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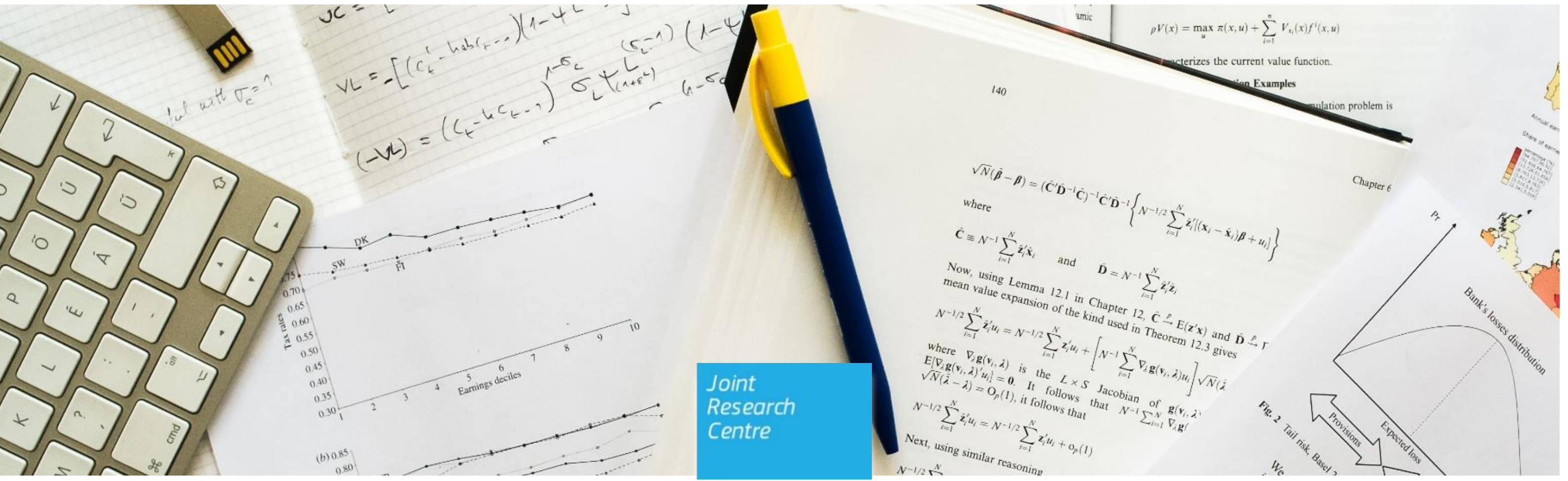

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Income inequality and private bank credit in developed economies

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Abstract

The influence of financial deepening on income inequality in developed economies is studied with particular interest in the European Union member states that have large penetration of bank credit. Building on the model of financially open economies (Kunieda et al., 2014) and extending its implications for the top-income shares, it is shown that a simultaneous increase in private bank credit relative to the gross domestic product (GDP) and the gap between real interest rate and GDP growth rate increases inequality, as measured by both the Gini index and the top-income shares. To establish the effect on the top-income shares, a simultaneous estimation procedure is proposed that exploits the implications of the fact that a higher income range is well-characterized by the Pareto distribution.

Keywords: credit, financial deepening, European Union, income inequality.

JEL Codes: D31, E51, G21, O16, O41.

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1 Introduction

In many developed economies, income inequality has increased sharply during the recent decades (see, for example, OECD, 2015). This increase is often connected with several intensive and intertwined processes that can be observed during this period, including the technological and skill-bias change, globalisation, financial deepening, and so on (see ibid.). This paper considers the contribution of financial deepening to income inequality in developed economies, stressing the importance of its interaction with the difference between the (lending) interest rate and the gross domestic product (GDP) growth rate.

Taken separately, this difference ('$r-g$') plays a central role in the framework of inequality as advanced by Piketty (2014) (see also Piketty and Zucman, 2015). However, to our knowledge, the importance of its interaction with the financial deepening has not been explored while, intuitively, the difference $r - g$ and, maybe even more importantly, its sign signal if an economy fails/succeeds to generate sufficient income growth to cover the obligations to the financial sector. In the latter case, the benefits from financing is spreading to the whole economy instead of concentrating mostly within the finance sector; that is, benefiting mostly the owners and workers of it. At the same time, greater net returns could make capital owners more capable and/or willing to share the surplus with workers in comparison with the situation where interest rates are squeezing their profits. Thus the influence of the financial deepening on income inequality might be conditional.

