 2007-2008 financial crisis.

Our findings are extremely robust to all these sensitivity exercises. An exogenous one-standard deviation increase in the Gini index and Top 10% income share generate, respectively, a 5.5-8 pp and 5.5-9.7 pp expansion in the ratio of household credit over GDP. In addition, the impact is 1.4 to 2.6 times stronger when top incomes increase relatively to middle incomes, rather than at the expense of bottom incomes. Interestingly, when replicating our estimates on a sample exclusively based on developing/emerging countries, we find that all these effects vanish, consistently with binding credit constraints preventing bottom incomes to access credit and insufficiently important middle income categories.

Our work has important implications regarding financial crises prevention. In order to avoid financial crises such as the one of 2007-2008, 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: 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 A.1: Data sources

Variable	Description	Source
	Credit	
Household credit/GDP		BIS, CB
log(Household credit/price level)	GDP deflator from World Bank	BIS, CB, WB
Firm credit/GDP	Credit for non-financial firms	BIS, CB
Private credit/GDP	Total non-financial credit (Households and firms)	BIS, CB
Domestic bank credit/GDP	Total non-financial credit from domestic bank	BIS, CB
	Inequalities	
Gini		WIID 4.1, SWIID
Top 10	Share of income owned by the Top 10% (corresponding to incomes after the 9^{th} decile)	WIID 4.1, WID
$\frac{Top\ 10}{Mid.\ 30-90}$	Ratios between income shares	WIID 4.1
$\frac{Top\ 10}{Bot.\ 0-30}$	Ratios between income shares	WIID 4.1
$\frac{Top\ 10}{Mid.\ 50-90}$, $\frac{Top\ 10}{Bot.\ 0-50}$	Ratios between income shares	WID
	Control Variables	
GDP per capita	Log-linearized and relative to the general price level	World Bank
M2	Ratio divided by GDP or log-linearized and relative to the general price level	World Bank, CB
Credit deregulation	Index from 0 to 10 about financial deregulation. Summary index	Fraser Institute
Financial openness	Country's degree of capital account openness	Chinn-Ito
Real house prices	Relative to the general price level	BIS, Cesa-bianchi et al. (2015)
Housing Gross Fixed Capital Formation	Households' investment in real-estate Ratio divided by GDP or log-linearized and relative to the price level	OECD
	Instruments	
ILO conventions	International Labor Organization conventions ratifications	ILO
Agricultural land share	Share in agricultural land (%)	FAO
K L intensity	Net capital stock at constant prices divided by total hours worked	AMECO, Total Economy Database
Mean years of schooling	Average number of years of total schooling across all education levels, for the population aged 25 and plus	Barro-Lee (2018), UNDP-HDR (2018)
	Global Variables	
World GDP	Log-linearized. World GDP, constant 2010 US dollars	World Bank
Oil prices	Log-linearized.	FRED St Louis
Fed Funds rate		FRED St Louis
VIX		FRED St Louis

Table A.2: List of advanced economies: Time coverage and main sources

	Baseline coverage	SWID coverage	WID coverage	WIID Source	Household Credit
Australia	1981-2014	1977-2016	1977-2016	LIS	BIS
Austria	1996-2017	1996-2017	1996-2016	Eurostat	BIS
Belgium	1995-2016	1980-2016	1990-2016	Eurostat	BIS
Bulgaria	2006-2017	2005-2017	2005-2016	Eurostat	CB
Canada	1981-2013	1970-2016	1970-2010	LIS	BIS
Cyprus	2006-2017	2006-2017	2006-2016	Eurostat	CB
Czech Republic	1999-2013	1999-2017	1999-2016	LIS	BIS
Denmark	1994-2013	1994-2017	1994-2016	LIS	BIS
Estonia	2004-2017	2004-2017	2004-2016	Eurostat	CB
Finland	1970-2016	1970-2016	1980-2016	Eurostat, National Source	BIS
France	1978-2010	1977-2016	1977-2014	LIS	BIS
Germany	1978-2015	1970-2016	1980-2016	LIS	BIS
Greece	1995-2017	1995-2017	1995-2016	Eurostat	BIS
Hungary	1995-2015	1995-2017	1995-2016	LIS	BIS
Iceland	2004-2016	2000-2015	2000-2016	Eurostat	CB
Ireland	2002-2017	2002-2017	2002-2016	Eurostat	BIS
Italy	1986-2014	1970-2016	1980-2016	LIS	BIS
Netherlands	1995-2016	1990-2016	1990-2016	Eurostat	BIS
New Zealand	1990-2017	1990-2017	1990-2016	National Source	BIS
Norway	1979-2013	1975-2017	1980-2016	LIS	BIS
Poland	2004-2016	2004-2017	2004-2015	LIS	BIS
Portugal	1995-2016	1988-2016	1988-2016	Eurostat	BIS
Romania	2009-2017	2009-2017	2009-2016	Eurostat	CB
Slovakia	2005-2017	2006-2016	2006-2016	Eurostat	CB
Slovenia	2007-2017	2007-2017	2007-2016	Eurostat	CB
Spain	1980-2016	1980-2016	1981-2016	LIS	BIS
Sweden	1981-2017	1980-2017	1980-2016	LIS, Eurostat	BIS
Switzerland	2007-2016	1999-2016	1999-2016	Eurostat	BIS
United Kingdom	1970-2017	1970-2017	1981-2016	IFS, Eurostat	BIS
United States	1979-2016	1970-2017	1970-2014	LIS	BIS

