ERASMUS UNIVERSITY ROTTERDAM
Erasmus School of Economics

Master Thesis – Economics & Business

The effect of Bank lending on Income inequality in Europe: Evidence from disaggregated credit channels.

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DATE OF FINAL VERSION: **XXX**

Abstract

Using a panel of 25 European countries between 1990 and 2015, this thesis empirically examines the relationship between bank lending and income inequality. Bank lending is disaggregated into credit to non-bank financial institutions, credit to households for consumption purposes, mortgages and credit non-financial firms. As dependent variables, Income shares of the top 10% and the bottom 50% of the distribution of incomes are considered. The literature relating financial developments and income inequality indicate several transmission channels: increased investment, human and physical capital accumulation and increased wages suggest a negative relationship, while realised capital gains and high wages in the financial sector could positively affect income inequality. This empirical analysis finds that while lending to the non-bank financial sector is robustly linked to an increase in the income share for the top 10% of the income distribution, no other credit channel consistently correlates with changes in income inequality.

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1. Introduction

Public interest in inequality has risen in recent years. Not only do 60% of the world's population perceive inequality as a major societal challenge (Pew Research Centre, 2014), also former US president Barack Obama referred to it as the "defining issue of our time" (McGregor & Munshi, 2013). The benefits of economic growth, so the narrative goes, have disproportionately fallen on the rich, while the poor have been left behind. This narrative is supported by empirical data. Within the last four decades, most developed economies have seen the distribution of wealth and income become more polarized (Milanovic, 2016; Piketty, 2014) and the gap between rich and poor has reached peak levels since data collection has started (OECD, 2015). Consequently, this trend and the perception of the economic system as favouring the better-off strata of society has propelled inequality on the agenda of policymakers and in the focus of election campaigns. Such as in the case of the primary elections of the Democratic party in the US this year, where (wealth) inequality has drawn considerable attention (Stevens & Astor, 2020).

Academic interest in inequality has risen as well. While inequality and its determinants have been studied by economists for a long time, the field has recently seen new developments (De Haan & Sturm, 2017). Notably the long time series of top income shares published in the World Inequality Database (WID) and key publications such as "Capital in the 21st century" (Piketty, 2014), have contributed to a new round of academic debate. The aftermath of the financial crisis of 2008 has provoked renewed interest for the macroeconomic effects of finance, among them income inequality. As a result, a growing body of literature has focused on the relationship between financial sector developments and the distribution of incomes. The reason for the investigation rises from two simple stylized facts: at the same time in which developed economies are experiencing rises in inequality, the financial sector has grown significantly relative to the rest of the economy (Botta et al., 2019).

Overall, the existing literature has offered several explanations for the upward trend of income inequality in developed economies (Dabla-Norris et al., 2015; Roine et al., 2009; Tridico, 2018). While some scholars have highlighted the role of unemployment (Mocan, 1999), skill-biased technological change and the degree of trade and financial openness (Furceri et al., 2019; Van Reenen, 2011; Young & Tackett, 2018), which have progressively weakened the position of unskilled workers versus their skilled counterparts, others have emphasized the role of political and economic institutions, such as government distributive preferences and labour market institution in supporting incomes (Jaumotte & Buitron, 2015). To date, existing literature linking financial development and inequality measures has provided mixed predictions, both on theoretical and empirical levels. On one hand, bank lending could decrease inequality by allowing poor households to smoothen consumption and to invest in human capital (Beck et al., 2007; Galor & Moav, 2004), with positive effects on income. On the other hand, more lending could benefit well-off households by providing better

investment opportunities and by increasing capital gains by supporting rising asset prices (Bengtsson & Waldenström, 2018; Botta et al., 2019; Greenwood & Jovanovic, 1990).

This thesis tries to shed light on previous studies' inconsistent findings by taking a novel perspective and investigating the effect of bank lending on the share in total income for the top 10% and the bottom 50% of income earners. Using a panel regression approach including country and time fixed effects on a sample of European countries from 1990 to 2015, we test whether different bank lending channels have a heterogeneous effect on the income share of the top and/or bottom parts of the income distribution. By using this particular approach we follow the recommendations by Bezemer and Samarina (2016) and Beck et al. (2012) who argue that past empirical analyses which used total bank lending as main explanatory variable suffer from over aggregation. Bezemer, Samarina and Zhang (2017) note that the recent evolution of finance has not only been in quantitative terms; bank lending itself has experienced a "sea change" in the composition of its loans (Bezemer & Samarina, 2016, p. 4).The last decades have seen a relative increase in mortgage lending and financing for non-bank financial corporations, while lending to households for consumption purposes and the more traditional lending to non-financial firms have either stagnated or decreased (Bezemer et al., 2017). We extend the existing literature by addressing each of the bank lending channels above separately; hence, to our knowledge this thesis is the first study providing an estimate of the correlation between separate credit channels and the top and bottom parts of the income distribution.

The prominent position taken by the financial sector in the wellbeing of modern economies calls for a better understanding of how financial dynamics affect macroeconomic outcomes, such as financial stability, growth and the distribution of economic rewards; an accurate diagnosis of the causes behind income inequality are a necessary first step towards "tackling the ever growing income divide" (Kus, 2012, p. 493). Looking at the issue from a policy perspective, the distributive impact of banks' lending practices has acquired new relevance (Dolado et al., 2018; Draghi, 2015); after the financial crisis in 2008 central banks throughout the world have intervened in the banking sector, often deploying policies aimed at directing banks' lending towards the real economy (Bats & Hudepohl, 2019). Hence, our study has a high practical relevance, as research that clarifies the distributive impact of finance can help to better appreciate the outcomes of policy decisions and contribute to their optimal design.

This thesis is structured as follows: Section 2 reviews the literature on the drivers of income inequality as well as the contributions investigating the relationship between financial developments and the distribution of incomes. Section 3 presents the data and the methodology employed in the empirical part of this paper. Section 4 presents the results from our econometric analysis as well as several robustness checks. Section 5 presents some concluding remarks.

2. Literature review

Issues relating to inequality, whether of income, wealth or opportunity are increasingly relevant both in academic and political settings. Although none of the aspects of inequality can be fully understood in isolation from each other (Kanbur & Stiglitz, 2015), throughout this thesis we will focus only on one specific dimension, namely income inequality. We will start by reviewing the main drivers of income inequality in advanced economies, to then move to literature relating financial development to changes in the distribution of income.

Skill-biased technological change, the first driver of inequality indicated upon by literature, refers to technological developments staring in the 1990s which have increased the wage premium going to skilled labour over low and unskilled jobs (Jaumotte et al., 2013). New technologies have, in simple terms, either replaced humans in performing certain tasks or made it harder to obtain the skills needed to retain a job. Due to this change, many developed economies have experienced a decline in the labour share of income, accompanied by a stagnation of the income share of the middle and lower ends of the distribution (Dabla-Norris et al., 2015), not explainable by productivity alone. Arpaia et al. (2009) address this topic, focusing on 15 European countries between 1970 and 2004. The authors highlight several contemporaneous dynamics that explain the decreasing trend in labour share in Europe. First, economies have gradually moved towards employment sectors with a structurally lower labour share, among which finance, insurance and real estate sector. Then, the authors report that capital-augmenting technologies - which are complementary to skilled workers but substitute to unskilled labour - explain most of the variation in labour share for the period in question. A decrease in the labour share of income results in an increase of inequality as wages form most of the income for the lower parts of the income distribution. On the other end of the scale, capital is more unevenly distributed than labour income. Since a declining share of labour income implies a rising share of capital income, the net result is a concentration of income in the upper parts of the distribution (Bengtsson & Waldenström, 2018).

Alongside technological change, another driver of the decrease in the labour's income share is globalization. Understood as a process of economic integration and interdependency between countries, globalization is characterised by increased mobility of resources, higher levels of trade and financial flows, and it can be a powerful driver of competitiveness and efficiency (Jaumotte et al., 2013). It can also increase inequality. The relationship between international openness and inequality is a long standing area of economic research, dating back to Stolper and Samuelson (1941) which proposed that in an international trade setting the returns to factors of production change depending on the relative endowment between countries. For developed economies, the application of the theorem indicates that the income share of low-skill labour will decrease as production of labour-intensive goods moves abroad. Young and Tackett (2018) find evidence of a negative relationship between trade openness and the labour share of income for an extensive panel of OECD and non-OECD countries

over the 1970-2009 period. Employing a panel estimator with country and time fixed effects, they find evidence supporting a negative relationship between openness and the labour share of income for OECD countries, whilst not finding significant results for countries outside the OECD. Additionally, they argue that while more trade or financial flows weaken the bargaining position of workers, more openness and mobility of people and ideas increases labour's income share. Further they state that these two independent variables influence the relative bargaining power of labour versus capital, which is in accordance with the Stolper-Samuelson model of trade. The increased mobility of capital, both financial and not, has allowed firms to move production in order to minimize labour costs. This has de-facto increased the competition for wage-earners competing with international labour supply, undermining their ability to bargain for their share in income (Tridico, 2018).

Van Reenen (2011) adds another point to the discussion. While he finds that skill-biased technological change is the main driver of the increase in wage inequality in developed economies, he also finds evidence that trade itself might have contributed to inequality by exacerbating technological investment that complements skilled workers. His reasoning is that beyond Stolper-Samuelson effects, trade with labour abundant countries might have forced firms to "innovate or die" (Van Reenen, 2011, p. 740) and invest in productivity-enhancing technologies. An additional aspect of globalization which will be explicitly considered in my econometric setup is the increased international dimension of financial flows, which from here on we refer to as financial globalization. Financial globalization could increase inequality by concentrating foreign investment in capital and skill-intensive sectors, adding to the relative demand for skills (Furceri et al., 2019). Furthermore, financial deregulation and globalization could have increased the skill intensity and wages in the financial sector, which is independently cited as a channel through which financial development affects inequality (Denk, 2015). Jaumotte, Lall and Papageorgiou (2013) find in a panel of 50 countries over the period 1981-2003 that technological change is the main driver of inequality when compared to trade. They argue that the limited effect of trade on inequality is due to the pooling of trade and financial globalization; while the first decrease inequality, the second increases inequality.

Interest in the effect of financial sector dynamics on macroeconomic outcomes has surged after 2008, and the nexus between financial development and inequality has seen new contributions. The field has so far yielded contrasting results, with both theory and empirics providing a varied set of conclusions. On the theoretical level, a first strand of the literature highlights the equalizing effect of financial development on inequality. The core idea is the following: by reducing the negative impact of financial frictions, financial development allows higher levels of investment in human and physical capital for a larger share of the population, expanding economic opportunities and reducing intergenerational persistence of relative incomes (Beck et al., 2012; Becker & Tomes, 1979; Demirgüç-Kunt & Levine, 2009; Galor & Moav, 2004; Greenwood & Jovanovic, 1990). Demirguc-Kunt & Levine (2009) build on previous work (Becker & Tomes, 1979, 1986) and develop a formal model in which human capital is a function of ability and years of schooling, which are

complementary in determining human capital. In the absence of financial frictions high ability individuals receive schooling irrespective of parental wealth, and the socially efficient allocation of schooling is reached. In the presence of imperfect credit markets, human capital accumulation will be restricted for poor individuals, leading to persistent intergenerational differences in income and wealth. Galor and Zeira (1993) show under the assumption of homogeneous ability among individuals that credit market imperfections and a fixed cost of schooling limit human capital accumulation when initial wealth endowments are unequal. In their setting the initial level of inequality is persistent over time and relative incomes do not converge across generations. Subsequent extensions have proposed a non-linear effect of finance on inequality: at the onset of the development process, financial development generates returns for the part of the population that has the means to invest while the poor will be excluded (Greenwood & Jovanovic, 1990). The income distribution will thus expand as gains from economic growth fall disproportionally to the top. The process then tapers off when financial development reaches a certain level and greater parts of the population are served by the financial sector (Greenwood & Jovanovic, 1990).