Most theoretical models, at least of a closed economy, predict that the removal of financial constraints and increasing amounts of borrowing lead unconditionally to the reduction of income inequality (see, for example, Banerjee and Newman, 1993, Galor and Zeira, 1993) or at least for more developed countries due to the inverted U-shape relationship in terms of development level (Greenwood and Jovanovic, 1993). The previous econometric evidence, especially using earlier data periods, also corresponded rather well with these predictions (see, for example, Levine, 2005, Clarke et al., 2006, Beck et al., 2007, Kim and Lin, 2011).

Recently, contrary empirical findings have started to accumulate evidence that a larger financial deepening may actually have increased inequality instead of reducing it (see, for example, Claessens and Perotti, 2007, Kunieda et al., 2014, Denk and Cournede, 2015, Haan and Sturm, 2016, Jauch and Watzka, 2016). This paper uses private bank credit to GDP as a financial deepness indicator and it contributes to the empirical literature on income inequality by: a) exploring several panels of relatively homogeneous developed economies; b) testing additional implications of Kunieda et al. (2014) model of financially open economies for the Gini-based inequality and linking them to the $r - g$ impact on inequality; c) extending the implications of the model also for the top-income shares; and d) proposing a joint estimation procedure for the top-income shares which exploits the fact that a higher income range is well-characterized by the Pareto distribution.

The consideration of many countries at various levels of economic development might be tailored (and very useful) for the identification of the factors that are crucial for development; that is, the factors explaining the differences of inequality at lower and higher income levels. However, this might hide the drivers of inequality in developed economies alone because they might be dominated or insufficiently strong to be observable in a mixed sample of countries.

Consequently, this paper concentrates only on the developed economies. Namely, several panels are under consideration of countries entering the Organisation for Economic Co-operation and Development (OECD), the European Union (EU), as well as the most homogeneous set of countries from the Economic and Monetary Union that originated the union (EMU1999). The interest in the EU and, especially, the EMU1999 member states emerges mainly because of their highly bank-biased financing systems (Langfield and Pagano, 2016), and also because of their higher mutual integration and similarity relative to other countries. Consequently, it is expected that similar principles apply in countries with a more uniform impact of financial deepening in terms of bank credit (Benczúr et al., 2017). Furthermore, consideration of a group of similar countries relaxes the need to control for many variables that would otherwise be importantly shaping the differences in development. Hence, a smaller set of other control variables is expected to be sufficient as compared with the case where a diversity of countries is under consideration.

For the empirical analysis, the implications derived for open economies in Kunieda et al. (2014) seem to be especially relevant in our case because the countries that are under consideration are developed and financially open economies. Hence, this model lays the ground for our empirical and theoretical analysis but its predictions are extended along a few lines.

First, relying on the Kunieda et al. (2014) model, the implications for the top-income shares are also derived (Kunieda et al., 2014, considered only the Gini index) defining the conditions for the top-income inequality to increase with the relaxation of the financial constraint. Consequently, both the global inequality as measured by the Gini index and the top-income inequality as measured by the top-income shares received by the 1%, 5%, and 10% largest income earners will be taken under consideration. This paper is concentrated on these three shares, leaving out the even smaller ones, because a smaller share makes the precision of the corresponding income estimate likely to be less accurate.

Second, following the main prediction by Kunieda et al. (2014) that, in financially open economies, financial deepening leads to increasing inequality as measured by the Gini index, this paper further tests the significance of non-linearity emerging due to the interaction between the financial development with other components, which was not considered by these authors in their empirical application. Using a few approximations, it is revealed to be linked to the $r - g$ impact on inequality through an interaction term with the financial deepening.

As a by-product of the previously discussed model, the analysis of the sign of the impact of '$r - g$' on inequality is performed, which is of utmost importance in the Piketty theory. In the specification predicted by the model, the sign of the impact of $r - g$ alone (without taking the bank credit into account) is negative (inequality decreasing), which is consistent with the view advanced in Krusell and Smith (2015), or Acemoglu and Robinson (2015) and which is in contrast with the Piketty prediction. However, the interaction term of $r - g$ with the private bank credit share in GDP has the inequality-increasing effect whenever $r > g$ and, therefore, it is potentially consistent with the Piketty prediction provided that a sufficiently large bank credit penetration coexists with the previously defined condition.

Finally, from the methodological point of view, the contribution of this paper is the proposed simultaneous estimation of the impact of financial deepening measures on the top-income shares that exploits the fact that a higher income range is well-characterized by the

Pareto distribution (see, for example, Atkinson et al., 2011). This simultaneous estimation is introduced to solve the problem of the small number of observations that is caused by that the number of countries with the data on top-income shares is much scarcer.

