CESifo Working Papers

www.cesifo.org/wp

Financial Development and Income Inequality: A Panel Data Approach

Sebastian Jauch

Sebastian Watzka

CESIFO WORKING PAPER NO. 3687

CATEGORY 6: FISCAL POLICY, MACROECONOMICS AND GROWTH

ORIGINAL VERSION: DECEMBER 2011

THIS VERSION: OCTOBER 2012

CESifo *Working Paper No. 3687*

Financial Development and Income Inequality: A Panel Data Approach

Abstract

We analyze the link between financial development and income inequality for a broad unbalanced dataset of up to 138 developed and developing countries over the years 1960 to 2008. Using credit-to-GDP as a measure of financial development, our results reject theoretical models predicting a negative impact of financial development on income inequality measured by the Gini coefficient. Controlling for country fixed effects and GDP per capita, we find that financial development has a positive effect on income inequality. These results are robust to different measures of financial development, econometric specifications, and control variables.

JEL-Code: O150, O160.

Keywords: financial development, income inequality, global, panel analysis.

Sebastian Jauch
Seminar for Macroeconomics
Ludwig-Maximilians-University Munich
Ludwigstrasse 28 Rgb.
Germany – 80539 Munich
sebastian.jauch@lrz.uni-muenchen.de

Sebastian Watzka
Seminar for Macroeconomics
Ludwig-Maximilians-University Munich
Ludwigstrasse 28 Rgb.
Germany – 80539 Munich
sebastian.watzka@lrz.uni-muenchen.de

October 2012
We thank Gerhard Illing, Mathias Hoffmann, Carsten Sprenger, Mark Gradstein, and the participants in seminars at the University of Munich, the DIW Macroeconometric Workshop 2011 in Berlin, the CESifo Macro Money and Finance Conference 2012 in Munich, the Fiscal Policy Conference Barcelona 2012, and the National Bank of Serbia Young Economists Conference 2012 for their helpful comments. All errors are our own.

1 INTRODUCTION

In the aftermath of the economic crisis of 2008-09, many public commentators debated over the benefits and harms of the financial sector for the rest of society. The privatization of banks' profits and the socialization of their losses is a common bon mot in political debates in many developed countries. Together with widening income gaps and social inequality in the United States, United Kingdom, Germany and many other countries, this crisis has led the question of the contribution of the financial system to the economy and, more generally, to society, to arise. The merits of efficient financial systems fall short in being acknowledged by the public as bankers are recognized as highly paid individuals who serve only their own interest. In the view of many economists, there exists a more benign view of the financial sector: financial markets boost economic growth, enable wealthy as well as poor people to borrow and finance investments, and thereby ensure capital is distributed most efficiently – and, in particular, in a manner unrelated to inherited wealth. Generally, so the story goes, when financial markets are more efficient and well developed, a specific borrower can borrow more with a given amount of collateral. The success of microcredits for the poor in developing countries is just one example of what banks are able to do for society.[3] There are parts of society that were previously unable to borrow and now can build their own businesses, increase income and climb the social ladder. The remaining income inequality would then be optimal or justified in the sense of being independent of inherited wealth. However, there are also more critical voices that have recently been raised. In particular, banks and financial markets are highly criticized for being ruthless in developed countries where almost everybody is supposed to have access to finance and where income inequality is a phenomenon thought to be part of the past. Anecdotal evidence appears to provide arguments in favor of and against an inequality-reducing effect of financial development.

We thus aim to empirically assess the link between financial development and the distribution of income in a society. Does financial development always reduce income inequality in society? Are there important differences across and within countries based on their stage of economic development, or is the influence the same around the world, independent of country characteristics and the time we live in? We analyze the link of financial development and income

[3] Demirgüc-Kunt and Levine (2009) provide a brief overview of the relation between microfinance and income inequality and also cite studies that do not confirm that microfinance lowers inequality.

inequality using standard proxies in the financial development literature, the ratio of private credit over GDP and the Gini coefficient of income distribution within countries.

We extend the existing literature by using a larger database covering a longer time horizon and more countries. We further control for year effects and time-invariant country characteristics. Finally, we conduct various robustness checks for our benchmark specification. These include a sample split of the dataset in subsamples according to income levels. In contrast to previous empirical work on this topic, we reject theories that predict an income inequality-reducing effect of financial development. This finding is robust over most specifications. Due to these more general and robust findings, we believe that our work is of importance to the literature and the profession.

While investigating the link of financial development and income inequality, we do not judge or examine whether there exists an optimal or fair level of inequality. On the one hand, higher levels of inequality may have boosting effects on an economy from an incentive point of view. If everybody was receiving the same final incomes, independent of effort, naturally nobody would have an incentive to incur extra efforts for the production of goods and services, and the economy would suffer. On the other hand, excessive inequality may lead to social unrest and political instability.

The remainder of the paper is structured as follows: section two of the paper presents an overview of related literature and what we contribute to the literature. Section three describes the data used in our work. In section four, we conduct the econometric analysis, section five presents our robustness tests, and section six concludes.

2 LITERATURE

Our work adds to the literature on financial development, income inequality, and economic development. There is an extensive literature on the link between financial development and growth. A good overview of theoretical as well as empirical work on this issue has been provided by Levine (2005). In general, financial development is expected to enhance growth by enabling the efficient allocation of capital and reducing borrowing and financing constraints. However, this literature does not address the issue of which part of society benefits from the growth enabled by financial development. Growth may benefit the poor by creating more employment opportunities, but it may also favor entrepreneurs and their profit margin. The relationship between the distribution of income and economic development was initially investigated by Kuznets (1955), who established the inverted U-shaped path of income inequality along economic development – the well-known Kuznets curve. Kuznets' argument was that rural areas are more equal and have a lower average income compared to urban areas in the beginning of industrialization and thus that through urbanization, a society becomes more unequal. When a new generation of former poor rural people who moved to cities is born, they are able to profit from the urban possibilities. Wages of lower-income groups rise, and overall income inequality narrows. One factor backing Kuznets' argument of urban possibilities is financial development, which enables formerly poor migrants to choose the education they desire and to build their own businesses – regardless of their inherited wealth. This is the basic reasoning why economic theories predict a negative impact of financial development on income inequality. Financial development fosters the free choice regarding education and the founding of businesses. Because both lead to growth and growth is associated with more jobs, average income will rise, and inequality will fall.

The three major theoretical papers explaining the financial development and income inequality nexus are by Banerjee and Newman (1993), Galor and Zeira (1993) and Greenwood and Jovanovic (1990). Whereas the first two predict that better developed financial markets lead to a reduction in income inequality, the latter predicts an inverted-U-shaped relationship between financial development and income inequality. In other words, in the early stages of financial development – during which only a small part of society benefits from this development – income inequality increases. However, after a certain stage of financial and economic development is reached, more financial development begins to reduce income inequality.

Whereas the specific economic mechanisms behind these predictions differ, the key reason why better developed financial markets – at least after some stage – reduce income inequality is always that better credit availability allows household choices and decisions to be made based more on economic optimality and less on inherited wealth. The relevant choices differ according to each study, but they all concern the individual's future income possibilities and whether these are optimal for the individual. To that end, Banerjee and Newman (1993) model households' occupational choice, which depends on credit availability. Alternatively, Galor and Zeira (1993) model human capital investment, which again depends on credit. Finally, Greenwood and Jovanovic (1990) model household portfolio selection where the use of financial intermediaries generally improves household capital incomes but comes at a small fixed cost. Initially, poor households cannot afford using banks for their savings, leading inequality to increase with financial development, as only wealthy-born households are able to use bank finance. However, as the economy develops and grows over time, poorer households become richer and can also begin using bank finance. Therefore, inequality after some point decreases with financial and economic development.

These models theoretically motivate the use of the ratio of private credit over GDP as a proxy for financial development. On the one hand, better-developed financial markets lead to either more investment in occupational choice or human capital, which requires financing by credit. Consequently, financial development and private credit growth should go hand in hand. On the other hand, better-developed financial markets allow more households in society to benefit from improved use of investment possibilities through the financial sector. This should thus increase bank deposits and overall savings in the economy as well as being funneled into more credit in the economy.

These theories are subjected to empirical research that uses cross-country datasets on income inequality to test for the negative and inverted U-shaped relationships of financial development and income distribution. Clarke, Xu, and Zou (2003) test these different theories. Using a dataset of 91 countries over the period from 1960 to 1995 and averaging the data over five-year periods, they confirm the theories of Kuznets (1955), Banerjee and Newman (1993), and Galor and Zeira (1993) and reject Greenwood and Jovanovic's (1990) model. To construct a measure of financial development, they use both private credit over GDP and bank deposits over GDP. The control variables are GDP per capita and its squared term to follow the Kuznets curve. Further control variables include the risk of expropriation, ethno-linguistic fractionalization, government consumption, inflation and the share of the modern sector. In addition to the linear negative impact of financial development on income inequality, the maximum of the Kuznets curve is calculated – depending on the econometric specification – as approximately 1,400 USD and 2,350 USD.

Beck, Demirgüc-Kunt, and Levine (2004) also test the three theories about the impact of financial development. They use private credit over GDP as a proxy for financial development and, in contrast to Clarke et al., use not 5-year averages but the average over the entire time horizon covered per country with a between estimator. Their 52-country sample from 1960 to 1999 also confirms the linear negative influence of financial development on income inequality. Li, Squire, and Zou (1998) explain variations in income inequality across countries and time. They approximate financial development as M2 over GDP, which has a significantly negative effect on inequality in their sample of 49 countries. They also distinguish between the effect of financial development on the poor and rich and find that it helps both groups. Further research backing Galor and Zeira and Banerjee and Newman is, for example, Kappel (2010), who uses a sample of 59 countries for a cross-country analysis and 78 countries for a panel analysis over the period 1960 to 2006. Kappel also distinguishes between high- and low-income countries. Whereas credit over GDP remains significant and negative for high-income countries, it does not show any influence for low-income countries. Jaumotte, Lall, and Papageorgiou (2008) investigate income inequality with a focus on trade and financial globalization. In their sample of 51 countries from 1981 to 2003, they have the measure of private credit over GDP only as a control variable. In contrast to Beck et al. and Clarke et al., they obtain a positive and significant coefficient for financial development in all different econometric specifications of their estimation. Without explicitly stating it, they thus reject the theories explained above and contradict work that simply focuses on the link between financial development and inequality. All of the described studies have in common that they examine a broad set of countries, development over time, and the theories we describe in detail. Furthermore, they begin with simple OLS estimations and pursue two-stage least squares estimation to tackle eventual omitted variable biases. Both random effect and between models are used, but no study compares fixed effect estimations with their results. Further empirical research (natural experiments, household studies, firm- and industry-level analyses, and case studies) on the link between financial development and income inequality is summarized in Demirgüc-Kunt and Levine (2009).