Table A.3: List of emerging economies: Time coverage and main sources

	Baseline coverage	WIID source	Household Cred.
Argentina	1994-2012	SEDLAC	BIS
Brazil	2001-2017	SEDLAC	BIS
Chile	2002-2017	SEDLAC	BIS
China	2006-2015	World Bank	BIS
Colombia	1996-2017	SEDLAC	BIS
India	2009-2012	World Bank	BIS
Indonesia	2002-2017	World Bank	BIS
Israel	1994-2016	LIS	BIS
Korea	2006-2012	LIS	BIS
Malaysia	2006-2016	World Bank	BIS
Mexico	2005-2016	SEDLAC	BIS
Peru	2000-2017	SEDLAC	CB
Philippines	2001-2015	World Bank	CB
Russian Fed.	2001-2016	LIS	BIS
Singapore	2008-2011	National Source	BIS
South Africa	2008-2015	World Bank	BIS
Thailand	1991-2017	World Bank	BIS
Turkey	2010-2016	World Bank	BIS
Uruguay	2005-2012	SEDLAC	CB

Table A.4: Alternative instruments: Time coverage and main sources

	Baseline coverage
Australia	1981-2010
Austria	1996-2010
Belgium	2000-2010
Canada	1981-2010
Denmark	1994-2010
Finland	1970-2010
France	1978-2010
Germany	1978-2010
Greece	1995-2010
Ireland	2002-2010
Italy	1986-2010
Netherlands	1995-2010
New Zealand	1990-2010
Norway	1979-2010
Portugal	1995-2010
Spain	1980-2010
Sweden	1981-2010
Switzerland	2007-2010
United Kingdom	1970-2010
United States	1979-2010

Table A.5: Sources of inequality measures after processing WIID

Source	Countries
Eurostat	17
Luxembourg Income Study (LIS)	16
World Bank	8
SEDLAC	7
National Sources	3
OECD	1

B Appendix B: Additional Test for Exclusion Restriction

Table B.6: Testing for exclusion restriction

Inequality measure	(1) Gini	(2) Top 10	(3) Gini	(4) Top 10	(5) $\frac{Top10}{Mid.30-90}$	(6) $\frac{Top10}{Bot.0-30}$
Ineq. measure	-0.519	-0.280	-0.468	-0.243	-0.026	-0.030
	(0.542)	(0.653)	(0.551)	(0.670)	(0.342)	(0.050)
ILO Conv.	-0.004*	-0.004*	-0.003*	-0.003	-0.003	-0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ILO Conv. *7377	0.004	0.006	0.004	0.005	0.005	0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ILO Conv. *9508	-0.001*	-0.001*	-0.001*	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDP per capita	-0.298	-0.309	-0.297	-0.307	-0.314	-0.302
	(0.216)	(0.214)	(0.215)	(0.213)	(0.214)	(0.213)
Broad Money Ratio	0.139	0.134	0.149	0.145	0.143	0.147
	(0.091)	(0.090)	(0.090)	(0.088)	(0.087)	(0.089)
Financial Openness	-0.043	-0.033	-0.029	-0.020	-0.015	-0.022
	(0.094)	(0.091)	(0.100)	(0.097)	(0.097)	(0.099)
Credit Deregulation	-0.001	-0.003	-0.001	-0.002	-0.003	-0.002
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Real House Prices	0.168**	0.166**	0.154**	0.152**	0.153**	0.153**
	(0.068)	(0.069)	(0.070)	(0.070)	(0.070)	(0.071)
Housing GFCF Ratio	-0.020	0.013	-0.025	0.005	0.022	0.007
	(0.302)	(0.290)	(0.303)	(0.291)	(0.285)	(0.297)
Obs.	726	726	698	698	698	698
Countries	30	30	29	29	29	29
adj. R^2	0.766	0.764	0.756	0.755	0.755	0.755