The rest of the paper is structured as follows. Section 2 presents some simple empirical evidence that will motivate further econometric investigations. Section 3 draws some predictions from the Kunieda et al. (2014) theoretical model of open economies and derives its implications for the top-income shares. Section 4 describes the data and defines the econometric framework that we have employed. Section 5 presents the empirical results. Finally, Section 6 concludes this paper.

2 Some empirical evidence

Before turning to the modeling, some stylised characterization of empirical developments is presented[1]. First, concentrating on the OECD member countries (MC), Figure 1 reveals the dynamics of the yearly medians of: i) a few income inequality measures (top-left figure); ii) the private bank credit and its change (top-right figure); iii) the difference between the real bank lending interest and real GDP growth rates as denoted by $r - g$ (bottom-left figure); and iv) the distribution of $r - g$ (bottom-right figure). The medians are used here to soften some peculiarities connected with the changing availability of data (partially also caused by the changing composition of the OECD), whereas the logarithmic transformations are applied (apart from $r - g$) to simplify the presentation on a single scale.

The dynamics of the yearly median inequality as measured both in terms of the overall inequality (Gini index) and top-income inequality is quite similar. It initially decreased (until about 1978, which is marked by a dotted vertical line in the figures on the left side). Meanwhile, the upwards trend dominated afterwards, at least until 2009, where some changes begin to appear, presumably in connection with the financial crisis.

At the same time, the median bank credit levels were quite steadily increasing during the period under discussion. This is likely to be one of the reasons for the varying results that may be found in the previously described empirical literature. Whenever one employed the early

[1]See Appendix A for the related data sources.