Finally, there is a new and growing strand of literature emphasizing the political dimension in the inequality and finance nexus. Rajan (2010), a leading proponent of this view, argues that the increased credit given to US households was a direct consequence of the rising inequality trend over the last two decades. Together with the political inability to use traditional forms of redistributive taxation, it seemed better and by far easier for politicians to improve access to credit for poorer American households. In this way, credit to GDP, or the literature's traditional measure of financial development, is influenced largely by politics and depends on increased inequality. Kumhof and Ranciere (2010) construct a theoretical model that endogenously explains how high credit growth and financial crises may result as a consequence of rising income inequality. The two argue that the periods 1920-1929 and 1983-2008 exhibited this type of pattern. However, the hypothesis that rising inequality generally leads to a credit boom is empirically rejected in a recent study by Bordo and Meissner (2012), who use a much larger dataset than Kumhof and Ranciere (2010) and conclude that there is no evidence that rising inequality leads to credit booms. This finding is naturally very important for our study because we ideally wish to treat financial development as a variable that is reasonably independent from income inequality. However, to be very sure, we add relevant robustness tests that also specifically allow for the endogeneity of financial development.

Our research adds value to the aforementioned literature, especially in the scope of analysis. The basic sample consists of 138 countries with observations covering the years 1960 to 2008. In total, we use 3228 country-year observations and 802 observations for the estimation with five-year averages. The large sample also allows us to distinguish between the effect of financial development in different country groups regarding income and region. This is to the best of our knowledge the largest dataset for an analysis of financial development and income inequality in terms of years as well as countries. This paper further controls for year effects with year dummies and country characteristics to isolate the effect of financial development and to reduce omitted variable bias. Finally, we conduct various robustness checks that support our key result that the data generally rejects the theoretical models.

3 DATA

(a) Description of dataset

We combine different datasets to derive what is to the best of our knowledge the largest dataset concerning financial development and income inequality. Income inequality is measured both as gross income before redistribution and net income after redistribution using the Gini coefficient. Redistributive policies may blur the theoretical relationship between financial development and income inequality, which is modeled without an explicit role for redistribution. Therefore, we use both gross and net Gini coefficients in our empirical analysis. The underlying source is Solt's Standardized World Income Inequality Database (SWIID) (2009), which "is the most comprehensive attempt at developing a cross-nationally comparable database of Gini indices across time" [Ortiz and Cummins (2011), p. 17]. The SWIID uses the World Income Inequality Database by the United Nations University, which is the successor of Deininger and Squire's (1996) database, data from the Luxembourg Income Studies (LIS), Branko Milanovic's World Income Distribution data, the Socio-Economic Database for Latin America, and the ILO's Household Income and Expenditure Statistics. The total coverage is at 171 countries with 4285 country-year observations and 802 observations for five-year averages.

The other important source for our research is the updated 2010 version of the Financial Structure Database by Beck, Demirgüc-Kunt, and Levine (2009), who collected data on both of our measures for financial development – private credit divided by GDP and bank deposits divided by GDP. Private credit is calculated based on the IMF's International Financial Statistics and consists of credit provided by deposit money banks and other financial institutions to the private sector. It does not include credit provided to the state or by central banks. Bank deposits are also based on the IMF's International Financial Statistics and consist of demand, time and savings deposits in deposit money banks. Both variables are standard measures of financial development and are used in the empirical literature described above.

Finally, we control for a host of other variables that have traditionally been used to explain inequality. GDP per capita is used in constant USD and taken from the World Development Indicators of the World Bank. Table 1 provides an overview of the definitions and sources of all variables used in this paper.[4]

[4] Table 11 in the Appendix provides an overview of our measures for financial development and income inequality for all countries in our sample. Figure 4 in the Appendix provides a 3-D chart of income inequality against GDP p.c. and financial development.

Table 1: Overview of variables and sources

Variable	*Definition*	*Source*
Gini (gross) and Gini (net)	Gini coefficient of gross and net income	Solt (2009)
Financial Development (1) – Private Credit/GDP	Private credit divided by GDP; claims on the private sector by deposit money banks and other financial institutions	Beck, Demirgüc-Kunt, and Levine (2009)
Financial Development (2) – Bank Deposits/GDP	Bank deposits divided by GDP; demand, time and savings deposits in deposit money banks	Beck, Demirgüc-Kunt, and Levine (2009)
GDP per capita	Constant 2000 USD; Country groups based on four income categories (high, upper middle, lower middle, and low income)	World Development Indicators, World Bank (2011)
Legal origin	Dummy variable regarding the origin of the legal system (UK, France, German, Scandinavian, Socialist)	La Porta, Lopez-de-Silanes, Vishny (2008)
Inflation	Consumer price index; change on previous year	World Development Indicators, World Bank (2011)
Agricultural Sector	Value added by the agricultural sector as a share of GDP	World Development Indicators, World Bank (2011)
Government Consumption	Government share of total expenditure	World Development Indicators, World Bank (2011)
Access to Finance	Different measures for the access to finance, e.g., number of ATMs per 100.000 inhabitants, minimum amount required to borrow as ratio over GDP p.c.	Financial Access Survey, International Monetary Fund (2011)
Ethnolingusitic Fractionalization (ELF)	Degree of the fractionalization of the population in 1985 with lower values indicating lower fractionalization	Roeder (2001)

Note: Tables 8a and 8b show the correlation coefficients for the variables used in this paper.

Private credit over GDP can be used as a proxy for financial development, as it reflects the ease with which households and corporations may obtain credit. When more credit is provided to the private sector, private institutions find it easier to signal their creditworthiness at the respective lending rate, and private individuals find credit markets to be more accessible. This argumentation does not always hold, as can be observed with real estate credit and the subprime crisis in the United States in 2007-08, but it is fairly robust over our entire sample. Furthermore, we do not have micro-level data regarding the distribution of credit in the population and among businesses and thus cannot asses how different groups in the population benefit from increasing credit provision and how this credit is used. Nonetheless, we do believe that it is a good proxy for financial development, as there is a high correlation between private credit over GDP and access to finance, measured by other measures such as the number of ATMs or number of bank branches per population or per square mile.[5] The alternative measure we use, bank deposits over GDP, serves as a proxy, as it again describes access to finance. With less or no financial development, fewer people have access to bank accounts. Lower values of bank deposits over GDP also reflect the lack of trust of creditors in their financial system and their banks. There are again some caveats, as we do not know the distribution of bank deposits among the population and businesses, and we have no data on the turnover rate of the deposits. Overall, and most importantly, both measures explain how well the financial system performs its inherent task – channeling funds and intermediating between creditors and debtors.

(b) Income inequality over time and around the world

Income inequality may be measured on a gross and on a net basis. Gross income excludes all income from non-private sources; i.e., it excludes pensions provided by the state to pensioners, all types of social transfers to economically poor people, and abstains from subtracting taxes as well as social contributions. Net income, in contrast, includes all types of public transfers and deductions. Net income measures the amount an individual possesses and may use for consumption and saving. Neither gross nor net income is the right instrument to measure the market outcome when individuals determine whether to follow a career opportunity, as gross income does not reflect what amount an individual can spend and save today, and net income does consider individuals' earning entitlements on pensions and other social benefits. This paper consequently uses both measures of income inequality and investigates how gross and net income inequalities are affected by financial development and other explanatory factors.

Income inequality (gross and net) is measured with Gini coefficients. The Gini for gross (net) income inequality is normally distributed for the entire pooled sample with a mean of 44.3 (38.4),

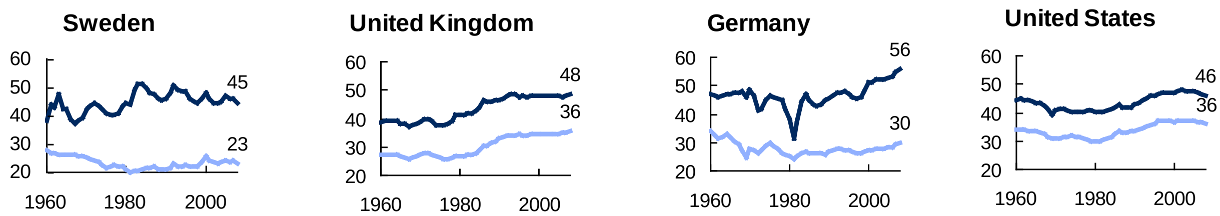
[5] Cf. table 7 for correlations between different measures of financial development.

standard deviation of 9.6 (10.1), skewness of .36 (.41) and kurtosis of 3.0 (2.5).[6] Income inequality generally changes only slowly over time. Splitting the sample in observations by year, the Gini coefficient becomes more normally distributed over time with lower standard deviations. This process is accompanied by higher means. Figures 2a and 2b in the Appendix show the distribution of gross and net inequality around the world, measured as the average over the years 2000 to 2004. Inequality is highest in Latin America and Sub-Saharan Africa. Very high and increasing levels of gross income inequality can also be observed in developed countries, such as Germany, the United Kingdom, and the United States. However, the level of net income inequality, i.e., after redistribution, is much lower than gross income inequality in developed countries, as shown in figure 1a. Even countries that are considered as being very equal, such as Sweden, have a high level of gross income inequality. These examples show that in discussing equality aspects, one must be explicit whether equality before or after redistribution is considered. In Germany and Sweden, net inequality is relatively constant compared to gross inequality, unlike the United Kingdom and the United States, where net and gross inequality move in parallel. Redistribution in these countries does not change when gross inequality increases or decreases. This is a very interesting result on its own, as it demonstrates how different societies address the issue of unequal income distribution.