All estimations include country fixed effects and time dummies. Intercept not reported. Robust standard errors in parentheses, with *, ** and *** respectively denoting significance at the 10%, 5% and 1% levels. Sample in column (3) to (6) exclude New Zealand, for which detailed income data by decile is missing.

C Appendix C: Additional Robustness Checks

Dependent variable: Log(Household Credit). 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 behave when we use instead the log of household credit as a dependent variable in equation 3. The results of this modification are reported in Tables C.7 and C.8, which replicate, respectively, the structure of Tables 5 and 10.

Both Tables support, though with a weaker significance on the complete period, a positive impact of inequality on the log of household credit, whatever the variable used to proxy inequality. As for quantifications, ignoring the insignificant estimates in Table C.7, we find that a one-standard deviation in the Gini index generates a 13 to 14% increase in household credit, while the latter moves up by 15 to 17% following a one-standard deviation rise in the Top 10% share. Once again focusing on significant estimates, Table C.8 shows that the growth in household credit generated by a one standard-deviation rise in the Top incomes over Middle incomes ratio (implying a relative impoverishment of middle classes compared to the Top 10%) is equal to 1.3 to 1.5 times the growth stemming from a one-standard deviation incrase in the ratio of Top 10% over Bottom incomes - see the row "Quantif. Middle/Bottom" at the bottom of the Table. All in all, these results are very similar to our benchmark estimates, and keep validating our two testable relationships.

Income transfers between middle and bottom incomes. The various theoretical frameworks surveyed in section 2 focus on income transfers between top and bottom (including middle and low) incomes, and do not deliver straightforward predictions regarding income transfers middle and bottom incomes categories. Nevertheless, Table C.9 reports estimates of a specification including the ratio of Middle to Bottom incomes as inequality indicator. Columns (1) to (4) replicate the specifications from the same columns in Table 10, while columns (5) to (8) mimic the specifications and set of instruments displayed, respectively, in columns (5) to (8) from Table 12. The ratio of middle to bottom incomes displays a positive and significant impact on household credit over GDP in five columns over eight. Results are especially mild in terms of significance when we use some sets of alternative instruments, which appear particularly weak in columns (5) and (6). Keeping these statistical limitations in mind, and restricting to specifications with significant impacts of the inequality indicator, we see that a one standard-deviation increase in the ratio of middle to bottom incomes brings between 5.3 and 7.7 percentage points of additional household credit over GDP.