Galor and Moav (2004) consider the evolution of economic growth and income inequality in a unified theoretical framework. At an earlier stage of development more inequality increases growth, as funds get directed to individuals with a high marginal propensity to save and invest, thus increasing physical capital accumulation. Once a certain level of development is reached, they assume human capital to have a higher rate of return than physical capital, thereby making a more equal income distribution the engine of growth. As a larger section of the population is able to invest in schooling, income will grow and the gap between rich and poor shrink. In this setting financial development that reduces financial imperfections can have an equalizing role as it allows for higher levels of investment in human capital.

The income-equalizing effect of financial development is not undisputed, however. Some contributions have conditioned the effect on good economic and political institutions (Claessens & Perotti, 2007; Rajan & Zingales, 2003). Inequality, if not curbed by institutions that ensure competition, transparency and accountability, could generate de-facto political influence and the risk of capture of financial regulation by vested interests. In this setting, financial development would be steered towards rewarding an influential elite and not on expanding economic opportunities for the bottom of the income distribution. Law et al. (2014) investigate the relationship between banking sector developments and the disposable income Gini index conditional on institutional quality - as measured by a composite index containing indicators of corruption, law and order, bureaucratic quality, government repudiation of contracts and risk of expropriation. They argue that banking sector developments reduce inequality only for countries that have high institutional quality. In countries below a certain level, financial development has no significant effect on inequality.

A recent contribution by Botta et al. (2019) proposes an agent-based model that links financial development and income inequality. The authors structure their simulation around consumers with

heterogeneous incomes who can borrow to finance consumption, investors that demand remunerative assets and a financial sector which caters to both demands by lending to consumers and selling securitized assets to investors. In their model inequality and finance reinforce one another. As inequality increases, poor households increase their demand for bank funding in order to reach their desired consumption level -a "Keep up with the Joneses" motive (Botta et al., 2019, p. 5). Through the interaction of the three sectors, financial development and innovation result in a flow of funds from lower income households to investors that worsens inequality.

The multitude of outcomes proposed by the theoretical literature is not resolved in empirical analyses. Several studies find evidence that finance does indeed help in reducing inequality. Beck et al. (2007) find evidence of a negative relationship between the value of credit over GDP and Gini growth (and various measures of poverty) in a panel of 72 developing and developed countries over the period 1960-2005. Their methodology relies on cross country OLS regressions and a dynamic panel estimator, as well as using the legal origin of countries as instrumental variable. They conclude that more financial development disproportionately favours the poor, this is, beyond its effect on GDP growth. Legal origins (common law versus civil law countries) have been shown to positively correlate with the development of the financial system (La Porta et al., 1997, 1998) and have ever since become a common source of exogenous variation in the financial development literature. Similar results are found for the timeframe 1960-95 (Clarke et al., 2006) by employing cross-sectional variation at country level and instrumenting by legal origin and lagged values of financial development. Additionally, Clarke et al. (2006) test for the presence of an inverted U-shape relationship between inequality and financial development as proposed by Greenwood and Jovanovic (1990) but find little support for it. The presence of a nonlinear relationship between financial development and inequality has been further investigated by Kim and Lin (2011) . The authors employ a threshold regression model on a panel of 65 countries over the period 1960-2005 and argue that finance reduces income inequality, but only after a certain level of financial development has been reached. They employ three measures of financial development (financial sector credit to private sector, liquid liabilities and bank assets) and use the growth of the income Gini index as dependent variable. To address endogeneity issues, they employ a set of instrumental variables (initial level of financial development, creditor rights, legal origins, ethnic fractionalization and religious composition) and find the results to be robust.

Recent contributions to the literature have proposed a negative relationship between various measures of financial development and income inequality. For instance, De Haan and Sturm (2017) study the relationship between financial development – measured as credit to the private sector over GDP, financial liberalization and financial crises on the market-outcome Gini index, that is, the Gini index before accounting for taxes and transfers. Their study analyses a panel of 121 countries between 1975 and 2005 and employs a panel regression approach with country fixed effects. All variables are constructed as 5-year averages and the dependent variables are lagged by one period to control for

endogeneity issues. The authors also test for interaction effects between their explanatory variables and two measure of economic development and institutional quality. In the robustness checks, they present results when credit to the private sector is instrumented by the legal origins of the country. The paper's findings suggest that all three explanatory variables are positively related to the gross Gini index. As a comparative check with previous literature, they employ the cross-country variation of their sample and find that for the cross-sections covering 1991-1995 and 1991-2000, credit to the private sector is negatively correlated with income inequality.

In a second paper, De Haan et al. (2018) test the relationship between credit to the private sector – as a proportion of GDP – and the gross Gini index conditional on the level of financial liberalization of the country, proxied by an index summarising credit and interest rate controls, reserve requirements, prudential regulation and public intervention in the banking sector (Abiad et al., 2008). Their sample covers 89 countries in the same time frame as the previous study and they employ a panel regression approach with country fixed effects. Their results suggest that credit over GDP is positively linked to inequality, and that the relationship is stronger in countries with a higher degree of financial liberalization. Jauch and Watzka (2016) find evidence of a positive correlation between credit to the private sector and the gross and net Gini index in a sample of 138 countries over the years 1960-2008. Their base methodology relies on a panel regression approach including country and time fixed effects, but they test their results also instrumenting for bank deposits and by dividing their dataset based on the income level of countries. Their specification includes controls for GDP per capita, inflation, the value added of the agricultural sector and government expenditures. All variables are included in logs and averages are computed over 5-year intervals.

While the majority of the empirical literature tends to rely on an aggregate measure of financial development – such as private credit as a percentage of GDP – in its econometric setup, a branch of the literature has started to question whether disaggregated credit variables could provide additional insights into the relationship between financial dynamics and income inequality (Beck et al., 2012; Bezemer et al., 2017; Bezemer & Samarina, 2016). The first paper to contribute to the literature in this respect is the work by Beck et al. (2012), which construct a dataset that disaggregates bank lending into credit flowing to enterprises and credit flowing to households for 45 countries over the timeframe 1994-2005. The authors use the data to test whether different credit flows have heterogeneous impact on GDP growth and inequality, proxied by the Gini index and the growth in income for the first 50% of the income distribution. Focusing on their analysis on inequality, their econometric setup relies on traditional OLS as well as an instrumental variable approach using religious composition and legal origin as exogenous variables, controlling for the initial level of their independent variable, schooling, government consumption, trade openness and inflation. The paper finds that credit to enterprises is positively linked to GDP growth and negatively linked to inequality for both variables taken into consideration. At the same time, credit to households shows no significant effect to either GDP growth or inequality. They conclude that finance exercises most of its effect on income growth through the

efficient allocation of capital and by easing credit constraints of firms, rather than extending access to credit for households.

A second contribution to the literature relating disaggregated bank lending and income inequality -and an important basis for this thesis- comes from the work of Bezemer and colleagues (Bezemer et al., 2017; Bezemer & Samarina, 2016). The authors collect data on bank lending from central bank statistics, disaggregating total bank lending into credit to households for consumption purposes, mortgage credit, credit to firms in the non-financial sector and credit flowing to the non-bank financial sector (Bezemer et al., 2017). Their data collection efforts show that bank lending has gone through two main changes in the past few decades. On one hand, total bank lending as a share of GDP has increased significantly both in developed and developing economies between 1990 and 2015. In 19 Euro area countries, bank lending has increased from and average value (as percentage of GDP) of 61% in 1995 to 110% in 2013. This increasing trend is common in all developed economies and is visible also in emerging and developing nations, although the levels of total bank lending over GDP are lower. On the other hand, the composition of total credit has changed as well. Credit to financial sector firms and mortgages have seen the fastest growth in European countries from the 1990's onwards, compared to a more moderate increase in household consumption credit and lending to non-financial sector enterprises. The quick rise in bank balance sheets is thus linked to the rapid rise of the first two lending channels rather than a balanced increase in all bank lending activities, a phenomenon that the authors call "debt shift" (Bezemer et al., 2017, p. 13).

These descriptive findings have an implication for the empirical literature to date. To the extent that different lending channels impact income inequality heterogeneously, empirical studies employing an aggregate measure of financial development -such as total private lending over GDP-could suffer from over-aggregation (Bezemer & Samarina, 2016). In cross country analyses, opposite effects of bank lending channels could cancel each other out. Furthermore, the sample of countries in empirical studies could matter in determining the results based on the composition of bank lending underlying aggregate credit measures. The authors proceed to test the relationship between bank lending channels and the net Gini coefficient employing a panel regression approach with country fixed-effects and controlling for common covariates in the inequality literature such as income levels, income growth, inflation, unemployment, levels of education, government expenditures and trade openness. In addition, they add wage shares, labour union strength, the economy's industrial structure, population growth, financial deregulation, asset prices, and capital flows. The paper uses two explanatory variables: mortgages and lending to the financial sector (% of GDP) are grouped together under the title of FIRE (Finance and Real Estate) credit, while lending to non-financial businesses and household consumption credit (% GDP) are grouped in a second variable called BusinessCredit. Both variables are included simultaneously in the main specification with a one period lag, to account for reverse causality. The authors run the main specification at yearly and 3-year frequency and introduce the second and third lag of the credit variables as instruments in the robustness section.

Their findings suggest that FIRE credit is significantly correlated to an increase in inequality, while Business Credit shows the opposite, significant, correlation.

If different credit channels have a different impact on the distribution of incomes, what are the mechanisms at play? As reviewed before, the traditional argument for inequality-decreasing effects of financial development proposes increased consumption smoothing, reduced risk and higher investment in human and physical capital. This theoretical channel seems fitting for credit to non-financial firms and consumer credit, where financial development has the potential to support investment and demand in the real sector and participate in the income and wage formation processes, potentially reducing inequality (Demirgüç-Kunt & Levine, 2009; Galor & Moav, 2004). Furthermore, Bezemer and Samarina (2016) suggest that credit to firms or household consumption sustain supply and demand of goods and services, with consequences to wage formation for large swaths of the labour force. For credit to the real estate and financial markets other dynamics might come into play. Credit to asset markets - real-estate and financial – could generate capital gains, interest and rental incomes by sustaining asset prices (Bezemer & Samarina, 2016). By using household-level data of euro-area countries, Denk and Cazenave-Lacroutz (2015) report that the composition of assets and liabilities across the income distribution differs vastly, with household credit twice as unequal and stock market wealth four times as unequal as the distribution of household income. These arguments suggest that wealth concentration affects income inequality when rising asset prices become realized income.