A correlation analysis of gross and net Ginis with the other explanatory variables used shows that net income inequality has higher correlations with most variables compared to gross income inequality. From a theoretical point of view and with respect to the economic theories we outlined above, we must note that the theoretical case for financial development decreasing gross inequality may in fact be weaker than the case for financial development decreasing net inequality. Financial development may encourage risk taking, which may increase the gross Gini; meanwhile, financial development may allow households and countries to share their risks, thus reducing net Ginis. For all these reasons, we will focus on describing and interpreting the results of the estimations with net income inequality, but we will nevertheless report all results for gross income inequality throughout this paper.

[6] A normal distribution has a skewness of 0 and a kurtosis of 3.

Figure 1a: Inequality over time

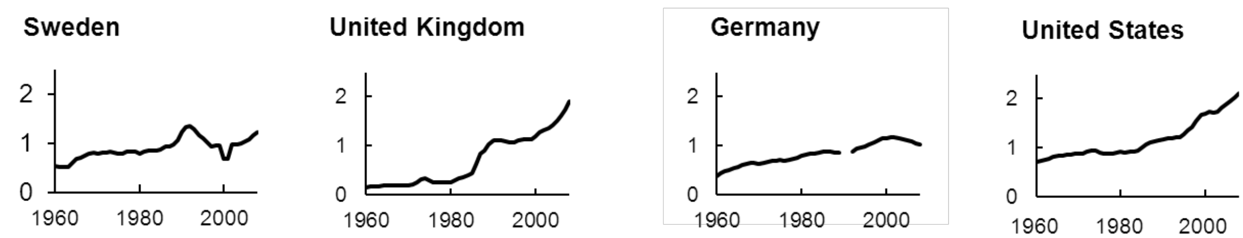


Note: The dark blue line shows gross income inequality. The light blue line shows net income inequality.

(c) Financial development over time and around the world

Financial development, defined by private credit over GDP, is increasing over time. Figure 1b shows our measure of financial development for a selection of developed countries. The process of financial development is generally more monotonic than the development of gross inequality. The mean for the entire sample is .45 with a standard deviation of .39. Figure 3 shows the stage of financial development for the countries in our sample for the years 2000 to 2004. As expected, financial development is especially high in OECD countries, with the highest levels found in countries of Anglo-Saxon origin. The countries with the highest values are Iceland, Luxembourg, and the United States. The distribution of financial development across countries and time is not as normal as it is for inequality, and thus, we transform the variable with logs for all estimations. This transformation changes the skewness from 1.5 to -.3 and the kurtosis from 5.0 to 2.8. In contrast to inequality, credit over GDP becomes more uniformly distributed across countries over time when examining different income country groups. Therefore, we do not observe a convergence to one level but rather that some countries remain at lower levels while other countries increase their credit provision more quickly. The second measure for financial development is bank deposits, which is used as a robustness check for credit over GDP. The development of bank deposits is similar to that of private credit (the mean is .42, and the standard deviation is .38). However, we point out that these measures do not determine each other equally. Whereas bank deposits are a prerequisite for the provision of credit and may be viewed as a main determinant of credit, this relation does not hold in the other direction. Financial intermediaries pool deposits and provide credit. Debtors use this credit to invest or consume but do not put this money in their bank account. Reverse causality can thus be excluded. This characteristic is important when we address potential endogeneity issues in the empirical part of this paper.

Figure 1b: Financial development over time



4 ECONOMETRIC ESTIMATION

(a) Basic estimation - Comparison with previous research

We test the hypotheses of Galor and Zeira (1993) and Banerjee and Newman (1993), namely that financial development has a negative impact on income inequality, and the hypothesis of Greenwood and Jovanovic (1990) that this influence follows an inverted U-shape. In the following, we label these hypotheses as GZ, BN, and GJ. Our basic estimation thus allows for nonlinearities due to the Kuznets curve as well as the first increasing and then decreasing influence of financial development. Equation (1) enables a comparison of our dataset with Gini coefficients that are suited for cross-country research with the results from other research.

(1) $Gini_{i,t} = \alpha + \beta_1 FD_{i,t} + \beta_2 FD^2_{i,t} + \ \beta_3 GDP\ p.c._{i,t} + \ \beta_4 GDP\ p.c._{i,t}^2 + \beta_j X_{i,t} + \varepsilon_{i,t}$

Following the hypothesis of a linear negative influence, β_1 should be negative and significant, and β_2 should be insignificant. According to the inverted U-shape hypothesis, β_1 should be significant and positive, and $\beta_2$should be significant and negative. We add *GDP per capita* and its squared term to control for the Kuznets curve. Therefore, β_3 should be positive and significant, and β_4 should be negative and significant. *Gini* is normally distributed and rather stable and consequently is not transformed into logs. Both *FD* (financial development) and *GDP p.c.* are transformed into logs, as both variables have a skewed distribution. The square of the variables is taken from the log. $X_{i,t}$ represents the control variables used. Following Clarke et al. (2003), we include ethnolinguistic fractionalization (*ELF*), inflation, the share of government expenditure in GDP and the share of the agricultural sector in total value added.[7] All measures but *ELF* are transformed in logs. Our second proxy for *FD* is *bank deposits*, which is also log-linearized and treated similarly to *credit*. We estimate the model with ordinary least squares (OLS). One impediment to our estimation is heteroskedasticity, which we address by using heteroskedasticity-robust standard errors. Furthermore, there are different approaches on how to proceed with yearly data.[8] Yearly data may represent cyclical movements, whereas using a five-year average yields a more balanced panel but at the same time means a loss in the number of observations. To compare the results of this larger and more suitable dataset with previous work, we focus on five-year averages. Most variables change slightly between years, which also leads to greater variation with five-year averages.

Table 2: Basic estimation

	Model				
	Gini (gross)		Gini (net)		
	(1a)	(1b)	(2a)	(2b')	(2b)
FD	-3.17	-0.83	-6.83***	-4.17**	-2.33
FD²	0.58*	0.25	1.17***	0.72**	0.44
GDP p.c.	13.39***	13.11***	22.42***	21.83***	21.85***
GDP p.c.²	-0.93***	-0.87***	-1.68***	-1.62***	-1.63***
ELF		6.57***		9.25***	9.08***
Inflation		-0.46			-0.20
Gov. expendit.		1.66*		-1.26	-0.96
Agriculture		0.33		-1.57***	-1.56***
Constant	3.90	-9.79	-20.82***	-20.99**	-24.27***
N	802	637	802	666	637
R²	0.07	0.10	0.38	0.45	0.44
Max/Min of:					
FD (priv. credit)	strictl. positive	not significant	18.48%	18.11%	not significant
GDP (in USD)	1,376	1,933	784	832	828

***, **, * denote statistical significance levels at 1%, 5%, and 10%

[7] Clarke et al. use the share of the modern sector (industry and services), which is equivalent to one minus the agricultural share.

[8] Romer and Romer (1999) and Papageorgiou et al. (2008) use yearly data. Five-year averages are used by Clarke et al. (2003), Li et al. (1998), and Kappel (2010). Beck et al. (2004) and Kappel (2010) do not use information provided by yearly data or averages over several years and estimate the effect of financial development on income inequality with country means.

Note: Income inequality, measured as the Gini coefficient, is the dependent variable for all models. Model 1 uses the Gini coefficient of gross income, and model 2 uses the Gini coefficient of net income. All data are five-year averages, and the models are estimated with default heteroskedasticity-robust standard errors. Model *a* is estimated without control variables, and model b includes control variables. Model 2b' includes all control variables except inflation, as omitting inflation increases the adjusted R^2. The Max/Min of FD (financial development) and GDP indicate the level at which the sign of the explanatory variable changes. Neither country fixed effects nor time dummies are included to make the results comparable to previous research. We also abstain from using cluster-robust standard errors to compare these results with previous research. The estimation results with bank deposits as a proxy for financial development are found in table 10 in the Appendix.

Using the approach of previous research, not correcting for clusters in the sample and not including a time trend or time dummies, this dataset confirms some of the earlier results. Pooling all observations while disregarding time-invariant country characteristics shows that *GDP per capita* is positive and significant in its linear form and negative and significant in its quadratic from. Therefore, the influence of *GDP per capita* mirrors an inverted U-shape – a Kuznets curve. Kuznets' hypothesis on the development of income inequality during the process of economic development appears to be true, and the values for gross income inequality are in line with Clarke et al. (2003), who estimated the maximum of the Kuznets curve between 1,250 and 2,350 USD. The maximum net income inequality is reached earlier at approximately 800 USD. This finding indicates that societies begin to redistribute income before the peak in gross income inequality is reached.

The effect of financial development on income inequality is not so clear. Controlling for other factors, there is no significant effect of financial development on gross income inequality, which does not support the above theories. Estimating the effect on net income inequality, financial development appears to generate a U-shaped response in inequality, which is contradictory to the theories. BN and GZ are backed only up to a certain degree of development, whereas GJ can reasonably be rejected. Up to the provision of private credit over GDP of approximately 18%, financial development lowers net income inequality but increases inequality afterwards. A robustness check with the second proxy for financial development indicates that financial development does not have a significant effect on net income inequality and has only a small negative effect on gross income inequality (cf. Table 10 in the Appendix). The results on the effect of financial development are consequently inconclusive, but we cannot fully confirm any of the theoretical models described above. In a second step, we correct the default standard errors in the pooled OLS estimation for clustered data.[9] The Kuznets curve remains apparent, but the link of financial development and income inequality disappears.

To summarize, using the approach of former papers with an advanced dataset confirms the results for the effect of GDP but backs the theoretical and known empirical effects of financial development only to a certain degree.

(b) Econometric hurdles

Former research considered endogeneity and used an instrumental variable approach to estimate the impact of financial development, allowing for the possibility that inequality influences financial development or for an omitted variable bias. The results did not differ much from the OLS approach. Instruments for financial development were in line with the literature on financial development and the origin of a country's legal system. Following the same approach and using *legal origin* dummies as exogenous instruments leads to a R^2 of 57% in the first-stage regression in our sample when we include *GDP p.c.*, the other exogenous explanatory variables of the second stage regression and the time dummies. The fitted values for *FD* have a correlation of 76% with the original values and thus may viewed as having a good fit.