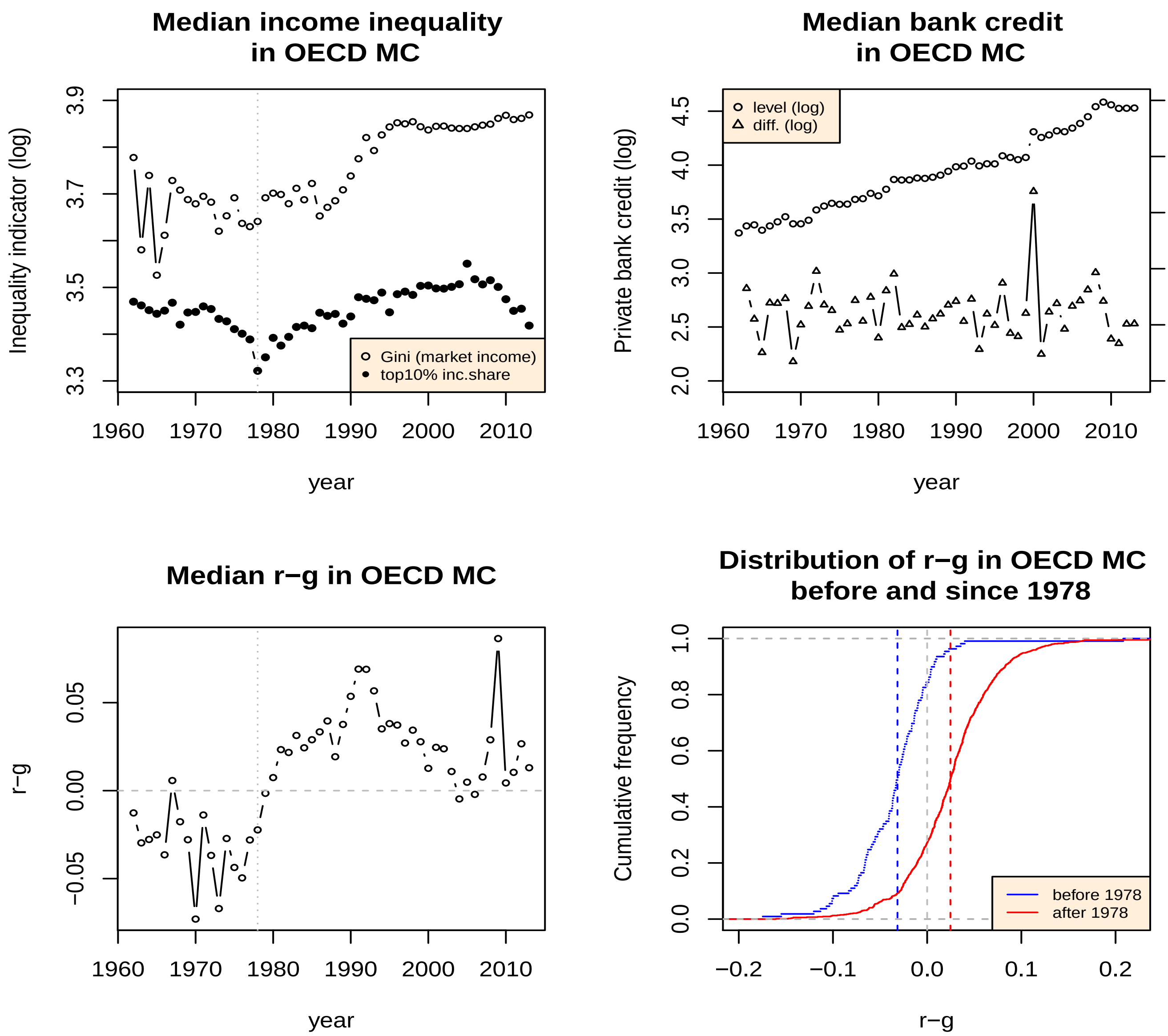

Figure 1: Dynamics of median yearly values in the OECD member countries (MC) and the distribution shift of '$r - g$'. Note: the availability of data for different countries varies over time.

data period, an increasing level of bank credit could have been pointing to the reduction in inequality levels. Meanwhile, the later periods (or whenever their weight became dominant) would associate the increasing credit levels with the observed upwards shift in inequality. Otherwise, there seems to be few noticeable common patterns in the dynamics of inequality and bank credit (or its change).

In contrast, a first look at the dynamics of the median $r - g$ values seems to indicate more commonality with the patterns of changes of median inequality. Nevertheless, neither the simple scatter-plots of data at country-year level (see Appendix B) nor the econometric evidence to be presented next yield strong confirmation that in a panel of countries such connections are highly significant. However, the interesting and important feature is that, prior to the increase in inequality levels, the real interest rates of bank lending were almost always smaller than the GDP growth rates (the horizontal dashed line in the bottom-left figure identifies the threshold of their equality). Since about 1978, the GDP growth rates became mostly lower than the real interest rates[2] (the bottom-right figure presents the distribution of $r - g$ in the respective periods at a country-year level), whenever the general increase of inequality also started to appear more clearly. This pattern of inequality direction change can also be observed at a separate country level. Figure 2 illustrates this using the Gini index of market income for Germany and the United States[3].

Merging all of these features through their interaction leads to the main finding of this paper, which will be steadily observed in the econometric estimations for both the Gini index and the top-income shares. Namely, the impact of bank credit to GDP on income inequality is conditional – when the real (bank lending) interest rates are greater than the real GDP growth rate ($r > g$), the financial deepening in terms of larger bank credit to GDP tends to increase income inequality. When the interest rates are smaller than the growth rate ($r < g$), larger bank lending penetration can even decrease the inequality of income.

Figure 2 illustrates these effects for the OECD, EU, and EMU1999 MC in a simple

[2]It is possible that the increase in real interest rates was caused by the pricing of additional macro risks connected with higher inflation and potential slumps that became apparently important after the turmoil of oil prices and economic activity during the 1975–1979 period.

[3]This figure is produced and copied directly from the Standardised World Income Inequality Database (Version 5.1) online page at http://fsolt.org/swiid/.

Figure 2: Dynamics of overall income inequality (Gini index) in Germany and the United States.

scatter-plot, where the red and blue colors are used to signify whenever the $r > g$ and $r < g$ conditions hold, respectively. The solid red (bold) and the dashed blue lines represent the estimated linear relationship in a particular state[4]. These lines reveal a steadily positive and higher slope of the solid (red) line—that is, whenever '$r > g$' holds—in comparison with that of the dashed blue line—that is, whenever '$r < g$' holds—which sometimes even becomes downwards sloping. For the EMU1999 case (the last row of figures), such a sign switch (upwards and downwards sloping lines), connected with the $r > g$ and $r < g$ cases, holds for all of the considered cases of inequality indicators. This is of interest because of the higher homogeneity of these countries as well as, and even more importantly, because of the heavy weight of bank finance in their economies.

[4]For the "OECD, Gini" and "EMU1999, Gini" cases (the top-right and bottom-right figures), the red and blue lines represent the estimates after dropping the observations of outlying groups. Namely, in the case of the OECD group, Chile, Mexico, and Turkey were omitted because their observations form the outlying group of observations seen above the main cluster. In the case of the EMU1999 group, Italy, Spain, and Portugal were omitted because their observations constituted the cluster above the main one. The estimated regression lines before these omissions are colored in grey: the solid line and dotted lines represent the $r > g$ and $r < g$ cases, respectively.