While the relationship between wealth and income inequality is relatively unexplored, there is some evidence that connects the two. For example, Bengtsson and Waldenström (2018) find a strong and positive correlation between the share capital share in national income and top personal income shares for a sample of 21 -mostly developed- economies over the course of the 20th century. Moreover, an analysis focusing on Sweden compiles the composition of incomes from survey microdata and shows that capital gains are an important component of top incomes especially since the 1980s, likely driven by the increase in asset prices on deregulated financial markets (Roine & Waldenström, 2012). A second channel that could relate expansion of credit to financial-sector firms and increased inequality runs through financial sector compensation. Denk (2015) finds that financial sector employees are disproportionately represented at the upper end of the income distribution (e.g. 19% among the top 1% of income earners are financial sector workers), which creates a channel between financial sector employment and greater income inequality. Additionally, financial sector employees are found to enjoy a large wage premium compared to workers with similar characteristics in other sectors. Based on these dynamics, the author argues that financial sector compensation explains about half of the overall negative relationship between finance and income inequality found in a companion paper (Denk & Cournede, 2015) which regresses the Gini coefficient on the value added of the financial sector, intermediated credit and stock market capitalization (as percentages of GDP) for OECD countries.

3. Data description

The aim of this thesis is to assess empirically the relationship between bank lending and income inequality. More specifically, the focus is on how bank lending to the financial sector, lending to households for consumption purposes, lending to non-financial businesses and mortgage lending have impacted the income shares of different parts of the income distribution.

This section describes the data sources used. For our empirical analysis, we choose a sample of 25 European countries; observations are available at a yearly basis and cover 25 years (1990-2015). This choice has two main rationales: the relationship between bank lending and inequality is likely to be depend on the level of development and on characteristics of a country's financial sector which we cannot readily observe from quantitative data (Bezemer & Samarina, 2016; Denk & Cournede, 2015). By focusing on a set of countries that share cultural and economic traits we minimize this source of heterogeneity. The second reason is that disaggregated bank lending data, while available for many countries, is often restricted in its time dimension. We remedied this issue by choosing European countries that have an advantageous longer panel.

Dependent variables

The main dependent variable is the share of total national income before taxes and transfers captured by different parts of the income distribution. This measure incorporates labour and capital incomes and is retrieved from the World Inequality Database (WID), which combines fiscal, survey and national accounts data and offers complete coverage of European countries from 1990 to 2015. Compared to other datasets such as the World Income Inequality database (UNU-WIDER, 2018), the WID has the advantage of using a unified income definition across countries and years. For the purposes of this analysis, we will focus on the top 10% and the bottom 50% of the income distribution. To asses income dynamics at the very top of the income distribution we will also extract from the dataset the income share of the top 1%.

As an addition to the income shares, we will use the gross Gini index, defined as the Gini index before redistribution through taxes and transfers. This measure allows to review outcomes in inequality levels before accounting for specific redistributive preferences of governments, and it gives a closer representation of inequality outcomes if the government did not intervene with redistributive policies. This measure is retrieved from the SWIID database (Solt, 2019), which aims at maximising comparability between Gini coefficients of different countries and is based on micro-data from the Luxemburg Income Study database (LIS). The gross Gini index is widely employed in the literature and serves two main uses in my empirical setting. First, it makes the results comparable with a large portion of the literature, thus setting a baseline; and second, the Gini Index offers a clean interpretation of the effect of finance on inequality, as it summarizes the dispersion of the whole distribution.

The choice for income shares is one of the main distinguishing features of this thesis. There are two main reasons to use income shares versus an aggregate measure of inequality like the Gini index.

The first reason is related to the construction of the data: the Gini index is often derived from survey data, as is the case for the SWIID, which suffers from the under-representation of top income shares (Alvaredo, 2011; Jaumotte & Buitron, 2015). This reduces its ability to portray changes in income inequality faithfully when income growth is concentrated at the top of the income distribution. The second reason is that most of the literature linking financial development to inequality, by using the Gini coefficients as its main dependent variable, is not able to locate the changes on the income distribution. By employing income shares as dependent variables, this is to a certain extent possible.

Conversely, the interpretation of effects on income shares presents one limitation. Income shares are defined as the income accruing to a section of the income distribution over total income. Sharing a common denominator, a change in one part of the distribution is bound to affect in the opposite direction other parts of the distribution in a mechanical fashion. The result is that the interpretation of the correlation between bank lending and changes in income shares is limited to the "gross" effect, in other words the total effect deriving from the direct effect of bank lending plus the mechanical redistribution across shares. Nonetheless, exploring the relationship between finance and income shares provides an original contribution to this field of literature.

Independent variables

The independent variables come from the dataset assembled by Bezemer, Samarina and Zhang (2017), which is constructed from national central banks' consolidated reporting of bank lending to the national economy. The dataset provides yearly data on bank credit split into four categories: (1) home mortgages, (2) consumer credit (lending to households to finance consumption), (3) bank loans to non-bank financial institutions, and (4) bank lending to non-financial businesses.

Non-financial business credit includes loans to non-financial companies, which comprise businesses in the agricultural, industry and services sectors excluding public, financial and real estate services. Credit to financial businesses includes loans to insurance companies, pension funds, other financial intermediaries and non-bank financial institutions. Interbank lending is excluded from this variable (Bezemer et al., 2017). Due to the nature of the datasets provided by central banks, mortgages data only includes household mortgages and excludes business mortgages. Few countries report business mortgage lending separately, preferring to include it in total lending to businesses.

Household consumption credit includes all lending to households that is not mortgage lending. For instance, this variable includes loans for the purchase of passenger cars, student loans, durable consumption goods and credit card advances.

The dataset excludes non-bank credit (such as commercial paper and bonds) and securitized lending, which does not appear on banks' balance sheet. The consequence is that this empirical setup does not capture the full spectrum of funding channels from which households and firms draw from and instead focuses on direct bank credit.

Control variables

The choice of control variables follows from Bezemer and Samarina (2016) and De Haan and Sturm (2017). We include a total of nine control variables in our specification.

The first two control variables account for Financial and Economic globalization. According to traditional trade theory, increasing economic integration results in higher relative wages for skilled versus unskilled workers in advanced economies and places deflationary pressure on income of unskilled workers (Furceri et al., 2019; Stolper & Samuelson, 1941; Young & Tackett, 2018). Financial globalization could provide more investment possibilities to well-off households but also result in cheaper credit for the national economy. Therefore, we employ two indexes, one for economic globalization and the other for financial globalization, from the *KOF globalization index* database (Gygli et al., 2019). The KOF index is a composite measure of globalization which can be decomposed in sub-indexes along the economic, social and political dimension. We prefer it to trade as a percentage of GDP, traditionally used in the literature, as it includes both *de jure* and *de facto* measures of globalization and considers international financial flows. While the KOF composite index incorporates social and political measures, we are interested in controlling only for the economic dimension. Due to that, we employ only two sub-indices summarizing globalization in trade and globalization in financial flows.

Our third control variable, the rate of unemployment, is likely to impact income inequality the most in the short term. Rising unemployment results in a direct loss of income and undermines the earnings and bargaining position of low skilled workers who are more easily substituted than skilled workers. This data is retrieved from the World Bank's World Development Indicators (WDI). The fourth control variable is annual per capita GDP growth, retrieved from the WDI. GDP growth could affect inequality if it is distributed heterogeneously along the income distribution. Hermansen et al. (2016) empirically address this question and find that GDP per capita growth has a neutral impact on inequality across OECD countries, suggesting that the observed increase in inequality is driven by other factors. Nonetheless, this variable will be included as it is widely employed in the empirical literature.

Another factor which could influence income inequality are demographic dynamics. As the income shares that form my dependent variable include the elderly, the ageing of the population needs to be taken into consideration. We include the percentage of the total population above 65 years of age to account for the reduced income of retired people. This variable is retrieved from the WDI.

In European economies, the redistribution by governments has been for the most part effective in curbing inequality (Hermansen et al., 2016). Our dependent variables, whether the Gross Gini or income shares, are computed before the government's redistribution, but it is possible that government expenditures influence inequality indirectly through the stimuli they provide to investment and demand. To account for this, our specification includes government final consumption expenditures as

percentage of GDP. The data is retrieved from the World Development Indicators and accounts for all final purchases of goods and services, including the compensation of public employees.

A further element that could influence income inequality is the industrial structure of an economy, understood as the mix between manufacturing, agricultural, industrial and service sectors (Hartmann et al., 2017). There are several ways in which the productive structure of the economy could influence inequality: firstly, as countries open to trade, employment could suffer more in economies that are in direct competition with other exporting countries. Secondly, to the extent that economies have moved towards manufacturing and services with high technological content, industrial structure could influence the returns to skilled labour and to ownership of capital (Arpaia et al., 2009; Young & Tackett, 2018). In our empirical estimation we employ the value added of agriculture and industry (which includes construction and manufacturing) to control for these effects.

Another common control variable in the inequality literature is educational levels, which may influence inequality in a non-linear fashion. An increase in the education of the labour force could at first increase inequality, but in the long run the availability of skilled employees reduces the wage premium to skills and contributes to economic development, so that the net effect is negative (Abdullah et al., 2015). In our sample of developed economies, the wage premium of skilled versus unskilled workers could be affected by the availability of skilled employees, so that inequality is lower in well-educated populations. Abdullah et al. (2015) conduct a meta-analysis of the available empirical studies and conclude that an increase in education has a negative and significant effect at the top of the income distribution and a positive and significant effect on the bottom incomes. They also suggest that secondary education has a bigger impact on inequality than the completion of primary schooling. To control for these effects, we include as a regressor the share of the working population with advanced education, i.e. has completed a short-cycle tertiary education such as a bachelor's degree or equivalent (World Development Indicators).

A first look at the data

Income inequality

This section aims at highlighting the major trends in income inequality in the countries that compose our sample. We will start off by describing inequality through the Gini Index (gross) and then move on to the dynamics of the quantiles of the income distribution.
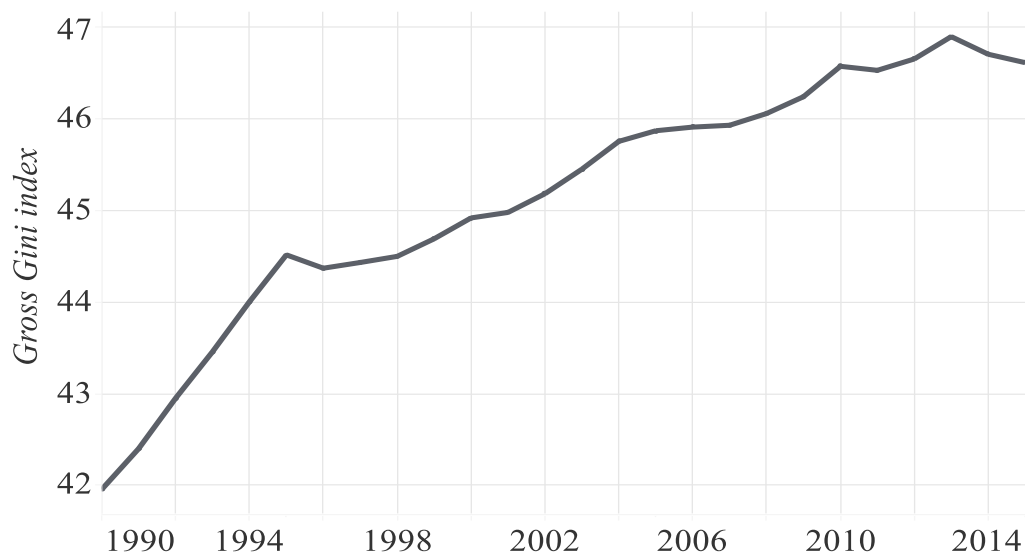
Figure 1 – Trend in the Gini coefficient

Figure 1 presents the yearly average of the gross Gini coefficient across all 25 countries in our sample. Income inequality has been trending upwards across the whole time frame of reference
.