However, legal origin may not be a good instrument for financial development when investigating the inequality nexus. The famous French slogan "liberté, egalité, fraternité" of course includes equality. This characteristic shows that the origin of the legal system is not independent of inequality and is consequently not suitable as an instrument. To ensure that reverse causality is still not a problem, we conduct estimations with lagged explanatory variables, two-stage least square estimations and GMM estimation in our robustness section (please see section 5 below).

However, an endogeneity problem may also occur due to omitted variables. We address this issue by using a fixed effects regression including time dummies, which is also the main difference separating our econometric approach from previous research. Country dummies are included to control for country-specific characteristics that do not change over time but are potentially influential with regard to income inequality. These can be cultural factors, religion, colonial background and others. Time dummies are included to control for common shocks for all

[9] Clarke et al. (2003) and Kappel (2010) do not report what type of standard errors they use. Therefore, we compare heteroskedasticity robust as well as cluster robust estimations with their results.

countries such as major international political events or large business cycle fluctuations. Finally, we allow for a linear time trend, as we expect *Credit* and *GDP p.c.* to grow over time as countries become better developed and richer.

Another problem often occurring in estimations is multicollinearity. Multicollinearity reduces the power of the OLS estimator, but the estimator remains unbiased and efficient. The Variance Inflation Factor (VIF) shows a high degree of multicollinearity, which is due to the structure of our base estimation with linear and squared terms of financial and economic development. Estimating the influence of financial and economic development on income inequality with either linear or squared terms only reveals a low result for the VIF and confirms that multicollinearity is not an issue in estimation.

The estimations in table 2 may face an omitted variable bias because there are no country-specific effects included aside from ethnolinguistic fractionalization that explains income inequality. Therefore, as a next step, we control for country-specific effects by conducting a fixed effect estimation. Fixed effects are not a cure for all omitted variable problems as time-variant country characteristics are not included, but it is a good first approach to tackle a potential omitted variable bias (cf. Acemoglu et al. (2008)). A further potential critique regarding the estimation process is endogeneity caused by reverse causality. An option to solve reverse causality is to use a two-stage least squares (2SLS) estimation, which is performed in the next section.

(c) Fixed effect estimation

Key to this paper is the explanation of the influence of financial development on income inequality within and not between countries. Therefore, the results are not to be used to compare the levels of income inequality across countries. The estimation results answer the question how financial development in the countries included in this broad dataset influences the income distribution. To estimate this influence, we use the fixed-effect estimator, also known as a within estimator. The within estimator has the advantage of controlling for country characteristics and, in contrast to the between estimator, uses all observations of the dataset and developments over time. Amending the basic estimation (1) by time dummies γ_t and country-specific time-invariant effects α_i leads to the new estimation equation (2).

(2) $Gini_{i,t} = \alpha + \beta_1 FD_{i,t} + \beta_2 FD_{i,t}^2 + \beta_3 GDP\ p.c._{i,t} + \beta_4 GDP\ p.c._{i,t}^2 + \beta_j X_{i,t} + \gamma_t + \alpha_i + \varepsilon_{i,t}$

The fixed-effect estimator subtracts the country-specific mean from each variable so that all time-invariant factors drop out. Table 3 shows the results of the fixed-effect estimation. To ensure that reverse causality does not disturb the estimation, the results of a two-stage least squares estimation (2SLS) with bank deposits taken as exogenous variable are included in table 3. As before, yearly data and five-year averages lead to similar coefficients, and we report five-year averages.

Table 3: Fixed-effect and 2SLS estimation

	Model					
	Gini (gross)			Gini (net)		
	(3a)	(3b)	(3c)	(4a)	(4b)	(4c)
FD	2.57***	2.75***		1.76***	1.89***	
FD - fitted			2.82***			2.13***
FD²		not significant[1]			not significant[1]	
GDP p.c.	-24.10***	-21.90***	-21.86***	-6.88	-9.04**	-9.31**
GDP p.c.²	1.56***	1.40***	1.39***	0.43	0.56*	0.57*
Inflation		-0.53*	-0.55**		-0.35*	-0.34*
Govern. exp.		1.38	1.20		0.84	0.68
Agriculture		0.13	0.07		-0.05	-.08*
Constant	133.95***	123.39***	124.10***	61.15***	64.00***	65.69***
N	802	668	669	802	668	669
R^2 (within)	0.25	0.26	0.23	0.08	0.12	0.10
Max/Min of:						
FD (priv. credit)	strictl. pos.	strictl. pos.	strictl. pos.	strictl. pos.	strictl. pos.	strictl. pos.
GDP (USD)	2,240	2,547	2,659	not signif.	3,090	3,797

***, **, * denote statistical significance levels at 1%, 5%, and 10%

[1]Both terms for *FD* are insignificant in a quadratic estimation; therefore, *FD* only enters linearly in the model

Note: Model 3 is estimated with Gini coefficients of gross income as the dependent variable, and model 4 uses Gini coefficients of net income. Model a is a fixed effect estimation without further control variables, model b is a fixed effect estimation with control variables and model c is a 2SLS estimation, where the first-stage results are shown in table 9 in the Appendix. All models use data averaged over five-year periods and are estimated with heteroskedasticity-robust standard errors. Max/Min of *FD* (Financial development) and *GDP p.c.* indicate the level at which the sign of the explanatory variable changes. Both models include time dummies. The estimations with bank deposits as proxy for financial development are found in table 10.

We proceed in several steps, each of which produces similar results for the influence of financial development on income inequality. Independent of the inclusion of control variables, of the investigation of gross or net income, and of a fixed effects or 2SLS-fixed effects model, financial development has a significantly positive effect on income inequality. In other words, our findings somewhat surprisingly suggest that financial development increases income inequality. The distribution of gross income reacts more strongly than the distribution of net income to financial development. For the normal fixed effect models, the impact is approximately 45% larger, and for the 2SLS, the magnitude of the effect is 33% larger. The influence is statistically highly significant, and its economic consequences are also considerable. An increase of financial development by ten percent increases the net Gini by approximately 0.2 points.

Equally surprising are our results for the effects of GDP per capita or economic growth on inequality. In contrast to Kuznets' inverted U-shaped hypothesis, income inequality first decreases with the process of development and increases after surpassing a threshold of roughly 2,500 USD for gross income and over 3,000 USD for net income. A possible explanation for this behavior is that Kuznets was focusing on the time of industrialization over the 19^{th} and early 20^{th} centuries. The time period covered in this paper begins much later. The earliest observations in our dataset are from the 1960s, enabling an initial decreasing inequality to remain in line with Kuznets. However, when a country reaches a certain development level – which was not yet reached when Kuznets wrote his work – a small fraction of the population may be better able to extract rents from using their abilities, thereby increasing inequality again. Nevertheless, this fact does not exclude the possibility that the absolute income level of the poor also increases and that the poor benefit from economic and financial development.

Inflation is the only control variable that is constantly significant. Considering inflation as an indicator of macroeconomic stability, the estimation results indicate that higher levels of uncertainty tighten the income distribution. Nonetheless, the small coefficient of inflation signals that the effect is economically minor. The explanatory power of the fixed effect estimation differs between gross and net income. The within-R^2 for gross income is over twice the size of that for net income, and thus, the estimation is more effective in explaining the development of gross income inequality over time.

To summarize, both measures of financial development, private credit over GDP and bank deposits over GDP, support the first part of GJ that the use of financial intermediation does not hamper the poor but favors rich people. This claim is supported by our empirical analysis. In contrast, the predictions of BN and GZ are rejected by the estimation results. Because our results stand in contrast to theoretical models and some earlier empirical work, the next section will provide several robustness checks.

5 ROBUSTNESS CHECKS

The robustness checks include estimations for subsamples of countries (cf. table 5), additional estimations with a lagged dependent variable and lagged explanatory variables (cf. table 6) and correlation analyses to further support the ratio of private credit over GDP as measure for financial development (cf. table 7).

First, we investigate whether the effects on income inequality hold for different country groups. This estimation requires the use of yearly data, as five-year averages would provide an insufficient number of observations. We split the sample into four groups according to the income categories defined by the World Bank. The high-income group consists of 1035 country-year observations, the upper-middle-income group consists of 633, the lower-middle-income group consists of 637, and the low-income group consists of 349. All estimations are performed with fixed-effect estimators and yearly data, including time dummies, to identify the influence of financial and economic development on the variation of income inequality independent of a time factor and country-specific characteristics. We include the same control variables as before. Robust standard errors are used when necessary. Splitting the sample into country groups, we expect the signs of the coefficients for economic and financial development as follows:

Table 4: Financial Development and The Kuznets curve in different income groups

	Low Inc.	Lower Middle Inc.			Upper Middle Inc.			High Income			Rational
GDP	positive	Positive	or	positive	negative	or	positive	negative			Kuznets
GDP²	insig.	insig.		negative	insig.		negative	insig.			
FD	positive	Positive	or	positive	positive	or	positive	positive	or	negative	Greenw. &
FD²	insig.	insig.		negative	insig.		negative	negative		insig.	Jovan.

Depending on the exact turning point in the models of Kuznets and Greenwood and Jovanovic, the squared terms of GDP per capita and financial development in the lower and upper middle income group may be insignificant, and we expect different signs of the linear terms for the high- and low-income groups. Table 5 shows that splitting the countries into subsamples backs the results of the previous section.