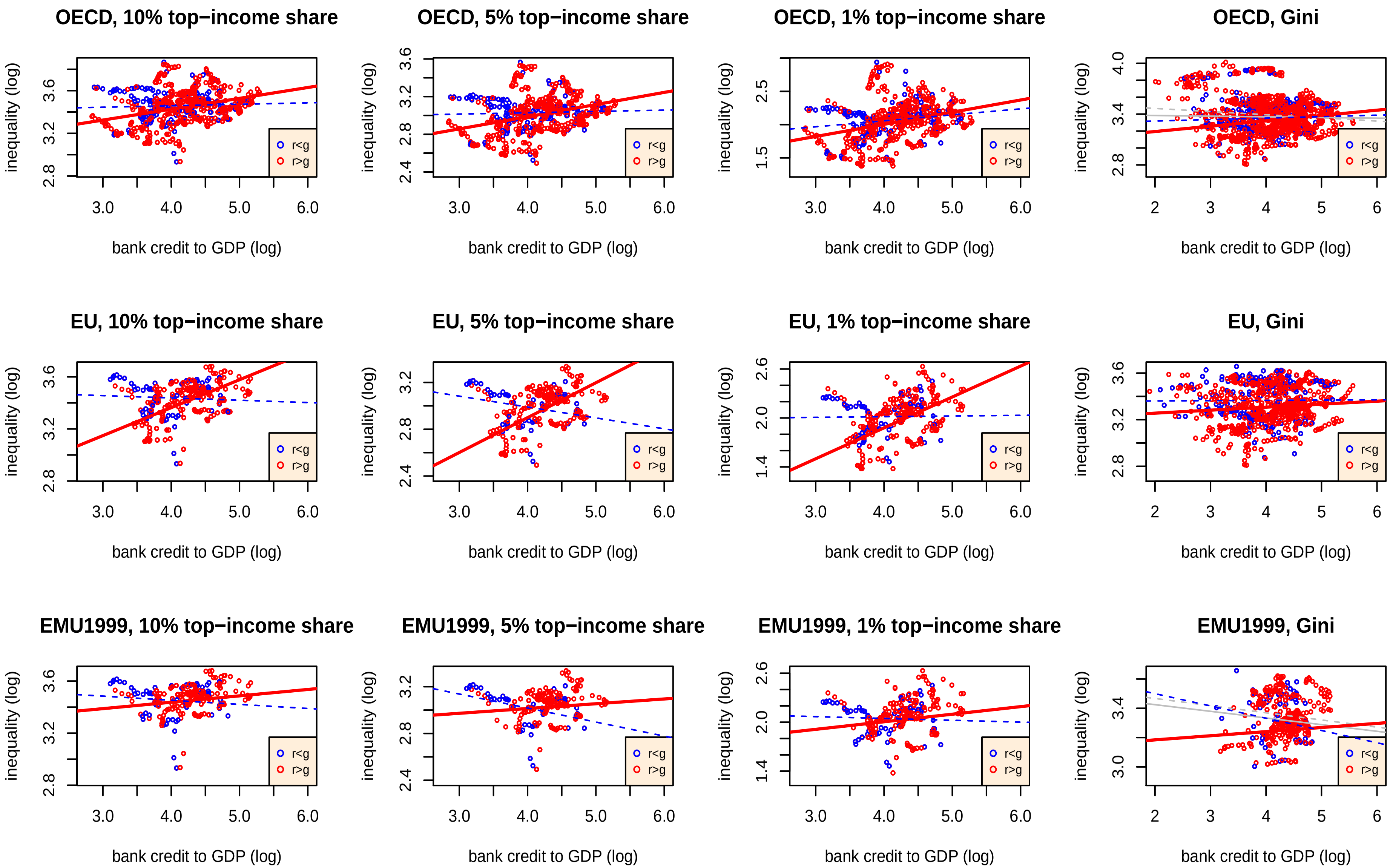

Figure 3: Scatterplots of (log) bank credit to GDP and (log) income inequality indicators.

In the scatter-plots, this feature is more pronounced for the top-income shares (income shares held by 1%, 5%, and 10% largest earners) and net income Gini inequality, which are less persistent, and are, therefore, plotted in the figure. Nevertheless, whenever the autoregressive influence is taken into account, the econometric results for the Gini inequality of market income will turn out to be the strongest.

These simple and otherwise unconditional scatter-plots already hint that there might be an important difference in bank credit impact on inequality in various states when characterised by the real bank lending interest rates and the GDP growth rates. How significant it is and whether there is a sign switch of the impact is to be determined shortly using further econometric refinements.

3 Some theoretical implications

In the sequel, the implications from an open economy version of the model proposed by Kunieda et al. (2014) are employed to study the financial deepening effect on inequality. The model is used to motivate the specifications that will be estimated later. First, the summary of the model is presented in Subsection 3.1. Then, the implications for the Gini index are discussed in Subsection 3.2. Finally, the results for the top-income shares are obtained in Subsection 3.3 (the respective derivations are presented in Appendix C).