Figure 1 plots the average value of gross Gini index from 1990 to 2015. There is a clear upwards trend through the whole of the sample period. The average level across all countries goes from a Gini of just below 42 up to 47 in 2015, with a growth rate that peaks in 1995 and continues steadily until 2015.
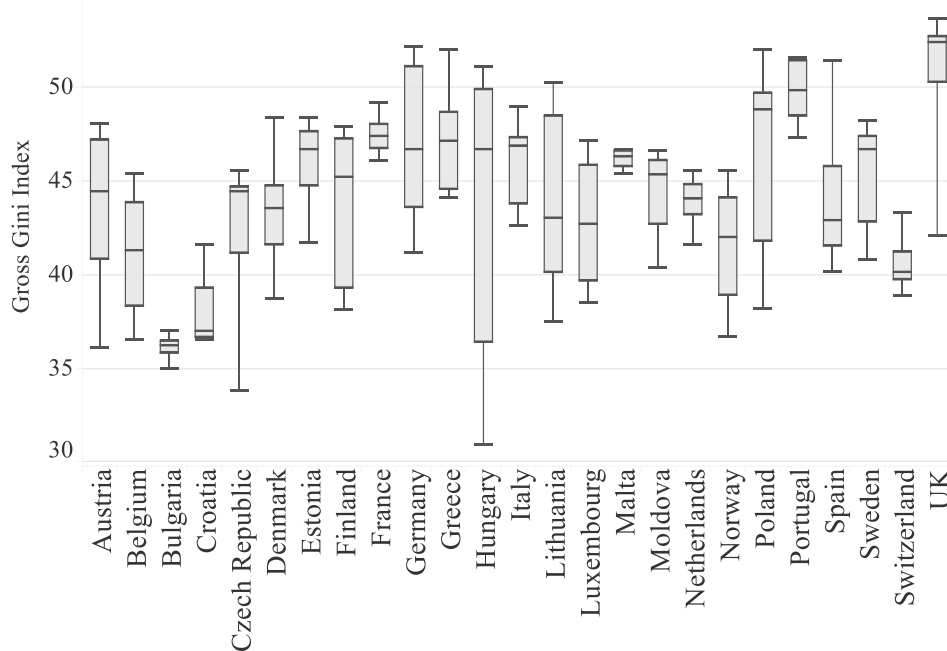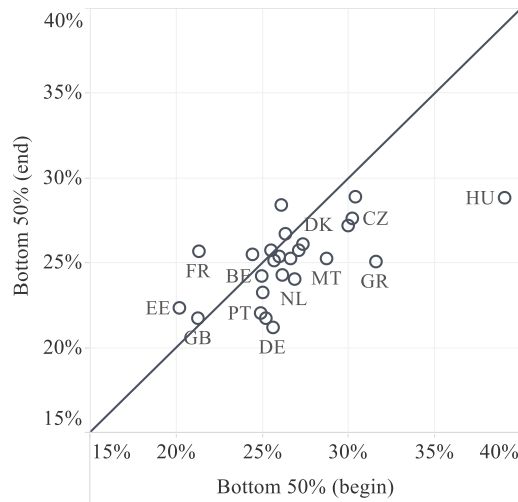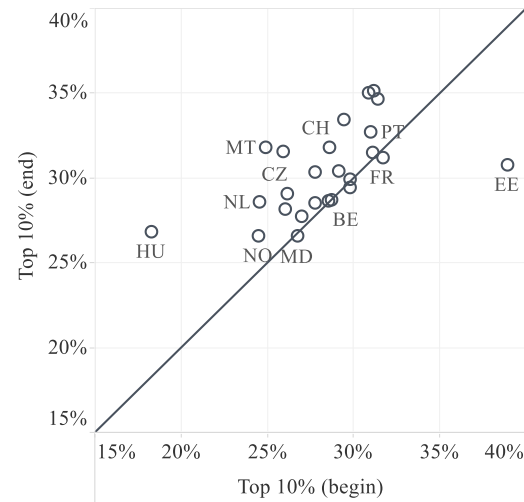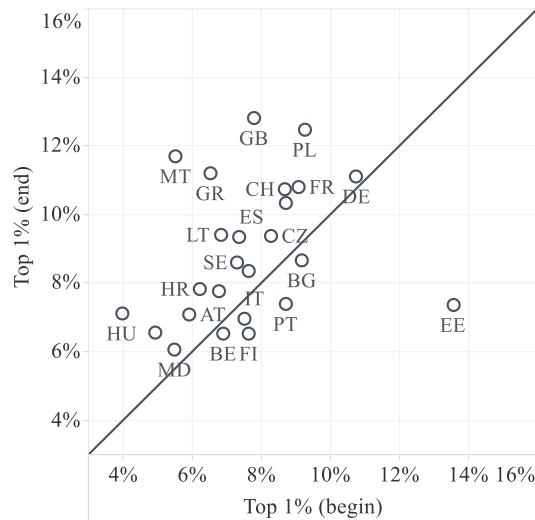
Figure 2

Figure 2 presents a boxplot of the distribution of gross Gini coefficients for all year-country observations in the sample. The boxes contain 50% of total observations, while the whiskers extend to include minimum and maximum values.

Figure 2 shows a boxplot of the values of Gross Gini by country, from 1990 to 2015, with the box containing 50% of the observations and the whiskers extending to include minimum and maximum values. The distribution of values across countries is quite heterogeneous: most values fall inside 38 and 52 Gini points, but within that range countries vary considerably both in median Gini and dispersion of values. The UK, Portugal and Poland stand out as having the highest mean levels of inequality across the time period as highlighted by the median line being close to the upper limit of the box; Switzerland and Bulgaria show the opposite, with little variance in the observations. In the sample we can also observe quite some differences in the dispersion of the values: Gini coefficients of Bulgaria, Malta, France and others have not changed much in the course of the last two and a half decades, while Poland, the UK and Hungary show greater variability. While Dispersion in Gini coefficients is not a problem for estimation purposes, outliers with respect to inequality and/or financial measures could drive the results of a regression estimation. We consider this eventuality in the robustness checks.

The dynamics of the bottom and top quantiles of the income share are consistent with the increase of Gini coefficient seen above. Figure 3A to 3C show how the income share of the bottom 50%, top 10% and top 1% in 2015 compares to the respective levels in 1995. In each scatterplot, an observation above the 45° line represents a higher income share in 2015 than in 1995. Most observations for the last decile and the top 1% are above the equality line, while most of the observations fall below for the bottom 50% of the income distribution. Panel A further highlights lower dispersion in the bottom deciles, compared to the top.

Figure 3A

Figure 3B

Figure 3C

Figures 3A to 3C present scatterplots of the income share of the bottom 50%, top 10% and top 1% of the income distribution. The horizontal axis shows the initial income share in the sample. The vertical axis is the ending value for each country in the sample (2015)

The upward trend of the top of the income distribution and the slow decrease in the bottom 50% is confirmed by Figure 4, which shows the average of the income share across all countries. Relative to 1990 levels, the bottom 50% has seen a decrease on in income share of almost 11%, the top 10% an increase of 19% and the top 1% of the income distribution has seen its share increase by 33%, capturing almost one third of the top 10%'s income share.
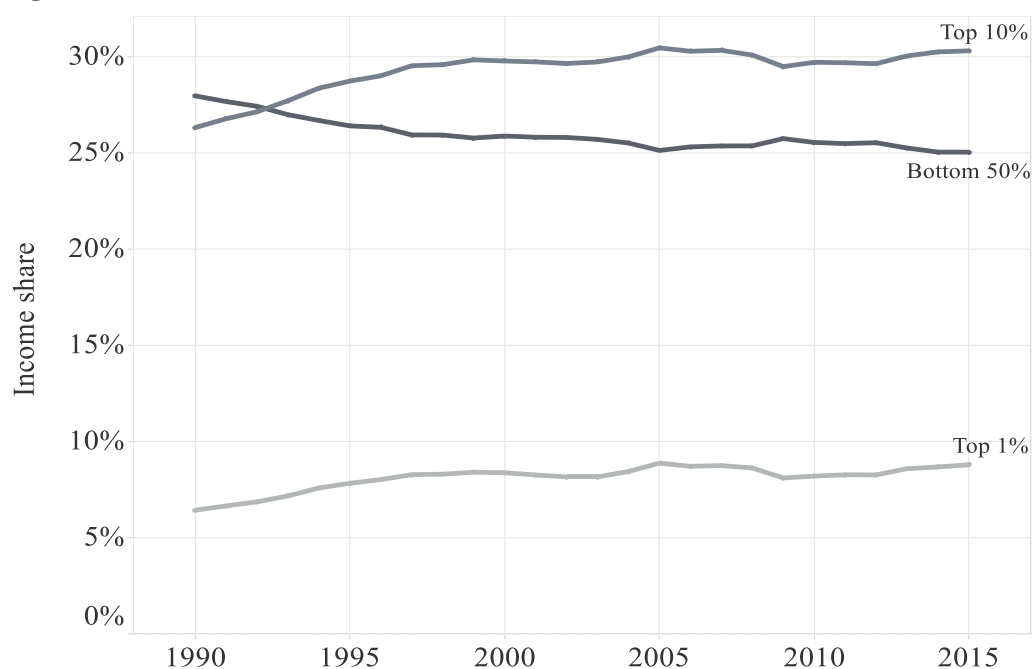
Figure 4

Figure 4 plots the evolution of the income shares of the bottom 50%, the top 10% and the top 1% of incomes. Values are unweighted averages of all countries in the sample

Bank lending

The sample of countries employed in this samples shows similar dynamics with respect to bank lending variables as those presented by Bezemer et al. (2017).