Table 5: Fixed-effect estimation by income group

Income level	Gini (gross): Low	Gini (gross): Lower Middle	Gini (gross): Upper Middle	Gini (gross): High	Gini (net): Low	Gini (net): Lower Middle	Gini (net): Upper Middle	Gini (net): High
FD	4.80**	2.81***	5.89*	15.87***	2.72**	2.26**	1.77***	1.75*
FD²	not significant[1]		-0.72	-1.70**	not significant[1]			
GDP p.c.	-0.18	18.39	34.41	-36.69*	-99.39*	23.38*	8.94	-16.46
GDP p.c.²	-0.16	-1.51	-2.43	1.67	9.32*	-1.90*	-0.55	0.61
Inflation	0.17	0.22	0.04	0.08	0.62*	-0.04	-0.04	-0.02
Govern. exp	-2.44	0.76	0.13	1.39	-0.56	-0.41	0.61	-0.64
Agriculture	-3.48	0.63	1.91***	-2.21*	-0.88	0.27	2.60***	-1.42
Constant	58.46	-15.69	-77.04	202.37**	302.04**	-32.74	-13.73	126.93**
N	349	633	637	1,035	349	633	637	1,035
R^2 (within)	0.39	0.27	0.45	0.29	0.29	0.15	0.24	0.29
Max/Min of:								
FD (credit)	Strictly positive	Strictly positive	Strictly positive	107%	Strictly positive	Strictly positive	Strictly positive	Strictly positive
GDP (USD)	not signif.	not signif.	not signif.	Strictly. neg	200	457	not signif.	not signif.

***, **, * denote statistical significance levels at 1%, 5%, and 10%

[1]Both terms for *FD* are insignificant in a quadratic estimation so that the *FD* only enters linearly in the model

Note: All estimations are fixed-effect estimations with time dummies and robust standard errors. Max/Min of *FD* and *GDP* indicate the level at which the sign of the explanatory variable changes. All data are yearly data, as there are too few observations for this robustness check using five-year averages. The correlation coefficients for income inequality, financial development and GDP per capita are provided in table 8a.

The estimation by country sample reveals that financial development has a positive effect on net income inequality for all country groups, which leads to the rejection of BN and GZ and confirms the part of GJ that explains rising inequality. For gross income inequality, we do find an inverted U-shaped influence. With regard to financial development, which is reflected by a ratio of private credit to GDP of 107%, increasing financial development leads to increasing income inequality.

Only after this level is surpassed is income inequality reduced. For the influence of GDP, we only observe significant effects on gross income inequality in high-income countries, where increasing income leads to a reduction in income discrepancy. For net income, there are only significant effects in the two lower-income groups. For very low incomes, i.e. below 200 USD, inequality is decreased before it rises. In the lower-middle-income group, inequality first increases and is reduced after reaching 457 USD. This finding indicates that a Kuznets curve may be observed for the lower-middle-income countries, but the p-values are close to 0.1. Furthermore, GDP is of no significant influence for upper-middle-income and high-income countries. As before, the control variables are mostly without a significant influence.

Second, we adjust the fixed-effect estimations to consider that income inequality changes slowly over time. Therefore, we include a lagged dependent variable that represents the long-term effects on income inequality. The variable is highly significant and shows that approximately half of gross income inequality is determined by its level of the previous five-year term. The coefficient for net income inequality is smaller, at approximately one third. Net income inequality thus reacts more to short-term factors and policy action compared to gross income inequality. Governments are consequently not as active (or as possible to act) on gross income inequality than they are on redistributing income and influencing the distribution of net incomes. Regarding the influence of financial development, the results are in line with our main fixed effect estimation: more financial development is associated with a more unequal income distribution, which is more pronounced for gross than for net income. For economic development, there is again an inverted Kuznets curve. Including the lagged dependent variable substantially increases the explanatory power of the estimations; the within-R^2 for the net Gini triples.

Third, we control for potential reverse causality by taking lags of the explanatory variables. Addressing the arguments that the explanatory factors need time to influence income inequality and that there could be a simultaneity bias, this estimation measures the influence of financial and economic development on the income distribution in five years. The explanatory power on gross income inequality is reduced but remains approximately the same for net income inequality. The sign of financial development remains positive, and the coefficient increases by 107% for the gross Gini and 70% for the net Gini. The medium-term influence of financial development on income inequality is a substantially more profound than the short-term influence. Furthermore, there is again the inverted Kuznets curve for gross income at the same GDP per capita level as without lagged variables. The influence of GDP per capita on net income inequality becomes negative. Higher levels of income, combined with increasing gross income inequality, therefore lead to higher redistribution and lower net income inequality. However, GDP per capita is significant at only the 10% level, with a p-value of 0.094.

As a fourth step, the first difference estimator and GMM estimators are taken as further approaches to exclude potential endogeneity problems. As discussed above in the literature review, there is an important recent view that growing inequality – at least in the US – was in fact the driving cause of the recent credit boom and subsequent financial crisis (see. e.g., Rajan (2010) or Kumhof and Ranciere (2010)). Whereas the issue appears to be empirically settled by Bordo and Meissner (2012), who use a large panel dataset and find that this view is incorrect, we nevertheless wish to examine how robust our results are to treating financial development as possibly endogenous variable and using a GMM estimator. The GMM estimator used tackles potential endogeneity problems by instrumenting the questionable variable with its own lag. A test on endogeneity of the financial development and GDP per capita variables following the GMM estimation states that the variables may be treated as exogenous and confirms the validity of our main fixed-effect estimation. The GMM estimation also results in an inverted Kuznets curve for gross and net income inequality; however, the levels of GDP per capita when the influence of economic development on income equality changes are substantially higher. Regarding financial development, the projection of Greenwood and Jovanovic (1990) is supported. Up to a provision of private credit to GDP of 127% for gross income and 140% of net income, more financial development leads to higher inequality. Thereafter, financial development reduces inequality. The predictable power of this result should be treated with caution, as only very few OECD countries reached this high level of credit provision in the five years averaging 2000-04 (cf. figure 3).

Table 6: First difference estimator and lagged variables

	Model							
	Gini (gross)				Gini (net)			
	(1) Lagged dependent	(2) Lagged explanatory	(3) First difference	(4) GMM	(1) Lagged dependent	(2) Lagged explanatory	(3) First difference	(4) GMM
Gini-lagged	0.48***				0.35***			
FD	4.35**	5.69**	1.39***	16.58***	3.61**	3.22**	1.34***	11.51***
FD²	-0.34	-0.61	0.43	-1.71*	-0.28	-0.30	0.56	-1.17**
GDP p.c.	-15.05***	-25.40***	-0.96	-38.51***	-8.40**	-7.89*	-2.86**	-16.54**
GDP p.c.²	0.85**	1.62***	4.43	2.06***	0.45*	0.48	10.33**	0.81*
Inflation	-0.12	-0.15	-0.37*	-0.23	-1.50	-0.44	-0.04	-0.25
Gov. exp	0.83	1.35	0.48	0.35	1.44	1.57	1.53	0.16
Agriculture	-0.06	-0.21	-1.18	-1.37	0.24	-0.10	-018	-0.71
Constant	76.64***	130.08***	-3.14		49.44***	60.62***	-0.64	
N	605	532	524	552	605	532	524	552
R² (within)	0.45	0.18			0.30	0.14		
Max/Min of:								
FD (credit)	strict. pos.	strict. pos.	strict. pos.	127%	strict. pos.	strict. pos.	strict. pos.	140%
GDP (USD)	6,836	2,530	not sig.	11,409	10,500	strict. neg.		26,372

***, **, * denote statistical significance levels at 1%, 5%, and 10%

Note: All estimations are performed for gross and net income inequality. The first model includes the lagged Gini coefficient and is estimated as a fixed effect model. The second model uses the first lag of all explanatory variables and is estimated as a fixed-effect model. The third model is a first difference model and estimates the effect of changes in the explanatory variables on changes of the dependent variable. The fourth model is a 2-step GMM estimation (STATA command xtivreg2) using lagged variables of financial development and GDP per capita as instruments. All data are five-year averages, and all models except GMM, which uses a time variable, are calculated with time dummies and robust standard errors.

Another possible criticism of our approach concerns our measure of financial development. Does the magnitude of credit provision truly indicate financial development? We strongly believe so. First, the amount of credit over GDP indicates the level of financial intermediation. If financial intermediaries were unable to assess credit risk, to overcome a maturity mismatch and to pool savings, they would provide less credit to households and enterprises. Second, the amount of credit may be biased towards few borrowers with high amounts outstanding and many borrowers with low amounts of credit and even more potential borrowers with no access to finance at all. We address this criticism, which essentially asks whether the amount of credit does in fact measure access to finance by investigating the empirical link between our measures of financial development and other maybe more direct measures of access to finance. The IMF's Financial Access Survey (2011) and Demirgüc-Kunt and Beck (2007) provide different measures for the access to financial intermediaries. Correlations of these measures with *credit* are shown in table 7.

Table 7: Access to finance and the provision of credit

	Access to finance				
Correlation coefficients	ATMs per 100,000 inhabitants (2004)	Loans per 1,000 people[1]	Bank branches per 100,000 people[1]	Minimum loan volume to SMEs as % of GDP p.c.[1]	Share of adult population with access to an account with a financial intermediary[1]
Credit over GDP	0.74	0.61	0.57	-0.29	0.69
# countries	71	39	86	48	80

[1]Year may differ by country; credit over GDP is taken as the average from 1999 to 2003

Note: The number of ATMs is taken from the IMF's Financial Access Survey. The other measures are taken from the World Bank.

The measures for access to finance are only available as cross-section data and not as panel data and differ with regard to the number of countries covered. Therefore, a replication of the previous fixed-effect panel estimations is not feasible, and a cross-country analysis remains the best option to investigate the appropriateness of the credit measure for financial development. The first out of five ratios under consideration is the number of ATMs per 100,000 inhabitants, which indicates how many people use bank accounts. If credit and bank access were only relevant for a few, there would be fewer ATMs. The correlation of 0.74 for a set of 71 countries backs our use of credit as a proxy for financial development. The number of loans and the number of bank branches point in the same direction. If only a small proportion of the population would use financial intermediaries for the provision of credit, there would be fewer banks and fewer loans. Financial development in the sense of Banerjee and Newman (1993) means that funding for small and medium enterprises becomes easier. In particular, small loans may help to start a business or grow a small business. The minimum loan volume should also be lower in better-developed financial markets, as credit evaluation and provision processes should be more efficient and worthwhile for banks, even for relatively lower amounts of credit. The negative correlation of minimum loan volume with total credits confirms this fact. Lower minimum credit volumes are associated with a greater the provision of credit. The fifth indicator we use is based on survey data and measures the overall access of the adult population to a bank account. Even developed countries in the European Union have values below 100%, as some people abstain from banking voluntarily or involuntarily due to discrimination or the fee structure. Again, more people using financial services are correlated with higher amounts of credit. All these correlations over different measures and different sets of countries legitimize in our view the use of the private credit over GDP ratio as a proxy for financial development.