3.1 A summary of the model

In a framework with (overlapping) generations of selfish individuals[5] living for the two periods and deriving their utility from individual consumption in the second period, Kunieda et al. (2014) introduce an endogenous growth model (due to learning by doing) with agents that are heterogeneous in their productivity at creating individual capital. In the first period the agents work and earn a homogeneous wage that is determined by the aggregate technology, whereas in the second period their earnings (which are spent on consumption) depend on individual productivity because persons endogenously choose at the end of the first period

[5]There is no bequest in the model.

to become lenders (earning interest rates) or capital builders (earning from creation of capital) depending on their private productivity, which is distributed uniformly over $[0, 1]$ and constant over time.

It should be pointed out that the (working) population mass (L_t) living in the first period is homogeneous and, therefore, the heterogeneity stems from the second period generation. Consequently, all of the results on inequality will concentrate only on it. Furthermore, it should be also pointed out that in such a model inequality of consumption is directly indicative of the (final) income inequality. Nevertheless, following Kunieda et al. (2014), the following discussion is centered around the consumption patterns.

At an individual level, an agent derives utility from the second period consumption (c_{t+1}) and, at the end of the first period, chooses to either lend in the second period the previously earned wage (w_t) or to invest it in the creation of individual capital (k_t), possibly with additional borrowing or lending ($b_t < 0$ or $b_t > 0$, respectively), depending on his/her random (uniformly distributed) productivity (ϕ), which is known to him/her but unobserved by others.

Given the credit constraint $b_t \leq \frac{\mu}{1+\mu}$, $\mu \geq 0$, an agent solves the following problem:

$$\max_{b_t, k_t} c_{t+1}, \text{ subject to:}$$

$$c_{t+1} \leq \phi q_{t+1} k_t + R_{t+1} b_t,$$

$$-\tfrac{\mu}{1-\mu} w_t \leq b_t \leq w_t,$$

$$k_t \geq 0, \; k_t + b_t \leq w_t,$$

$$\text{given } q_{t+1}, R_{t+1}, w_t > 0,$$

where q_{t+1} and R_{t+1} are the next period's real price of capital and the gross real interest rate paid/received for the borrowed/lent means, respectively. Different productivity defines the choice of an agent to become a lender or a borrower of capital in this economy. Namely, when the individual productivity is sufficiently high to render the rate of return of real capital investment higher than the interest rate on borrowing/lending, an agent becomes a real capital investor and, therefore, also a borrower.

Defining a ratio $\phi_t := R_{t+1}/q_{t+1}$, the aggregate capital level that fully depreciates over a period is consequently given by

$$Z_{t+1} = k_t L_t \int_{\phi_t}^{1} \phi \mathrm{d}\phi = \frac{w_t(1-\phi_t^2)}{2(1-\mu)} L_t,$$

because, for individuals with productivity $\phi > \phi_t$, the optimal choice is to invest by choosing $k_t = \frac{w_t}{1-\mu}$ and (borrowing) $b_t = -\frac{\mu w_t}{1-\mu}$. Whereas for less productive agents with $\phi \leq \phi_t$, it is optimal to lend the means ($b_t = w_t$) without any capital creation ($k_t = 0$). Consequently, the consumption of those lending and borrowing-investing is given by

$$c_{t+1} = \phi_t \alpha A^{\frac{1}{\alpha}} w_t \tag{1}$$

and

$$c_{t+1}(\phi) = \frac{\phi - \mu\phi_t}{1-\mu} \alpha A^{\frac{1}{\alpha}} w_t, \tag{2}$$

respectively.

At the aggregate level, the first order conditions under the perfect competition and the technological constraint of production

$$Y_t = A Z_t^{\alpha} H_t^{1-\alpha},$$

yield further $q_t = \alpha A^{\frac{1}{\alpha}}$ and $w_t = (1-\alpha)A^{\frac{1}{\alpha}} Z_t / L_t$. Here, the labor force L_t is enhanced with a learning by doing-implied augmentation parameter ($y_t = Y_t/L_t$) that yields the augmented labor force $H_t = y_t L_t$.

It should be further pointed out that, due to the described learning by doing and technological constraint, production satisfies $Y_t = A^{\frac{1}{\alpha}} Z_t$. Assuming a constant labor force ($L_t = L$), the growth rate of such an economy is given by

$$g_{t+1} = A^{\frac{1}{\alpha}} \cdot \kappa \frac{1-\phi_t^2}{1-\mu} - 1, \tag{3}$$

where $\kappa = \frac{1-\alpha}{2}$. Hence, in an open economy where ϕ_t is exogenously given by some $\bar{\phi}_t < 1$, which will be defined shortly, an increase in μ enhances economic growth as long as $\mu < 1$.