Figure 5 plots the evolution of the four bank lending variables considered in this study as a share of GDP over 1990-2015. Each line is the unweighted average value by year, considering all countries. Consumer lending and credit to the financial sector show a significant rise in the years preceding the global financial crisis.: consumer lending more than doubles and financial sector lending triples before the crisis. Both variables then revert and show a downwards trend until 2015. Mortgage lending presents a sharp increase as a share of GDP as well, although not in such a consistent fashion as the previous two variables. Between 1998 and 2008, the measure more than doubles in magnitude, although the years preceding 1998 show some volatile behaviour. After the global financial crisis, mortgage lending plateaus and remains stable until 2015. Lending to the non-financial business sector shows the most erratic behaviour: after a declining tendency between 1998 and 2004, it sharply increases by 30% until the crisis to then drop at a level similar to that in 1990. One thing to notice is that part of the jump in 1993 in mortgage lending is due to the entrance in the sample of Moldova and Lithuania, which had lower level of bank lending compared to other countries at the beginning of the '90s. Excluding them does not significantly change the general trend but removes the sudden drop.
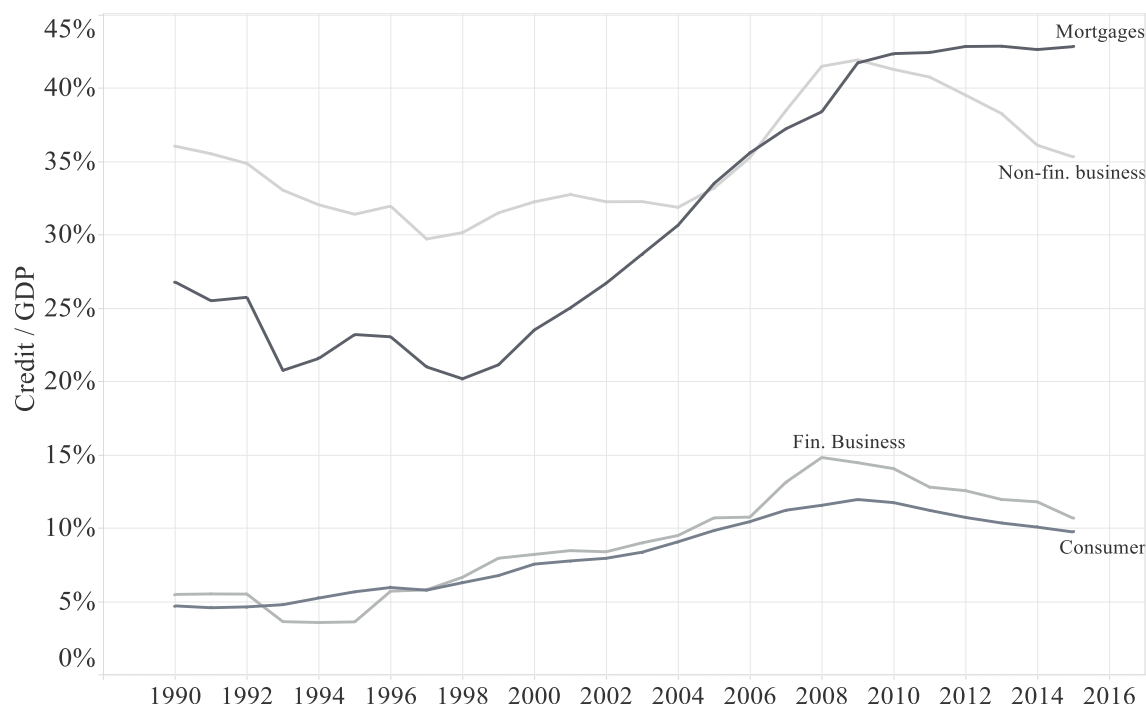
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Figure 5

Figure 5 plots credit as a share of GDP for each dependent variable. Values are the unweighted average of all countries in our sample

Figure 6A to 6C highlight the extent of debt shift presented in the literature review (Bezemer et al., 2017). Each panel presents on the horizontal axis the share in total credit at the beginning of the sample for each credit variable (from 1990 onwards), while the vertical axis presents the same share in total credit at the end of the sample. If a country is located below the 45 degree line, the corresponding credit variable's share in total credit has shrunk. The most notable shifts have happened in mortgage lending, which has increased relative to other credit types in virtually all countries in the sample (Figure 6B). The same shift in the opposite direction has happened for non-financial business lending, which has seen its relative importance decrease in the vast majority of countries (Figure 6D). The results are more heterogeneous when considering credit to financial institutions (Figure 6A) and consumel lending (Figure 6C), where the split between countries falling above and below the 45 degree line is more balanced. The plots allow for two general remarks. First, some countries show extremely high levels in one credit type when compared with other countries in the sample. This is for example the case of Luxemburg, Sweden and Great britain when considering credit to financial institutions, or Switzerland with respect to mortgage lending. Furthermore, Moldova and Bulgaria show considerably higher shares of non-financial business lending than any other country in the sample. This observational results are consistent with the findings in Bezemer et al. (2017), which suggest that one of the main drivers in the allocation of bank credit towards non-financial businesses is the level of GDP per capita. Second, the composition of total credit is quite heterogeneous among countries, especially in mortage and non-financial business lending. Heterogeneity is also present in

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the degree of debt shift, but we do not see extreme outliers in this regard: this is reassuring in view of our empirical estimation, as it suggests that no single country will disproportionately influence our results.

Figure 6A
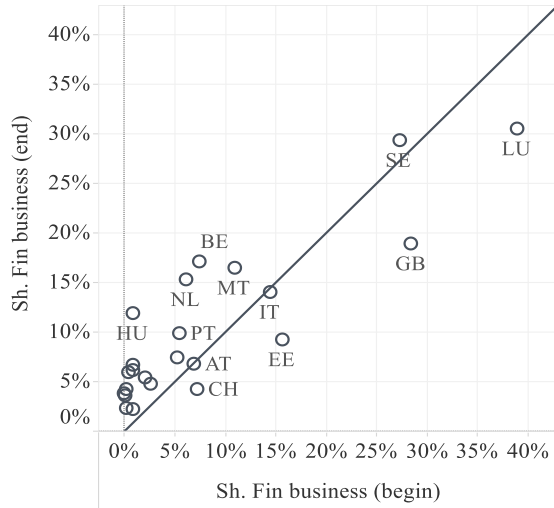
Figure 6B
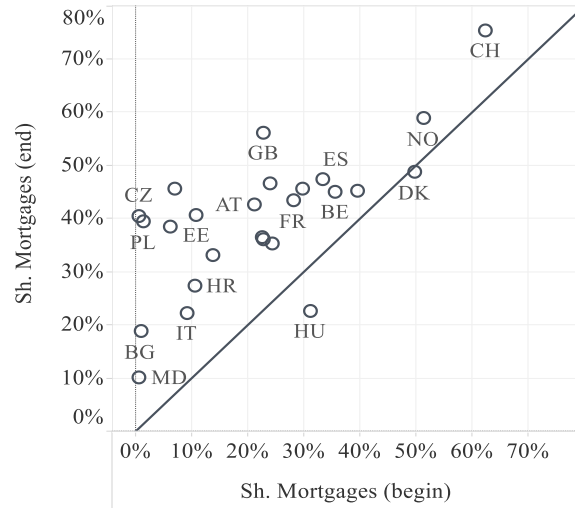
Figure 6C

Figure 6D
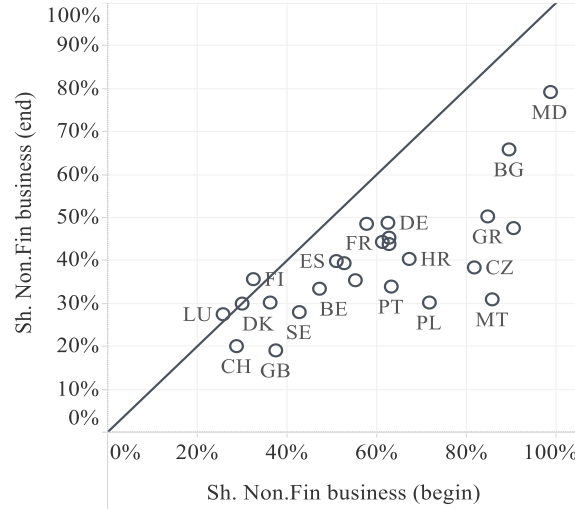
Figure 6A to 6D plot the beginning and ending share of each credit variable on total credit. If a country is located below the 45 degree line, the corresponding credit variable's share in total credit has shrunk between the first and last observation in the sample.

4. Methodology

This thesis employs a panel OLS regression approach to estimate the relationship between disaggregated bank lending and shares of the income distribution. The sample consists of an unbalanced panel of 25 European countries, with the full sample of countries represented from 2002 onwards. Regression equations include country fixed-effects to focus on the within-country

relationship between bank lending and income shares, as well as to account for any time-invariant unobservable characteristic. Furthermore, the main specification includes time fixed-effects, which allow to control for country-invariant year-to-year changes such as shocks common to all countries. Further, it enables us to partially absorb the rising trends in bank lending and inequality that most countries experienced in recent decades. This latter feature is important, as it prevents our results being driven by spurious correlations between dependent and independent variables. In order to account for heteroskedasticity and autocorrelation in the error term standard errors are clustered at country level.

The main specification is described by Equation 1:

$$I_{Share_{i,t}} = \beta_o + \beta_1 fin_{i,t} + \beta_2 nonfin_{i,t} + \beta_3 consum_{i,t} + \beta_4 mortgage_{i,t} + \beta_5 X_{i,t} + \rho_i + \tau_t + \epsilon_{i,t}$$

Where I_{Share} is the income share of either the bottom 50% or the top 10% of the income distribution for country i in year t. $Fin_{i,t}$, $nonfin_{i,t}$, $consum_{i,t}$ and $mortgage_{i,t}$ are the main explanatory variables and respectively represent bank lending to financial businesses, non-financial businesses, lending to households for consumption purposes and mortgages. All bank lending variables are included simultaneously in the regression equation to prevent omitted variable bias. Since different bank lending channels are correlated among each other and to inequality, omitting them would result in biased coefficients. X is the vector of controls for covariates of income inequality, which include GDP growth, the share of the population over 65, government final consumption expenditures as a share of GDP, the value added of Industry and agriculture, the share of the population with an advanced degree, unemployment and two indexes of economic and financial globalization. The parameters ρ and τ represent country and year fixed effects.

The results section will develop in two steps. First, the estimations from Equation 1 will be presented by using the Gross Gini coefficient (before taxes and transfers) as dependent variable. This allows for drawing an initial comparison with the findings of Bezemer and Samarina (2016) which use the Gini coefficient as proxy for inequality. The next step will continue by presenting results for the main specification. The goal is to observe the correlation of lending to financial businesses, non-financial businesses, households and mortgage lending on each income share of interest. I will include, alongside the bottom 50% and the top 10% of the income distribution the results when using the top 1% of incomes as dependent variable, to provide a reference on the concentration of the effect in top parts of the distribution. In both steps I will report the estimated coefficients from Equation 1 with and without the inclusion of time fixed-effects, to assess the impact that trends and shocks have on our findings.

In the robustness section, after the presentation of the main results, we will address the possibility of reverse causality between consumer and mortgage lending and the income share variables. An increase in income might influence the supply of mortgage loans. As households become wealthier, creditworthiness increases and mortgage lending increases. This would result in an upward

bias in the coefficients of mortgage lending with respect to the income of the bottom 50%. Similarly, as highlighted by several scholars (Botta et al., 2019; De Haan & Sturm, 2017; Denk & Cournede, 2015) rising income inequality could increase demand for consumer loans, as households rely more on financing to meet their desired consumption level. Reverse causality would thus result in overestimation of coefficient β_3.

Previous papers in the finance-inequality literature have addressed reverse causality in several ways. The first method is to employ an instrumental variable approach. As reviewed by De Haan and Sturm (2017), the most common exogenous variables are legal origin (civil versus common law countries), lagged values of financial development, latitude, creditor rights, religious composition and ethnic fractionalization. These instruments, excluding lagged variables of the dependent variable, are unsuited to the methodology in this thesis: first, it is rather unlikely that they are able to explain developments in disaggregated credit variables. Second, variables such as legal origin, religious composition, latitude, ethnic fractionalization and creditor rights are either fixed or likely to be quasi fixed for the sample of European countries, such that their influence would be absorbed entirely by the country fixed effects.

The concern of reverse causality will be addressed in two ways. First, mortgage and consumer lending will be replaced with their first lags, as done by Bezemer and Samarina (2016). Lastly, we will use a panel regression instrumental variable approach with lags of mortgage and consumer lending as instrumental variables.