Table C.7: Log of Household Credit as dependent variable (1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.				Log(Household Credit)				
Sample	All	All	Bef. 2008	Bef. 2008	All	All	Bef. 2008	Bef. 2008
Gini	16.22	7.606*	6.883*	7.301**				
	(11.10)	(4.544)	(3.527)	(3.070)				
Top 10					23.24	10.66*	10.28*	11.71**
					(15.52)	(6.122)	(5.265)	(5.110)
GDP per capita	0.736**	1.166***	2.105***	2.119***	0.350	1.062***	1.947***	1.892***
	(0.358)	(0.276)	(0.452)	(0.441)	(0.477)	(0.278)	(0.439)	(0.455)
Broad Money Log	-0.257	-0.00356	-0.0905	-0.0939	-0.195	0.0196	-0.0415	-0.0732
	(0.327)	(0.140)	(0.144)	(0.128)	(0.281)	(0.125)	(0.123)	(0.125)
Financial Openness	0.448**	0.558***	0.202*	0.397***	0.524**	0.597***	0.251*	0.439***
	(0.225)	(0.179)	(0.121)	(0.154)	(0.255)	(0.188)	(0.131)	(0.166)
Credit Deregulation	-0.0550	-0.0202	-0.0589	-0.0945**	-0.0394	-0.00880	-0.0581	-0.0897**
	(0.0504)	(0.0258)	(0.0380)	(0.0416)	(0.0407)	(0.0203)	(0.0370)	(0.0411)
Real House Prices	0.279***	0.114	0.220**	0.0891	0.358***	0.162**	0.301***	0.201*
	(0.0943)	(0.0723)	(0.0871)	(0.0992)	(0.119)	(0.0731)	(0.109)	(0.112)
Housing GFCF Log	-0.0616	-0.0722*	0.157***	0.163***	-0.0665	-0.0634	0.159***	0.193***
	(0.0581)	(0.0438)	(0.0548)	(0.0521)	(0.0583)	(0.0443)	(0.0546)	(0.0599)
World GDP	-0.203		-0.695		-0.267		-0.965	
	(0.673)		(0.756)		(0.710)		(0.779)	
Oil Price	0.331***		0.214***		0.337***		0.212***	
	(0.0985)		(0.0535)		(0.102)		(0.0522)	
VIX	0.000297		-0.0198		-0.0148		-0.0197	
	(0.0338)		(0.0320)		(0.0363)		(0.0311)	
FED Rate	-2.701***		-1.717***		-3.291***		-1.910***	
	(0.856)		(0.648)		(0.991)		(0.671)	
Quantification								
$\beta_{Ineq} * SD_{within}$	0.301	0.141	0.133	0.141	0.325	0.149	0.148	0.168
$KPF - stat$	4.93	12.4	19.15	20.65	4.69	12.68	16.9	15.33
Year Dummies	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	726	726	467	467	726	726	467	467
Countries	30	30	27	27	30	30	27	27

Robust standard errors in parentheses. All specifications includes country fixed effects. The critical value for the weak instruments test is based on a 10% (resp. 15%) 2SLS size at the 5% significance level, which is 16.4 (8.96) in all estimations. *, ** and *** denote respectively significance at the 10, 5 and 1% levels.

Table C.8: Log of Household Credit as dependent variable (2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.				Log(Household Credit)				
Sample	All	All	Bef. 2008	Bef. 2008	All	All	Bef. 2008	Bef. 2008
$\frac{Top\ 10}{Mid.\ 30-90}$	9.145	3.739	4.389*	5.043**				
	(6.424)	(2.550)	(2.387)	(2.221)				
$\frac{Top\ 10}{Bot.\ 0-30}$					0.835*	0.397	0.545*	0.575**
					(0.492)	(0.256)	(0.279)	(0.227)
GDP per capita	0.346	1.060***	1.952***	1.915***	0.776***	1.133***	2.140***	2.169***
	(0.460)	(0.258)	(0.414)	(0.422)	(0.245)	(0.241)	(0.404)	(0.379)
Broad Money (log)	-0.069	0.091	0.010	-0.022	-0.009	0.109	-0.019	-0.011
	(0.216)	(0.103)	(0.103)	(0.103)	(0.151)	(0.088)	(0.110)	(0.092)
Financial Openness	0.498**	0.579***	0.249**	0.443***	0.390***	0.526***	0.196*	0.410***
	(0.218)	(0.169)	(0.124)	(0.156)	(0.141)	(0.140)	(0.107)	(0.141)
Credit Deregulation	-0.024	-0.000	-0.041	-0.070*	-0.009	-0.001	-0.025	-0.066*
	(0.033)	(0.018)	(0.032)	(0.036)	(0.022)	(0.018)	(0.028)	(0.034)
Real House Prices	0.331***	0.135*	0.271***	0.162	0.261***	0.102	0.202***	0.058
	(0.115)	(0.070)	(0.105)	(0.105)	(0.071)	(0.063)	(0.078)	(0.088)
Real Housing GFCF (log)	-0.069	-0.070*	0.144***	0.173***	-0.080*	-0.089**	0.131***	0.120***
	(0.051)	(0.041)	(0.051)	(0.054)	(0.045)	(0.039)	(0.046)	(0.043)
World GDP	-0.208		-1.047		-0.267		-0.937	
	(0.593)		(0.733)		(0.495)		(0.711)	
Oil Price	0.307***		0.199***		0.275***		0.201***	
	(0.083)		(0.046)		(0.055)		(0.047)	
VIX	-0.013		-0.028		0.002		-0.027	
	(0.032)		(0.030)		(0.026)		(0.030)	
FED rate	-3.435***		-1.939***		-3.045***		-1.861***	
	(0.900)		(0.631)		(0.630)		(0.596)	
Quantification								
$\beta_{Ineq} * SD_{within}$	0.256	0.105	0.127	0.146	0.147	0.070	0.10	0.103
Quantif. *Middle/Bottom*	1.74	1.5	1.27	1.42				
$KPF-stat$	5.146	14.698	18.716	17.421	16.089	33.278	30.579	34.883
Year Dummies	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	698	698	449	449	698	698	449	449
Countries	29	29	26	26	29	29	26	26