6 CONCLUSION

Two phenomena can be observed over the last five decades around the world – increasing financial development and increasing gross income inequality in many countries, especially in the developed world. We discussed theoretical models, which explain the link between financial development and income inequality and predict that better-developed financial markets lead to decreasing levels of income inequality regarding labor and entrepreneurial income and first increasing and then decreasing levels regarding capital income. Earlier empirical research focusing on this financial development versus income inequality nexus has broadly confirmed the decreasing effect of financial development. This research either is built upon a pure cross-country perspective that cannot account for the many country-specific characteristics or uses panel data approaches but, again, neglect country-specific characteristics.

Using a broader data set and time-invariant country specifics in our panel estimation, we reach a different conclusion in the analysis of this nexus and reject these earlier theories and previous empirical research. Integrating time-invariant country characteristics, we find a positive relationship between financial development and income inequality within countries. Better-developed financial markets lead to higher gross income inequality. This finding holds for several robustness checks, e.g., for subsamples by different income groups, neglecting country characteristics and including further control variables, as well as bank deposits as an alternative measure for financial development. The positive relationship is highly significant but is only of a small magnitude. An increase in the provision of credit by ten percent leads to an increase in the Gini coefficient by 0.23 for the within estimation.[10]

We do not exclude the possibility that all income groups within a country benefit from more financial development, but we do find that those who are already better off benefit more because income inequality is increasing. These results add to the existing literature on financial development and income inequality by using new estimation techniques and a dataset with more countries for a longer time horizon compared to previous research. Our results should, at the very least, allow researchers to remain somewhat skeptical when confronted with the supposedly beneficial effects of financial development. It appears instead to be very important to target financial development towards the poorest in society. Only then can we hope for inefficient and excessive inequality to reduce. Nonetheless, the relationship between finance, financial development and income inequality offers more research opportunities and merits more resources and effort.

[10] This value ranges from 0.17 to 0.26 depending on the subsample and specification.

References

Acemoglu, D., Johnson, S., Robinson, J. A., & Yared, P. (2008). Income and Democracy. *American Economic Review*, *98*(3), 808–842.

Atkinson, A. B., Piketty, T., & Saez, E. (2011). Top Incomes in the Long Run of History. *Journal of Economic Literature*, *49*(1), 3–71.

Banerjee, A. V., & Newman, A. F. (1993). Occupational Choice and the Process of Development. *Journal of Political Economy*, *101*(2), 274–298.

Beck, T., Demirguc-Kunt, A., & Levine, R. (2004). *Finance, Inequality, and Poverty: Cross-Country Evidence* (No. 10979).

Beck, T., Demirguc-Kunt, A., & Levine, R. (2010). Financial Institutions and Markets across Countries and over Time: The Updated Financial Development and Structure Database. *World Bank Economic Review*, *24*(1), 77–92.

Bordo, M. D., & Meissner, C. M. (2012). Does Inequality Lead to a Financial Crisis? *National Bureau of Economic Research Working Paper Series*, *17896*.

Clarke, G., Xu, L. C., & Zou, H.-f. (2003). *Finance and income inequality: Test of alternative theories* (No. 2984).

Clarke, G. R. G., Xu, L. C., & Zou, H.-f. (2006). Finance and Income Inequality: What Do the Data Tell Us? *Southern Economic Journal*, *72*(3), 578–596.

Deininger, K., & Squire, L. (1996). A New Data Set Measuring Income Inequality. *World Bank Economic Review*, *10*(3), 565–591.

Demirgüç-Kunt, A., Beck, T., & Honohan, P. (2008). *Finance for all?: Policies and pitfalls in expanding access* (No. urn:nbn:nl:ui:12-3508393).

Demirgüç-Kunt, A., & Levine, R. (2009). Finance and Inequality: Theory and Evidence. *Annual Review of Financial Economics*, *1*(1), 287–318.

Galor, O., & Zeira, J. (1993). Income Distribution and Macroeconomics. *Review of Economic Studies*, *60*(1), 35–52.

Greenwood, J., & Jovanovic, B. (1990). Financial Development, Growth, and the Distribution of Income. *Journal of Political Economy*, *98*(5), 1076–1107.

International Monetary Fund. (2011). *Financial Access Survey*.

Kappel, V. (2010). *The Effects of Financial Development on Income Inequality and Poverty* (No. 10/127).

Kumhof, M. & Ranciere, R. (2010). *Inequality, Leverage and Crises* (No. 10/268).

Kuznets, S. Economic Growth and Income Inequality. *The American Economic Review*, *1955*(45), 1–28.

La Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (2008). The Economic Consequences of Legal Origins. *Journal of Economic Literature*, *46*(2), 285–332.

Levine, R. (2005). Finance and Growth: Theory and Evidence: 12. In Philippe Aghion & Steven Durlauf (Eds.), *Handbook of Economic Growth. Handbook of Economic Growth* (pp. 865–934). Elsevier.

Li, H., Squire, L., & Zou, H.-f. (1998). Explaining International and Intertemporal Variations in Income Inequality. *Economic Journal*, *108*(446), 26–43.

Ortiz, I. & Cummins, M. (2011). *Global Inequality: Beyond the Bottom Billion – A Rapid Review of Income Distribution in 141 Countries* (No. 1102).

Papageorgiou, C., Lall, S., & Jaumotte, F. (2008). *Rising Income Inequality: Technology, or Trade and Financial Globalization?* (No. 08/185).

Philippe Aghion, & Steven Durlauf (Eds.). (2005). *Handbook of Economic Growth*. *Handbook of Economic Growth*: Elsevier.

Rajan, R. G. (2010). *Fault Lines*. Princeton, NJ: Princeton University Press

Roeder, P. G. (2001). *Ethnolinguistic Fractionalization (ELF) Indices, 1961 and 1985.*

Romer, C. D., & Romer, D. H. (1999). Monetary policy and the well-being of the poor. *Economic Review*, (Q I), 21–49.

Solt, F. Standardizing the World Income Inequality Database. *Social Science Quarterly*, *90*(2), 231–242.

World Bank. (2011). *World Development Indicators*. Washington D.C.

APPENDIX

Tables

Table 8a: Correlation analysis

	Complete Dataset (N=3228)			
	Gini (gross)	*Gini (net)*	*FD*	*GDP p.c.*
Gini (gross)	*1.000*			
Gini (net)	*.7852****	*1.000*		
FD	*-.089****	*-.397****	*1.000*	
GDP p.c.	*-.145****	*-.537****	*.753****	*1.000*

	High Income (N=1285)				Upper Middle Income (N=739)			
	Gini(g.)	*Gini (n.)*	*FD*	*GDP p.c.*	*Gini (g.)*	*Gini (n.)*	*FD*	*GDP p.c.*
Gini (gr.)	*1.000*				*1.000*			
Gini (net)	*.525****	*1.000*			*.825****	*1.000*		
FD	*.142****	*.063***	*1.000*		*.298****	*.301****	*1.000*	
GDP p.c.	*.048****	*-.231****	*.642****	*1.000*	*.054*	*.206****	*.235****	*1.000*
Gini (gr.)	*1.000*				*1.000*			
Gini (net)	*.826****	*1.000*			*.903****	*1.000*		
FD	*-.083***	*-.049*	*1.000*		*.048*	*-.001*	*1.000*	
GDP p.c.	*.242****	*.350****	*.511****	*1.000*	*.256****	*.254****	*.259****	*1.000*
	Lower Middle Income (N=765)				Low Income (N=439)			

*,**,*** represent the significance level of the correlation coefficient (10%, 5%, and 1%);

Notes: Correlation of Gini coefficients with financial development (credit over GDP) and GDP per capita for the full sample and for subsamples along income groups. Correlations and significance levels were calculated in Stata by *pwcorr*, *sig*; FD (Financial Development, i.e., private credit over GDP) and GDP p.c. are in logs.

Table 8b: Correlation analysis

	Gini (gross)	**Gini (net)**	FD (credit)	FD (depos.)	GDP p.c.	Infla-tion	Share of Gover. Expenditure	Share of Agricult. in GDP	Ethno-Ling. Fractio-nalization (ELF)	Leg. org. UK	Leg. org FR	Leg. org GE
Gini (gross)	**1.00**											
Gini (net)	**0.71**	**1.00**										
FD (credit)	**-0.04**	**-0.38**	1.00									
FD (deposits)	**-0.14**	**-0.40**	0.86	1.00								
GDP p.c.	**-0.12**	**-0.53**	0.74	0.68	1.00							
Inflation	**0.08**	**0.23**	-0.41	-0.40	-0.29	1.00						
Gov exp.	**-0.02**	**-0.31**	0.37	0.37	0.43	-0.21	1.00					
Agriculture	**0.08**	**0.42**	-0.69	-0.66	-0.87	0.35	-0.41	1.00				
ELF	**0.20**	**0.45**	-0.34	-0.35	-0.52	0.11	-0.24	0.36	1.00			
Legal org. UK	**0.13**	**0.12**	-0.02	0.04	-0.13	-0.01	0.02	0.03	0.30	1.00		
Legal org. FR	**0.04**	**0.27**	-0.19	-0.18	-0.16	0.12	-0.22	0.19	0.06	-0.69	1.00	
Legal org. GE	**-0.22**	**-0.31**	0.17	0.15	0.20	-0.09	0.09	-0.19	-0.31	-0.25	-0.37	1.00

Notes: Correlation of Gini coefficients, measures for financial development (both, private credit over GDP and bank deposits over GDP), GDP per capita and the control variables used in the analyses (N = 2,565).