5. Results

This section presents the empirical results from the regression analyses specified in the methodology. Table 1 summarizes the effects of disaggregated bank lending on the Gross Gini coefficient. The first column presents a fixed effects regression of the Gini coefficient on the four variables of interest, without controls or time fixed-effects, which are introduced in columns two and three respectively. All coefficients of interest can be interpreted as the absolute increase in the gross Gini index resulting from a 1% increase in disaggregated bank lending relative to GDP, all other things equal, when computing an average over all countries in the sample.

Lending to financial businesses and mortgage lending positively correlate with income inequality. The coefficients in column 1 show that a 10% increase in financial business and mortgage lending are respectively associated with a 0.36 and 0.49 points increase in the Gini index and that the results are significantly different than 0 at the 95% confidence level. Once we introduced the control variables, the coefficient on mortgage lending halves in size from 0.049 to 0.024 and becomes insignificant.

Table 1

	(1) Gross Gini	(2) Gross Gini	(3) Gross Gini
Financial Business	0.0356**	0.0415***	0.0237
	(0.0152)	(0.0124)	(0.0150)
Non-financial Business	-0.0322	-0.0200	-0.00000591
	(0.0233)	(0.0203)	(0.0199)
Consumer lending	0.0312	-0.0372	-0.0119
	(0.0522)	(0.0652)	(0.0670)
Mortgages	0.0495**	0.0245	-0.0267
	(0.0215)	(0.0216)	(0.0291)
GDP growth		0.0122	0.0281
		(0.0286)	(0.0360)
Population over 65		0.388**	0.230
		(0.186)	(0.293)
Government Expenditure		0.0598	0.0215
		(0.112)	(0.125)
Industry: value added		0.0555	0.0388
		(0.0878)	(0.0800)
Agriculture: value added		-0.153	0.145
		(0.244)	(0.267)
Advanced education		-0.0182	0.0670
		(0.0766)	(0.0638)
Unemployment		0.122***	0.147***
		(0.0434)	(0.0506)
Trade Globalization		-0.0239	-0.0391
		(0.0401)	(0.0415)
Financial Globalization		0.00794	-0.00533
		(0.0382)	(0.0377)
Constant	46.59***	40.32***	35.68***
	(0.752)	(7.746)	(9.615)
Year FE	No	No	Yes
Observations	542	477	477
Countries	25	25	25
F	5.339	9.563	.
R^2: within	0.225	0.449	0.514

The coefficients on financial business lending is statistically significant and increase in size from 0.036 to 0.041 once controls are introduced, but then turns insignificant once time fixed-effects are added to the regression equation. This suggests that part of the association between financial lending and the Gini coefficient is captured by country-invariant shocks or trends. No evidence was found that either consumer lending and non-financial business lending affect inequality: the coefficient on consumer lending varies in sign and magnitude across the three specifications and is never significant, while lending to non-financial businesses is consistently negative but insignificant in each estimation. Furthermore, the coefficient progressively approaches 0 when including first the set of control variables and subsequently time fixed-effects. As we have shown in the descriptive analysis of bank lending variables, consumer lending shows the least variability among the explanatory variables, hovering around 5-10% of GDP in our sample, which could partially explain the insignificant results. Among all control variables, only unemployment and the share of the population over 65 are significantly related to inequality, with the latter losing significance, as expected, once we control for common trends in column 3.

Table 1 provides a benchmark to compare our results with those by Bezemer and Samarina (2016). The authors do not include each bank lending variable separately in their regressions but aggregate lending to financial businesses and mortgages together as FIRE (*Fi*nance and *Re*al estate credit) and lending to non-financial businesses and consumer credit as Business Credit. Furthermore, they use one-year lags to control for reverse causality and do not include time fixed-effects. As reviewed in section 2, they find a positive and significant effect of FIRE credit on the Gini Index and a negative and significant effect of Business Credit. Our results only partially support their conclusions. The coefficients in column 2 are signed consistently with their findings, but three out of four coefficients are indistinguishable from zero at a statistically significant level 0f 0.1. Lastly, the magnitude of the coefficient on financial business lending is two and a half times larger than their coefficient on FIRE sector credit, which could suggest that financial business credit is the main driving force behind their results. The comparison holds also if the estimation in column 2 is repeated using lagged values for all bank lending variables (not reported). Financial business lending shows the only statistically significant coefficient, with a magnitude of 0.039 and standard error of 0.0121 (p-value < 0.05).

Table 2

	Panel A			Panel B		
	(1)	(2)	(3)	(4)	(5)	(6)
	Bottom50	Top10	top1	Bottom50	Top10	Top1
Financial Business	-0.0511***	0.0609***	0.0362**	-0.0429**	0.0449**	0.0282*
	(0.0155)	(0.0207)	(0.0154)	(0.0167)	(0.0196)	(0.0148)
Non-financial Business	0.0279	-0.0358	-0.0213	0.0133	-0.0197	-0.0125
	(0.0171)	(0.0241)	(0.0184)	(0.0161)	(0.0251)	(0.0210)
Consumer lending	-0.0873	0.0752	0.0303	-0.0925	0.0963	0.0506
	(0.0744)	(0.0782)	(0.0392)	(0.0720)	(0.0768)	(0.0400)
Mortgages	0.0247	-0.0208	0.00846	0.0510	-0.0555**	-0.0120
	(0.0209)	(0.0227)	(0.0126)	(0.0306)	(0.0214)	(0.0132)
GDP growth	-0.0325	0.0625	0.0489	-0.0508**	0.0817	0.0563
	(0.0205)	(0.0420)	(0.0353)	(0.0245)	(0.0571)	(0.0492)
Population over 65	-0.486***	0.330	0.0598	-0.357*	0.275	-0.00959
	(0.116)	(0.232)	(0.187)	(0.209)	(0.268)	(0.216)
Government Expenditure	-0.0469	-0.0136	-0.125*	-0.0197	-0.0333	-0.111
	(0.0557)	(0.0865)	(0.0668)	(0.0644)	(0.0978)	(0.0745)
Industry: value added	-0.0742	0.0121	-0.0488	-0.0591	0.0258	-0.0151
	(0.0756)	(0.137)	(0.103)	(0.0760)	(0.125)	(0.0939)
Agriculture: value added	-0.140	0.150	0.111	-0.301	0.429	0.224
	(0.185)	(0.209)	(0.167)	(0.189)	(0.255)	(0.202)
Advanced education	-0.0733	0.0475	0.0541	-0.105**	0.126**	0.101
	(0.0493)	(0.0608)	(0.0561)	(0.0490)	(0.0588)	(0.0594)
Unemployment	-0.0161	-0.00831	0.0214	-0.0257	0.0279	0.0488
	(0.0268)	(0.0395)	(0.0511)	(0.0281)	(0.0369)	(0.0481)
Trade Globalization	-0.0548	0.103	0.0661	-0.0546	0.0997	0.0646
	(0.0448)	(0.0676)	(0.0484)	(0.0453)	(0.0775)	(0.0563)
Financial Globalization	-0.0256	0.0261	0.0145	-0.0276	-0.00469	-0.0109
	(0.0276)	(0.0491)	(0.0334)	(0.0295)	(0.0582)	(0.0413)
Constant	48.36***	11.12	-0.00324	49.67***	5.135	-3.893
	(6.532)	(7.542)	(5.999)	(7.444)	(6.970)	(5.773)
Year FE	No	No	No	Yes	Yes	Yes
Observations	470	470	470	470	470	470
Countries	25	25	25	25	25	25
R^2: within	0.392	0.332	0.228	0.419	0.378	0.287

Table 2 reports the results from the main specification (Equation 1). The income shares of the bottom 50% and the top 10% are regressed on the disaggregated bank lending variables and the set of controls. The top 1% of the income distribution is included to provide a sanity check on the coefficient of the top 10%: as we are proposing that mortgages and lending to financial institutions affect the income distribution through channels related to wealth concentration, including the top 1% as independent variable can provide a reference to gauge whether this is the case. Columns 1 to 3 do not include time fixed effects, which are present in columns 4 to 6.

In panel A, lending to financial businesses shows a significant and positive correlation with the two top income shares, with a coefficient close to 0.06 for the top 10% of incomes. The effect on the top 1% is roughly two thirds of the total effect, at 0.036. The coefficient remains significant but negative when the dependent variable is the income share of the bottom 50%, with magnitude -0.051. The results stay qualitatively the same when year fixed effects are added, although the magnitude is somewhat reduced, going from 0.061 to 0.045 for the top 10% and from − 0.051 to -0.043 for the bottom 50%, suggesting that shocks and trend play a role in the correlation. The ratio between the coefficients of the top 1% and the top 10% stays remarkably stable at 0.6. Any effect absorbed by the year fixed-effects does not affect the 1% of incomes differently than the 10%. All other things equal, a 10% increase in bank lending to the financial sector is associated with an average increase of the income share of the top 10% by 0.4 percentage points and a decrease of the bottom 50% by 0.41 percentage points.

The coefficients on lending to non-financial businesses are insignificant both with and without the inclusion of time fixed effects. Although the signs are consistent with a negative correlation between non-financial lending and inequality - with positive coefficients for the bottom 50% of incomes and negative coefficients for the top two income - they are not statistically different from zero. Furthermore, the magnitude of the coefficients in panel B is the smallest among bank lending variables. An important side note is that these results do not imply an insignificant effect of bank lending to non-financial firms on income growth: even in the presence of strong a strong causal relationship, the returns could be proportionally distributed among income shares and the effect on inequality neutral. Similarly to non-financial lending, coefficients for lending to households for consumption purposes are not significantly related to the dependent variables. Consumer lending is negatively correlated to the income share of the bottom 50% and positively correlated to the top two income shares, but the results are very dispersed.

In panel A, mortgage lending is not significantly correlated with incomes shares. When time fixed effects are introduced in panel B, the variable shows a significant negative correlation with the income share of the top 10% of -0.055 and a positive correlation of 0.051 with the bottom income share (p-value: 0.109, not reported), which suggests a negative relationship between mortgage lending and inequality. All other things equal, a 10% increase in mortgage lending is associated with a decrease in the income share of the top 10% by 0.055 percentage points.

The opposite signs on the coefficients must be considered with a certain caution: it is likely that income shares, keeping GDP fixed, negatively correlate in a mechanical fashion. We can view the opposite signs as composed by two effects: the first one is due to income accruing to one side of the distribution leaving the other one fixed, which naturally reduces the share in total income of the remaining part; the second is a redistribution of income from one side of the distribution to the other, which would affect income shares, and thus inequality, also without generating additional income. As seen in the literature review, there is (few) literature that argues for a redistributive effect of bank lending on income shares (Botta et al., 2019), but the disentanglement of these two dynamics is beyond the scope of my empirical exercise.