Robust standard errors in parentheses. All specifications includes country 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.9: Middle vs. Bottom incomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.				Household Credit/GDP				
Sample	All	All	Bef. 2008	Bef. 2008	All	All	All	All
$\frac{Mid.\ 30-90}{Bot.\ 0-30}$	0.188	0.259***	0.324***	0.331***	1.315	0.987	0.359***	0.365***
	(0.123)	(0.100)	(0.112)	(0.093)	(1.311)	(0.859)	(0.095)	(0.096)
GDP per capita	-0.290***	-0.366***	0.049	-0.024	-0.577	-0.465	-0.249*	-0.251*
	(0.077)	(0.087)	(0.140)	(0.133)	(0.622)	(0.424)	(0.149)	(0.150)
Broad Money Ratio	0.102*	0.074	-0.038	-0.034	-0.546	-0.367	-0.025	-0.028
	(0.054)	(0.046)	(0.087)	(0.072)	(0.742)	(0.491)	(0.070)	(0.070)
Financial Openness	-0.022	0.012	-0.122***	-0.048	0.298	0.200	0.012	0.014
	(0.038)	(0.048)	(0.042)	(0.051)	(0.399)	(0.275)	(0.066)	(0.066)
Credit Deregulation	-0.011	-0.019**	-0.019	-0.032**	-0.193	-0.151	-0.070***	-0.071***
	(0.008)	(0.009)	(0.012)	(0.015)	(0.171)	(0.114)	(0.018)	(0.019)
Real House Prices	0.166***	0.115***	0.123***	0.087**	-0.001	0.045	0.132***	0.131***
	(0.026)	(0.033)	(0.034)	(0.043)	(0.217)	(0.154)	(0.046)	(0.046)
Housing GFCF Ratio	0.041	0.078	0.161**	0.329***	0.151	0.152	0.155	0.155
	(0.063)	(0.134)	(0.071)	(0.117)	(0.350)	(0.273)	(0.136)	(0.137)
World GDP	0.520***		0.536**					
	(0.141)		(0.239)					
Oil Price	0.084***		0.091***					
	(0.013)		(0.022)					
VIX	0.014		0.004					
	(0.009)		(0.014)					
FED Rate	-0.893***		-0.469**					
	(0.185)		(0.236)					
Quantification								
$\beta_{Ineq} * SD_{within}$	0.039	0.053	0.066	0.067	0.276	0.207	0.075	0.077
Instruments	ILO	ILO	ILO	ILO	Agri	$\frac{K}{L}$+ Agri	$\frac{K}{L}$+ ILO	$\frac{K}{L}$ + Agri +ILO
$KPF-stat$	17.056	22.201	19.596	26.014	1.210	0.937	16.825	11.251
$KPF\ size\ -crit.value$	16.38	16.38	16.38	16.38	16.38	19.93	19.93	22.3
$KPF\ bias\ -crit.value$								13.91
$Hansen-stat$						0.597	0.214	2.580
$Hansen-p-value$						0.440	0.644	0.275
Year Dummies	No	Yes	No	Yes	Yes	Yes	Yes	Yes
Obs.	698	698	449	449	462	462	462	462
Countries	29	29	26	26	19	19	19	19

Robust standard errors in parentheses. All estimations include country fixed effects. The critical values for the weak instruments test are based on a 10% 2SLS size and a 5% IV bias at the 5% significance level. *, ** and *** denote respectively significance at the 10, 5 and 1% levels.