3.2 Implications for the Gini index

In a small open economy version of the characterised economy, the relaxation of the borrowing constraint μ produces a larger relative amount of financing and, increases the consumption inequality as measured by the Gini index (see Proposition 2 in Kunieda et al., 2014).

Namely, the Gini index is given (see ibid.) by

$$G_t = \frac{2\bar{\phi}_{t-1}^3 - 3\bar{\phi}_{t-1}^2 + 1}{3(\bar{\phi}_{t-1}^2 - 2\mu\bar{\phi}_{t-1} + 1)}, \tag{4}$$

where μ represents the financial deepening and

$$\bar{\phi}_{t-1} = \frac{\bar{R}_t}{\alpha A^{\frac{1}{\alpha}}} \in (0, 1). \tag{5}$$

Here $\bar{R}_t > 0$ stands for the gross (real) borrowing costs that are exogenously given, whereas $\alpha \in (0, 1)$ and $A \geq 0$ are the aggregate capital-linked parameter and the total factor productivity in the previously defined Cobb-Douglas production function, respectively.

Provided that the ratio is non-negative[6], it is indeed clear from eq. (4) that the increasing financial deepening (μ) increases inequality. However, the impact of μ on G depends also on the value of $\bar{\phi}_t$ due to the interaction term in the denominator of eq. (4); that is, the product term[7] $\mu\bar{\phi}_{t-1}$. Motivated by this and keeping in mind that technological progress is the main driver of long-run growth, in the empirical estimations the additional interaction terms of financial deepening with the real interest rates and growth rates will be used as proxies for the influence connected with the nominator and denominator of eq. (5).

In particular, up to the first order effects, we can obtain the following formal guidance.

[6] Since the nominator of eq. (4) is always positive for the admissible values of $\bar{\phi}_t$, the only condition for this to hold is that $\mu < \frac{1+\bar{\phi}_{t-1}^2}{2\bar{\phi}_{t-1}}$. It is also clear that $\mu < 1$ is a sufficient condition because $1 < \frac{1+\bar{\phi}_{t-1}^2}{2\bar{\phi}_{t-1}}$.

[7] An interesting aspect related to high(er) penetration of finance is that for larger values of μ the peak of $\frac{\mathrm{d}G}{\mathrm{d}\mu}(\bar{\phi}_t)$ shifts towards 1 in terms of $\bar{\phi}_t$, whereas for for $\mu = 1$, $\frac{\mathrm{d}G}{\mathrm{d}\mu}$ is monotonically increasing in $\bar{\phi}_t$.

First, let $r_t := \bar{R}_t - 1$. From eqs. (3) and (5) if follows that

$$\bar{\phi}_{t-1} = \eta(\mu)\frac{1+r_t}{1+g_t} - \eta(\mu)\frac{1+r_t}{1+g_t} \cdot \bar{\phi}^2_{t-1}, \tag{6}$$

where $\eta(\mu) = \frac{\kappa}{\alpha(1-\mu)}$. Since the positive $\bar{\phi}_t < 1$ (see the condition in eq. (5)), it also follows that the second term on the right side of eq. (6) with the $\bar{\phi}^2_{t-1}$ is only of the second order[8]. Hence, considering the first order effects, the following approximation of the interaction term emerges[9]

$$\mu\bar{\phi}_{t-1} \approx \eta\mu + \eta\mu\frac{r_t - g_t}{1+g_t}, \ \eta = \frac{1-\alpha}{2\alpha}, \tag{7}$$

leading to the appearance of '$r-g$' in the measurement of the impact[10].

It is clear that, given the highly stylised model and highly nonlinear relationship in eq. (4), we cannot expect the functional forms to hold exactly but we at least expect the signs of the interaction terms to be correct; that is, inequality increasing whenever $r_t - g_t$ is greater than zero and vice versa. In the sequel, both the linear and the interaction terms appearing on the right side of eq. (7) will be under consideration in the empirical estimations[11].

3.3 Implications for the top-income shares

This section will give the main results about the top-income shares. Since they hold for each fixed period, its index is dropped hereafter for the sake of simplicity of presentation providing the generic case. The proof of Proposition 1 is contained in Appendix C, whereas some shorter derivations are presented in the footnotes.