The findings from this paper's empirical estimation support the argument that disaggregation of bank lending is an important factor to estimate the relationship between bank lending developments and income inequality. As suggested by previous literature (Beck et al., 2012; Bezemer & Samarina, 2016) different bank lending channels could have different impacts on inequality, and we find that this is the case. The first explanatory variable in our specification, lending to the financial sector, shows the strongest relationship to income shares at the top and at the bottom of the income distribution among all our explanatory variables. The comparison of table 2's results with and without the inclusion of year fixed effects suggests that the relationship is not driven by a spurious correlation due to common trends. A 10% increase in bank lending to the non-bank financial firms is associated with an increase in the income share of the top 10% by 0.45% and in a reduction of the income share of the bottom 50% by 0.43%. This result is economically significant, especially when considering that the share of bank lending to the financial sector on GDP almost tripled between 1990 and its peak in 2008. Moreover, it is consistent with the findings of Bezemer and Samarina (2016) and the literature that proposes capital gains and financial sector wages as channels of transmission between financial dynamics and inequality (Bengtsson & Waldenström, 2018; Denk, 2015).

When considering lending to households for consumption purposes, our results reject a statistically significant correlation with inequality, in accordance with the argument by Beck et al. (2012) that distributive effects of bank lending are not driven by credit to households. Similarly, we find that credit extension to non-financial firms has no significant correlation with income shares at either end of the income distribution. As already mentioned above, our results are agnostic on the effect of bank lending channels on total income. Given the empirical setup of this paper, it is impossible to draw conclusions on the level of income resulting from different bank lending channel, but only that any change in income does not disproportionately accrue to one side of the income distribution. The last explanatory variable considered in our setup, mortgage lending, is harder to interpret. While Panel A of table 2 suggests that mortgage lending is not significantly correlated with the income shares analysed, Panel B provides weak evidence of a negative and significant correlation with the income share of the top 10% and a positive but barely insignificant correlation with the

income share of the bottom 50%. This second set of results is not consistent with the finding by Bezemer and Samarina (2016) that FIRE sector credit is positively linked to income inequality.

Our review of the literature does not provide a clear alternative channel through which mortgage lending could affect income shares. Our econometric setup allows to exclude the presence of a spurious correlation. Both the income share of the top of the distribution and mortgage lending have experienced an increasing trend in our sample: if the relationship was driven by this trend, the signs of the coefficient on mortgages would have the opposite to what we observe. We address two possible hurdles to a correct estimation in the robustness checks, namely that we are experiencing issues of reverse causality or that the experience of the global financial crisis affects our results to the point of observing spurious results.

Robustness checks

In the results section, we have reported the results of the empirical analysis associating bank lending and income shares at different points in the income distribution. We find that lending to financial businesses is robustly associated with inequality as it increases the income shares at the top of the distribution while showing a negative association with the income share of the bottom 50%. There is no evidence that lending to households for consumption purposes and lending to non-financial businesses has an effect on income inequality, while we see signs that mortgage lending is positively associated with an increase in the income share of lower parts of the distribution.

In this section, we will check the robustness of our results for the influence of reverse causality, to the countries included in our sample and to the effect that crises exercise on bank lending and income shares.

Reverse causality

Table 3 summarizes the results obtained when assessing the impact of reverse causality on my results (controls are omitted for readability).Panel A reports the coefficients of the baseline regression excluding mortgage and consumer lending. The coefficients on financial business lending remains significant and consistently signed. The negative correlation with the bottom 50% of the income distribution is slightly reduced from -0.042 to -0.039 but comparable to those in Table 2, column 4. The coefficient relating non-financial business lending and the income share of the bottom 50% of incomes increases in magnitude with respect to the result in Table 2 - column 4 from 0.013 to 0.025 and turns significant at the 0.1 significance level. This result cannot be interpreted as evidence of a positive correlation between non-financial lending and income inequality, as two explanatory variables have been excluded from the regression. The coefficients for non-financial business lending increase in magnitude for both the top and the bottom of the distribution and the correlation between the explanatory variable and the bottom 50% of incomes becomes statistically significant at the 0.1 significance level.

Table 3

	Panel A		Panel B		Panel C	
	Bottom50	Top10	Bottom50	Top10	Bottom50	Top10
Financial Business	-0.0390**	0.0422**	-0.0416**	0.0455**	-0.0350**	0.0423**
	(0.0147)	(0.0186)	(0.0172)	(0.0207)	(0.0166)	(0.0194)
Non-financial Business	0.0246*	-0.0334	0.0131	-0.0216	0.00813	-0.00272
	(0.0132)	(0.0206)	(0.0162)	(0.0242)	(0.0279)	(0.0362)
Consumer lending					-0.0651	-0.0111
					(0.108)	(0.128)
Mortgages					0.0600*	-0.0409
					(0.0338)	(0.0353)
Consumer lending $_{t-1}$			-0.0762	0.0907		
			(0.0717)	(0.0752)		
Mortgages $_{t-1}$			0.0518	-0.0563**		
			(0.0308)	(0.0253)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	48.81***	5.450	49.44***	6.546	49.05***	6.865
	(9.031)	(8.016)	(7.622)	(7.348)	(7.449)	(7.234)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	475	475	461	461	461	461
Countries	25	25	25	25	25	25
R^2: within	0.378	0.349	0.426	0.391	0.430	0.391

Panel B and C use two common strategies to minimize the effect of reverse causality: in the first case, the lagged values of mortgage and consumer lending are used. In the second, the third to eight lags of both variables are used as instruments. In both cases, results are consistent with the baseline regression when considering a full set of controls and year fixed effects. Conducting tests for the validity of the instrumental variables showed that the Hansen J statistic for overidentification does not allow to accept the null hypothesis of zero correlation between the instruments and the error term. The coefficients in panel C are thus not to be interpreted substantively, but just as a general indication that an alternative approach yielded estimations consistent with the results in table 2. While somewhat reassuring on the consistency of the results presented in table 2, both techniques offer a weak solution to the problem. To conclude, the only proper solution to control for reverse causality between measures of income (and inequality more broadly) and bank lending variables is to find a suitable instrumental variable. Regulatory developments that are strongly correlated with developments in bank lending, while being uncorrelated with the error terms and satisfying the exclusion restriction, seem a promising venue for further research.

To assure that our results are not driven by the dynamics of a single country, we perform a series of regressions on our main specification -including year fixed effects- removing at each round one country from the sample.

Table 4

	Bottom 50%			Top 10%		
	Min	Base	Max	Min	Base	Max
Financial business	-0.0655***	-0.0429**	-0.0317***	0.0340**	0.0449**	0.0722***
	(-0.0223)	(0.0167)	(-0.0099)	(-0.0151)	(0.0196)	(-0.0257)
Non-financial business	0.0062	0.0133	0.0269	-0.0421	-0.0197	-0.0063
	(-0.0161)	(0.0161)	(-0.019)	(-0.0293)	(0.0251)	(-0.0205)
Consumer lending	-0.1180	-0.0925	-0.0061	0.0365	0.0963	0.1400*
	(-0.0867)	(0.0720)	(-0.0394)	(-0.0707)	(0.0768)	(-0.0758)
Mortgages	0.0224	0.0510	0.0710**	-0.0657***	-0.0555**	-0.0380*
	(-0.0243)	(0.0306)	(-0.028)	(-0.0229)	(0.0214)	(-0.0189)

Note: the table reports the minimum and maximum coefficients for each bank credit variable in a series of OLS regression which exclude one country at a time. The Base column reports the same coefficients as in Table 2, columns 4 and 5, for comparison. All regressions include time fixed effects and a full set of control variables, dependent variables are the first five deciles and the last decile of the income distribution.

Standard errors are clustered at country level and reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results show that no single country drives our point estimates. Table 4 reports the minimum and maximum value of the coefficients when one country is removed, alongside the baseline point estimate from table 2. The coefficients keep consistent signs and significance levels with both the bottom 50% and the top 10% as dependent variables. The dispersion of the results is not minimal though: minimum and maximum values fall often beyond one standard deviation from our baseline.

Below, in figure 7, we investigate this observation further by presenting histograms on the distribution of the coefficients. The extreme minimum and maximum values are often determined by a single outlier country, that when extracted from the sample allows the point estimate to vary. Considering that the coefficients are an average over all countries, such deviation from the point estimate suggest that there is considerable heterogeneity among countries in the relationship between bank lending and income shares. From the inspection of the full results (not reported), we conclude that this does not happen systematically, i.e. no one single country is consistently driving extreme

results. Another observation of the same nature is that there is no evident pattern of extreme values across different bank lending measures.

From this analysis we can conclude that our results are robust to the choice of country sample. The heterogeneity that we observe across countries is an interesting venue for future research.
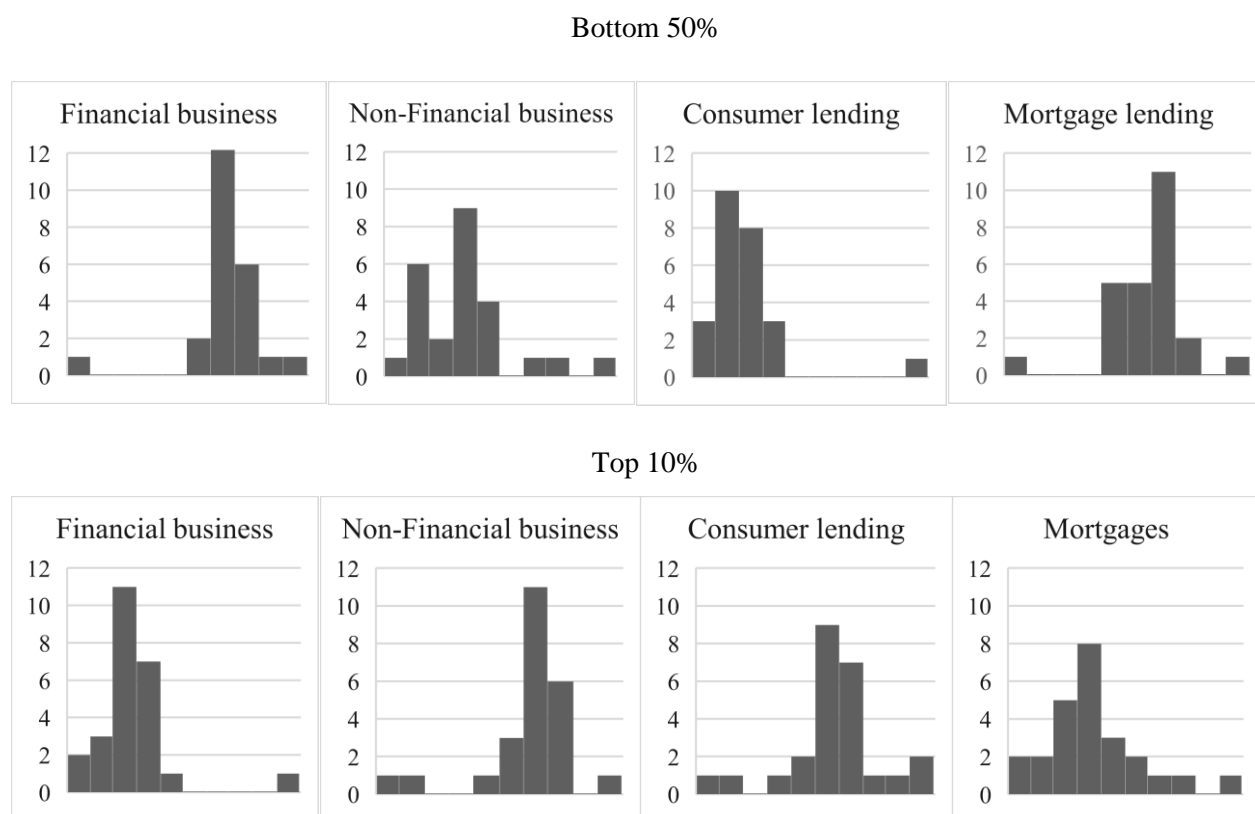
Figure 7

Bottom 50%

Top 10%

Figure 7 presents histograms for the distribution of the coefficients on bank credit variables when running a series of regression where at each round one country is removed from the sample. The extreme values of each histogram are reported in table 4.