Table 9: First stage regression – Financial development

Dep. var: FD (credit)	Coefficient	p-Value
Bank deposits	0.8145	0.000
GDP p.c.	0.3381	0.435
GDP p.c.^{2}	0.0057	0.845
Inflation	-0.0071	0.676
Government expenditure	0.1208	0.205
Agriculture	-0.0699	0.443
Constant	-2.3159	0.145
N	668	
R^2 - within	0.67	

Notes: The first-stage regression yields the fitted values of financial development (private credit over GDP) for the second-stage regression for the Gini coefficients. The estimation is a fixed-effect estimation with robust standard errors and time dummies.

Table 10: Robustness check with Bank deposits as proxy for financial development

	Model					
	Gini (gross)			Gini (net)		
	(1) Pooled OLS	(2) Pooled OLS-Cluster	(3) Fixed effects	(1) Pooled OLS	(2) Pooled OLS-Cluster	(3) Fixed effects
FD	-1.01*	-1.01	2.34***	-0.67	-0.67	1.72***
FD²	not signif.[1]	not signif.	not signif.[1]	not signif.	not signif.	not signif.[1]
GDP p.c.	12.05***	12.05***	-21.49***	20.38***	20.38***	-9.08**
GDP p.c.²	-0.81***	-0.81***	1.49***	-1.51***	-1.51***	0.67**
ELF	5.72***	5.72*	time invariant	9.23***	9.23***	time invariant
Inflation	-0.60*	-0.60	-0.52*	-0.37	-0.37	-0.31
Gov. exp	2.24**	2.24	1.78	-0.84	-0.84	1.04
Agriculture	-1.04*	-1.04	0.01	-1.81***	-1.81*	0.03
Constant	9.84	9.84	115.73***	-22.78**	-22.78	57.84***
N	638	638	638	638	638	638
R^2 (within)			0.25			0.12
Max/Min of:						
FD (deposits)	strict. neg.	not signif.	strict. pos.	not signif.	not signif.	strict. pos.
GDP (USD)	1,726	1,726	1,377	854	854	843

***, **, * denote statistical significance levels at 1%, 5%, and 10%

[1] Both terms of FD (bank deposits) in the quadratic form are insignificant, but FD is significant in its linear form

Notes: Bank deposits are used as a proxy for financial development. Model 1 is a pooled OLS estimation with heteroskedasticity-robust standard errors. Model 2 uses cluster-robust standard errors. Model 3 is a fixed-effect model with robust standard errors. All data are five-year averages and models are estimated with time dummies.

Table 11: Income inequality and financial development by country

Country	N	Gini (gross) Mean	Gini (gross) Min	Gini (gross) Max	Credit Mean	Credit Min	Credit Max
High Income	**1285**	**42.84**	**25.01**	**64.37**	**74.57**	**7.04**	**269.76**
Australia	44	39.76	31.29	43.96	50.24	19.31	121.43
Austria	33	42.85	33.08	51.81	80.59	38.14	111.58
Bahamas, The	32	54.05	48.20	61.43	50.96	31.85	69.94
Barbados	28	45.56	40.46	52.16	40.93	31.01	49.94
Belgium	36	34.01	25.01	51.29	45.82	11.23	93.70
Canada	46	39.46	35.82	43.82	78.13	17.73	183.83
Croatia	14	34.87	32.40	38.21	42.67	24.98	67.32
Cyprus	19	42.59	37.00	47.44	140.18	91.21	200.80
Czech Republic	15	35.50	33.58	36.81	48.72	29.21	69.25
Denmark	47	48.70	45.43	54.55	54.76	22.02	209.82
Estonia	16	48.79	43.93	51.56	41.50	9.47	99.25
Finland	44	42.96	36.38	64.37	55.73	37.18	93.26
France	35	42.22	31.28	54.70	73.82	22.36	106.75
Germany	37	46.36	31.43	55.95	91.10	63.09	116.93
Greece	41	44.67	38.55	55.23	37.04	13.48	91.66
Hong Kong	16	54.37	47.17	59.54	146.53	124.36	176.76
Hungary	26	41.00	28.16	48.28	33.78	16.18	64.21
Iceland	4	41.65	40.31	43.01	181.12	116.44	269.76
Ireland	44	44.45	38.87	47.43	70.71	30.42	205.77
Israel	30	41.29	30.67	45.08	57.34	31.66	88.39
Italy	42	45.23	38.18	51.12	64.67	47.56	103.33
Japan	45	37.87	34.26	41.70	126.38	51.27	200.61
Korea, Rep.	38	39.69	35.16	45.97	84.09	36.41	144.59
Latvia	15	47.19	42.15	53.20	34.42	7.04	94.72
Luxembourg	31	36.39	27.55	43.96	102.30	56.07	211.42
Malta	8	45.75	43.65	48.62	106.02	101.81	112.37
Netherlands	43	41.48	37.54	53.74	101.34	41.61	192.60
New Zealand	45	40.03	33.07	47.00	60.55	23.76	140.14
Norway	42	42.32	37.74	48.13	85.28	58.16	113.89
Poland	19	41.13	34.01	47.97	23.70	14.87	40.55
Portugal	32	53.44	46.42	61.05	90.08	47.99	171.69
Singapore	44	46.98	42.30	53.13	87.45	35.03	135.74
Slovak Republic	15	33.98	29.75	36.83	40.90	29.60	52.87
Slovenia	17	33.55	29.20	35.35	38.03	19.45	80.95
Spain	35	38.81	32.93	46.65	87.25	63.67	188.49
Sweden	49	44.60	36.94	51.09	89.64	51.37	134.88
Switzerland	26	42.29	39.17	56.64	146.44	100.84	162.99
Trinidad a. Tobago	34	44.69	37.83	64.06	39.84	12.28	62.16
United Kingdom	49	43.30	37.30	48.78	70.33	16.05	189.56
United States	49	43.50	39.33	47.93	116.43	70.53	210.73

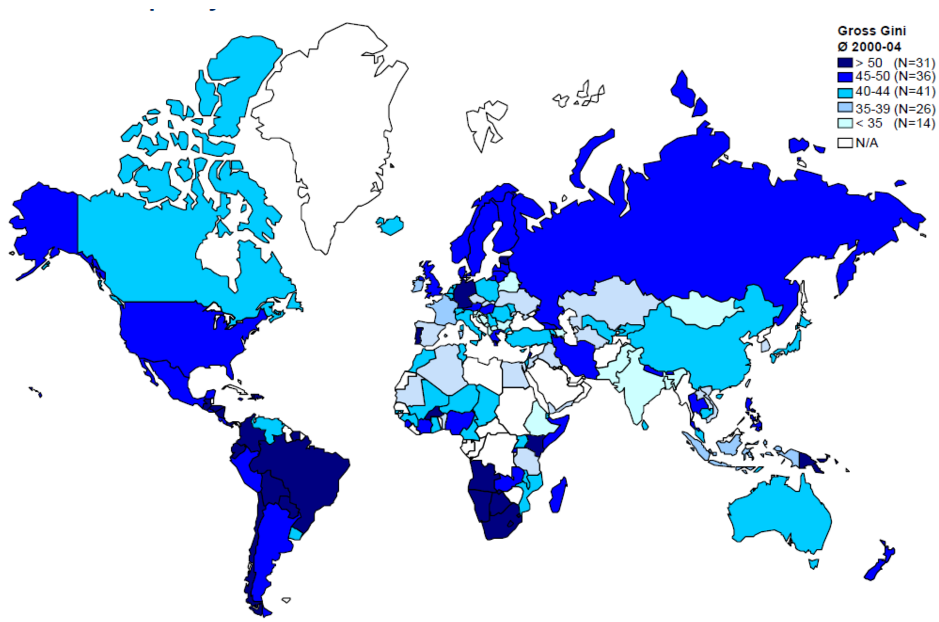
		Gini (gross)			Credit		
Country	N	Mean	Min	Max	Mean	Min	Max
Upper Middle Income	**739**	**49.49**	**27.52**	**77.28**	**32.31**	**2.80**	**155.25**
Albania	10	32.27	30.62	35.13	5.46	2.80	11.81
Algeria	23	37.71	35.28	40.75	26.11	4.14	68.29
Argentina	22	46.20	43.04	50.38	16.17	9.77	25.18
Botswana	24	55.86	52.60	59.64	12.68	6.54	19.65
Brazil	17	56.45	52.66	58.53	35.26	27.03	54.49
Bulgaria	17	32.62	27.52	38.39	34.22	8.94	68.19
Chile	30	52.76	50.91	54.45	52.84	11.08	74.34
Colombia	41	58.53	48.86	67.50	25.34	16.83	35.65
Costa Rica	38	48.55	43.30	60.89	22.45	10.47	51.96
Dominica	1	41.41	41.41	41.41	63.30	63.30	63.30
Dominican Republic	22	48.86	45.91	50.44	22.20	14.80	30.75
Fiji	17	52.46	50.30	54.29	26.51	18.04	38.25
Gabon	8	57.68	42.74	70.66	12.82	7.89	16.37
Grenada	1	53.19	53.19	53.19	67.08	67.08	67.08
Iran	35	47.26	42.95	53.25	28.16	18.64	43.62
Jamaica	37	59.57	47.56	77.28	22.95	13.15	30.66
Kazakhstan	13	37.11	34.01	41.94	14.72	4.97	36.83
Lithuania	15	47.83	47.07	48.71	23.30	10.22	61.23
Macedonia, FYR	14	32.88	29.72	38.94	23.66	17.38	37.01
Malaysia	38	51.85	40.32	67.17	75.53	7.10	155.25
Mauritius	31	47.98	39.73	56.62	38.34	20.63	72.35
Mexico	42	51.49	46.72	68.75	20.36	8.69	37.10
Panama	44	52.22	47.97	57.37	51.24	10.51	97.32
Peru	20	47.65	44.34	51.01	16.94	3.16	27.89
Romania	12	43.19	40.46	49.79	14.45	6.43	36.87
Russian Federation	16	47.48	43.48	51.34	18.78	6.78	48.54
Serbia	6	41.13	40.29	41.77	22.01	16.31	27.98
Seychelles	1	57.59	57.59	57.59	22.45	22.45	22.45
South Africa	38	65.45	61.70	70.24	80.68	43.44	132.56
St. Lucia	2	49.75	40.25	59.26	67.72	58.26	77.19
St. Vincent and the Gren.	1	66.41	66.41	66.41	43.94	43.94	43.94
Suriname	7	50.28	50.05	50.51	14.33	7.27	21.88
Turkey	25	45.36	41.75	50.84	14.67	10.91	18.79
Uruguay	28	41.39	40.10	43.00	33.56	19.99	67.05
Venezuela, RB	43	43.98	41.28	58.27	28.83	8.13	66.17