Financial crises

The time span of our sample includes two periods in which the financial sector experienced turbulence. The first one is dated around 1991 and protracted for several countries until 1994. The second one is the global financial crisis of 2008. As we can observe from the descriptive analysis presented previously, all measures of bank lending decreased relatively to GDP in both crisis episodes, apart from mortgage lending over GDP, which plateaued in 2008 and remained stable in the following years. The effect of financial crises on income inequality is still debated, but from our descriptive analysis we can see that the market-outcome Gini coefficient experienced a slowdown in its upward trend in 2008-2009 and a dip in 2013, likely due to a sudden drop in top income shares (Roine et al., 2009). To control for the effect of financial crises on income inequality, the main specification in Equation 1 is modified by adding a dummy variable assuming value 1 during the crisis years. The data on the incidence of financial crises is retrieved from the dataset by Reinhart and Rogoff (2011).

Table 5

	Panel A		Panel B	
	(1)	(2)	(3)	(4)
	Bottom50	Top10	Bottom50	Top10
Financial Business	-0.0439	0.0352*	-0.0535*	0.0402**
	(0.0269)	(0.0181)	(0.0271)	(0.0161)
Non-financial Business	0.000668	0.0194	-0.00973	0.0241
	(0.0143)	(0.0169)	(0.0144)	(0.0191)
Consumer lending	-0.0188	0.0470	-0.0170	0.0461
	(0.0365)	(0.0567)	(0.0337)	(0.0565)
Mortgages	0.00386	-0.0272	0.0101	-0.0304
	(0.0272)	(0.0234)	(0.0261)	(0.0231)
GDP growth	-0.0678	0.156***	-0.0768*	0.161***
	(0.0457)	(0.0492)	(0.0421)	(0.0480)
Population over 65	-0.814***	0.535**	-0.810***	0.533**
	(0.167)	(0.212)	(0.183)	(0.221)
Government Expenditure	-0.141	0.148	-0.140	0.147
	(0.147)	(0.173)	(0.141)	(0.170)
Industry: value added	-0.215***	0.220**	-0.197***	0.211**
	(0.0668)	(0.0798)	(0.0656)	(0.0799)
Agriculture: value added	-0.931***	1.363***	-0.922***	1.358***
	(0.259)	(0.341)	(0.257)	(0.339)
Advanced education	-0.123	0.104	-0.105	0.0944
	(0.0808)	(0.0673)	(0.0753)	(0.0644)
Unemployment	-0.0542*	0.0586	-0.0693**	0.0665
	(0.0294)	(0.0339)	(0.0307)	(0.0392)
Trade Globalization	-0.0312	0.0415	-0.0292	0.0404
	(0.0498)	(0.0506)	(0.0457)	(0.0489)
Financial Globalization	-0.0453	0.0400	-0.0416	0.0381
	(0.0296)	(0.0365)	(0.0285)	(0.0356)
Crisis			0.647	-0.336
			(0.428)	(0.448)
Constant	66.89***	-9.312	64.79***	-8.220
	(8.383)	(8.247)	(8.057)	(7.760)
Year FE	Yes	Yes	Yes	Yes
Observations	322	322	322	322
Countries	16	16	16	16
R^2: within	0.506	0.527	0.524	0.531

While their dataset distinguishes between banking, currency and sovereign debt crises, for the scope of our analysis we code our dummy variable only based on the incidence of banking or systemic crises. The dataset does not cover all countries in our sample and including the dummy variable results in a decrease of observations by 30%. A full list of the crisis episodes considered is available in the Appendix (Table A-3).

In order to distinguish between the effect on our estimates resulting from the loss of observations and the inclusion of the dummy, table 5 reports the baseline results -without the crisis dummy- in panel A, and the results when controlling for crisis episodes in panel B. The results in panel A are comparable with those in table 2 – panel B, although the reduction of the sample results in coefficients on bank lending variables being estimated with less precision. The coefficient of financial lending on the bottom 50% of incomes is non-significant, although the magnitude remains the same. For the top 10% of incomes, the coefficient decreases in magnitude from 0.045 to 0.035 and is significant only at a 0.1 significance level. Lending to non-financial businesses, mortgages and consumer lending are all undistinguishable from zero at the 0.1 significance level. The inclusion of the financial crisis dummy results in increased estimation precision for financial business lending and has virtually no effect on the other dependent variables. The crisis dummy itself shows no significant correlation with income shares at the bottom or at the top of the distribution, possibly because part of the shock is already absorbed by time fixed effects.

The results suggest that the inclusion of crisis episodes does not significantly alter our main conclusions. Lending to the financial sector is robustly linked to an increase in inequality, and the inclusion of crises episodes seems to further strengthen the correlation.

6. Conclusion

This paper examines the link between two topics that have seen renewed interest in policy and academic circles since the advent of the global financial crisis in 2008: financial developments in the banking sector and income inequality. Two stylized facts that stand out when analysing the two variables are that both have seen considerable increases in the last four decades. Bank lending has steadily increased its size relative to GDP in most developed economies, nearly doubling in relative size in three decades. Income inequality, in the same time frame, has also been steadily increasing, rising concerns about economic opportunities and social mobility (OECD, 2018). This paper addresses empirically the relationship between bank lending and income inequality in a sample of European countries between 1990 and 2015. In contrast to most of the literature relating financial developments and income inequality, we disaggregate bank lending into four components: credit to non-financial firms, credit to household for consumption purposes, mortgages and credit from banks to non-bank financial enterprises.

The literature relating specific lending channels to distributional outcomes is still in its first stages, and the specific channels at play need further research in order to be clarified. On one hand, the theoretical literature on financial developments has mostly highlighted how relaxing borrowing constraints for firms and households could benefit income growth and decrease inequality. By allowing for higher levels of consumption smoothing and fostering investment, bank lending could promote human and physical capital accumulation (Galor & Moav, 2004), stimulate supply and demand of goods and sustain wage formation dynamics (Beck et al., 2007). On the other hand, lending that results in rising asset prices or that supports wage premiums for financial sector workers will have a detrimental effect on inequality (Bengtsson & Waldenström, 2018; Botta et al., 2019; Denk, 2015). We investigate the distributional consequences for each bank lending variable separately, employing the top 10% and the bottom 50% of the income distribution as dependent variables.

The empirical results of this paper provide evidence that different bank lending channels have an heterogenous impact on income inequality. As predicted by previous research, lending to financial sector firms is robustly associated with an increase in the income share at the top of the distribution and a decrease in the income share of the bottom 50% of income earners. This finding is robust to checks accounting for reverse causality, the impact of the global financial crisis and composition of the sample of countries. It furthermore finds no evidence of an impact on inequality driven by lending to non-financial sector firms and to households for consumption purposes. In contrast with predictions by Bezemer and Samarina (2016), this paper finds weak evidence of a negative correlation between mortgage lending and income inequality. The finding is robust to checks for reverse causality and sample composition but disappears when financial crises are included in the control variables. Given the lack of literature focusing on the effects of mortgage lending for income dynamics, this paper doesn't draw any conclusion on the relationship, leaving it as a starting point for future research. When interpreting this paper's results, one should bear in mind several limitations. First, the econometric setup is not able to disaggregate between the direct effect of a given lending channel on changes in income shares and the mechanical relationship among different parts in the income distribution. The consequence of this is that our results are partly determined by the effect of the explanatory variables and partly by the effect that the same variable has on other parts of the income distribution. Nevertheless, the interpretation regarding the effect of disaggregated bank lending on total income inequality remains unscathed. Second, the methodology employed to control for the effect of reverse causality is far from perfect. While the use of lagged explanatory variables directly in the main specification or as instrumental variables is consistent with other approaches in the literature, more work must be devoted to finding robust solutions. Third, and most importantly, the empirical setup of this paper does not allow to estimate the impact of a specific causal channel in the relationship between bank lending and income growth. While the literature has proposed wage formation, investment in human and physical capital, the role of realized capital gains and the wage premium in the financial sector to explain the link between bank lending and income inequality, it is

still not possible to quantify how much each of these elements participates in determining income inequality. A significant venue for improvements in this regard is represented by more granular data: the decomposition of income between wages and capital gains, more precise estimation of the incomes of top earners and longer time series could provide valuable insights in this field of the literature.

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Appendix

TABLE A-3: CRISIS EPISODES

Country	Crises	Total episodes
AUT	2008-2011	4
BEL	2008-2014	7
CHE		0
DEU	2007-2010	4
DNK	1991, 1992 ,2008-2014	9
ESP	2008-2014	7
FIN	1991-1994	4
FRA	1994, 1995, 2008-2014	9
GBR	1991, 1995, 2007-2014	10
GRC	1991-1995, 2008-2015	14
ITA	1991-1995, 2008-2014	12
NLD	2008-2014	7
NOR	1991-1993	3
POL	1991-1995	5
PRT	2008-2014	7
SWE	1991-1994, 2008-2010	7

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TABLE A-4: COUNTRY-YEAR COVERAGE

COUNTRY	coverage	number of years
Austria	1995 - 2016	21
Belgium	1999 - 2016	17
Bulgaria	1997 - 2016	19
Croatia	1998 - 2016	18
Czech Republic	1993 - 2016	23
Denmark	2000 - 2016	16
Estonia	1997 - 2016	19
Finland	1997 - 2016	19
France	1993 - 2016	23
Germany	1990 - 2016	26
Greece	1990 - 2016	26
Hungary	1990 - 2016	26
Italy	1998 - 2016	18
Lithuania	1993 - 2016	23
Luxembourg	1999 - 2016	17
Malta	1996 - 2016	20
Moldova	1993 - 2016	23
Netherlands	1990 - 2016	26
Norway	1995 - 2016	21
Poland	1996 - 2016	20
Portugal	1990 - 2016	26
Spain	1994 - 2016	22
Sweden	1996 - 2016	20
Switzerland	1990 - 2016	26
United Kingdom	1990 - 2016	26

TABLE A-5: VARIABLES DESCRIPTION AND SOURCE

VARIABLE NAME	SOURCE
Independent variables	
Household mortgages (% gdp)	Bezemer, Samarina, & Zhang, 2017
Consumer credit (% gdp)	Bezemer, Samarina, & Zhang, 2017
Nonfinancial business (% gdp)	Bezemer, Samarina, & Zhang, 2017
Nonbank financial business (% gdp)	Bezemer, Samarina, & Zhang, 2017
Dependent variables	
Market gini index	SWIID
Income shares	World Inequality Database (WID)
Control variables	
Gdp per capita growth (annual %)	World Bank WDI
Population ages 65 and above (% of total population)	World Bank WDI
General government final consumption expenditure (% of gdp)	World Bank WDI
Agriculture, value added (% of gdp)	World Bank WDI
Industry, value added (% of gdp)	World Bank WDI
Labor force with advanced education (% of total working-age population)	World Bank WDI
Unemployment, total (% of total labour force)	World Bank WDI
Kof trade globalisation index	KOF Globalisation Index
Kof financial globalisation index	KOF Globalisation Index