Country	N	Gini (gross) Mean	Gini (gross) Min	Gini (gross) Max	Credit Mean	Credit Min	Credit Max
Lower Middle Income	**765**	**46.64**	**30.43**	**77.36**	**27.48**	**1.14**	**165.96**
Angola	6	60.34	60.06	60.61	3.12	1.14	4.45
Armenia	15	45.68	39.59	54.42	7.86	3.09	23.42
Belize	7	55.57	50.58	59.07	41.33	37.26	46.80
Bhutan	3	48.17	48.07	48.27	14.60	11.48	18.08
Bolivia	22	53.61	44.10	58.26	38.22	4.47	63.04
Cameroon	19	47.69	43.96	49.51	16.93	6.66	28.14
Cape Verde	17	50.06	42.35	55.89	24.15	3.02	41.13
Cote d'Ivoire	32	48.89	38.20	59.84	28.93	14.91	41.22
Ecuador	28	50.59	42.81	61.64	21.63	12.91	40.67
Egypt, Arab Rep.	41	36.32	32.71	51.35	25.89	11.43	53.38
El Salvador	42	51.16	47.46	63.71	28.01	16.82	43.53
Georgia	10	45.44	43.14	47.55	6.45	3.31	11.31
Guatemala	29	54.27	42.14	57.89	17.43	11.25	29.04
Guyana	5	44.62	43.94	45.60	41.49	23.17	54.89
Honduras	24	55.94	52.46	72.79	31.34	13.84	46.60
India	46	35.35	31.99	44.51	19.46	7.84	36.37
Indonesia	29	34.98	32.19	38.59	28.29	9.04	53.53
Jordan	30	39.88	35.08	48.67	63.62	32.15	83.50
Lesotho	18	59.67	51.95	64.54	13.78	5.60	20.05
Moldova	13	41.22	37.24	44.46	14.78	4.45	29.68
Mongolia	11	35.69	34.15	38.72	13.49	6.25	32.63
Morocco	38	47.48	37.71	69.06	31.34	11.74	60.91
Nigeria	35	50.80	43.40	65.16	11.20	3.33	18.93
Pakistan	43	39.05	30.43	44.15	21.92	12.83	27.57
Papua New Guinea	11	49.05	40.62	52.56	15.07	12.37	17.95
Paraguay	19	50.98	37.51	55.35	22.09	13.18	29.03
Philippines	45	55.42	45.83	61.30	30.64	16.94	54.06
Senegal	17	44.93	39.50	58.56	18.13	14.51	26.10
Sri Lanka	27	45.33	32.52	57.22	18.55	7.74	28.71
Swaziland	13	55.25	49.07	77.36	14.14	10.92	18.83
Thailand	36	50.18	43.98	60.27	68.38	15.07	165.96
Tunisia	18	41.01	39.03	42.02	60.64	48.67	66.60
Vietnam	11	37.60	36.34	38.64	36.33	17.23	64.37
Yemen, Rep.	5	36.51	32.24	39.03	5.64	4.67	6.47

Notes: Only country-year observations with information on income inequality (Gini), financial development (credit), and GDP per capita are included in the table, as other information were not used for the basic estimation.

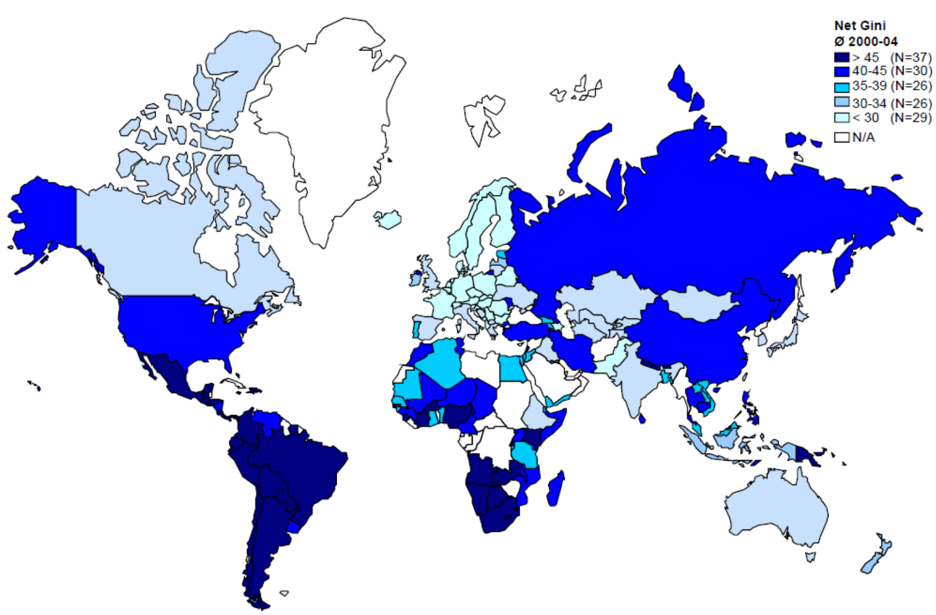
Figures

Figure 2a: Gross Income Inequality around the world



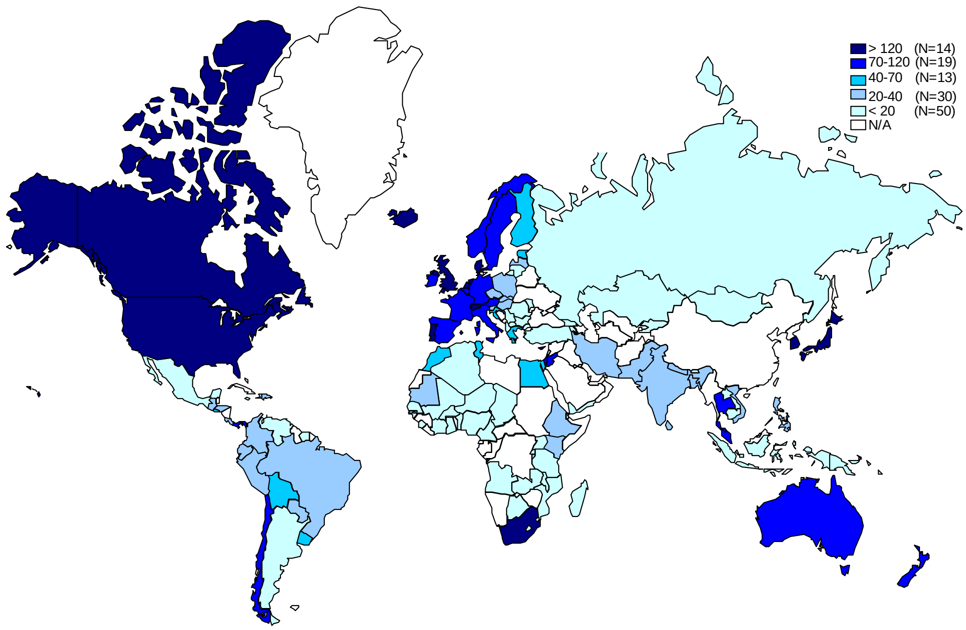
Notes: Income inequality is measured by the Gini coefficient of gross income. Data is based on averages from 2000 to 2004.

Figure 2b: Net Income Inequality around the world



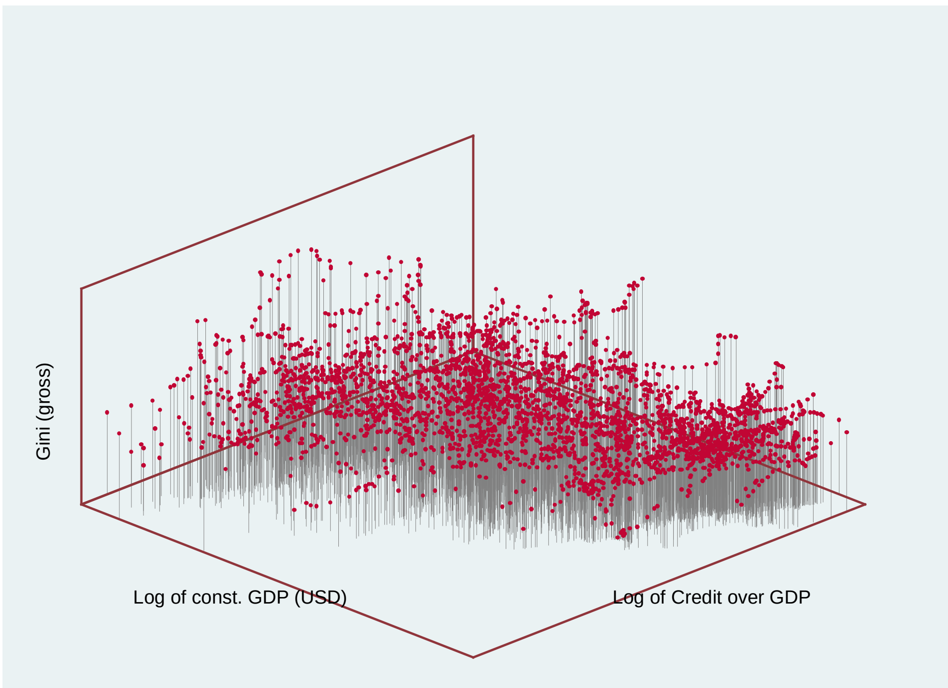
Notes: Income inequality is measured by the Gini coefficient of net income. Data is based on averages from 2000 to 2004.

Figure 3: Financial Development around the world



Notes: Financial development is measured by the average volume of private credit over GDP from 2000 to 2004

Figure 4: Financial Development, Economic Development, and Income Inequality



Notes: 3D-graph for the relationship between Gini, economic and financial development with all country-year observations