We denote the frequency under investigation by $p \in [0,1]$ and the consumption share of $1-p$ largest consumers by $S_p \in [0,1]$. Proposition 1 states the main implication derived

[8]It is also easy to derive the exact and unique positive solution $\frac{\sqrt{1+b_t^2}-1}{b_t}$, where $b_t = \frac{1-\alpha}{\alpha(1-\mu)} \cdot \frac{1+r_t}{1+g_t}$, but it is hard to use it in simple empirical estimations due to a non-linear form and unknown parameters.

[9]The following sequence leads to the result:

$$\mu\bar{\phi}_{t-1} \approx \eta(\mu)\frac{1+r_t}{1+g_t}\mu \ = \eta h(\mu)\frac{1+r_t}{1+g_t} = \eta h(\mu) + \eta h(\mu)\frac{r_t-g_t}{1+g_t}\bigg|_{\mu=0} \simeq \ \eta\mu + \eta\mu\frac{r_t-g_t}{1+g_t},$$

where $\eta = \frac{\kappa}{\alpha}$, and $h(\mu) = \frac{\mu}{1-\mu}$ is a monotonically increasing function in μ with $h(\mu)|_{\mu=0} \approx \mu$.

[10]It can be further observed that, because the value of g_t is in most cases close to zero, $\frac{r_t-g_t}{1+g_t}$ and $r_t - g_t$ will usually be good proxies for one another.

[11]In fact, better results are obtained using the log-transformed bank credit data for the μ.

for the top-income shares from the Kunieda et al. (2014) model, which is summarized in Subsection 3.1, whenever some p^{th} frequency is under consideration[12] that satisfies the condition

$$p \in (\bar{\phi}, 1). \tag{8}$$

Proposition 1. *In the open economy version of the Kunieda et al. (2014) model, for any p^{th} frequency that satisfies condition* (8)*, the share of consumption of the* $1-p$ *largest consumers is given by*

$$S_p = (1-p)\frac{1+p-2\mu\bar{\phi}}{\bar{\phi}^2-2\mu\bar{\phi}+1}. \tag{9}$$

Corollary 1. *Given* $\mu < \frac{1+\bar{\phi}_{t-1}^2}{2\bar{\phi}_{t-1}}$*, the necessary and sufficient condition for* $\frac{\mathrm{d}S_p}{\mathrm{d}\mu} \geq 0$ *is*[13]

$$p \geq \bar{\phi}^2. \tag{10}$$

It is obvious that the condition (10) holds whenever the initial condition required in eq. (8) is satisfied, because of the restriction given in eq. (5). In practical terms, when the value of the considered p is larger, it becomes more feasible that the financial development will be inequality increasing; that is, top-income shares will raise with the financial deepening.

It is again clear from eq. (9) that a higher financial penetration (a larger μ value) affects inequality through the interaction term $\mu\bar{\phi}$. Therefore, similarly to the case of the Gini index, we again can expect that the (interaction) terms defined in eq. (7) will be of importance.

[12]It should be noted that when population is ordered by the consumption size, p coincides with the quantile of population share by the definition.

[13]To see this one can either differentiate eq. (9) or, the addition and subtraction of $\bar{\phi}^2$ to/from its nominator leads at once to $S_p = (1-p)\left(1 + \frac{p-\bar{\phi}^2}{\bar{\phi}^2-2\mu\bar{\phi}+1}\right)$, which is evidently an increasing function in μ for $p > \bar{\phi}^2$, given the admissible ranges of parameter values discussed in Section 3.2 in the two paragraphs following eq. (5).

4 Data and econometric specifications

4.1 Data

In the sequel, we consider the impact of financial deepening on income inequality by separating the later one into the total inequality—as represented by the Gini index—and the top-income inequality—as represented by the top-income shares. The Gini index data on market income inequality is taken from the Standardised World Income Inequality Database (SWIID)[14]. The top-income data are taken from the World Wealth and Income Database (WID)[15].

The financial deepening variable under consideration is the (logarithm of) domestic bank credit to private sector relative to GDP. Two data sources are used for the bank credit: the World Bank Global Financial Development Database (GFDD) and the Bank for International Settlements (BIS) Credit to Non-financial Sector database. Each source has its own advantages: the GFDD provides information on a larger set of countries, whereas the BIS data are adjusted for structural breaks. Hence, to avoid having to make a hard choice between a larger number of observations and, likely, more comparable data, the results with the bank credit data from both data sources will be provided.

In addition to the real interest rates and GDP (per capita) growth rates, the usual set of further control variables includes initial income per capita, government consumption expenditure to GDP, trade openness to GDP, human capital, intensity of redistribution, inflation (of consumer prices), and the Chinn and Ito (2006) index of capital account openness[16]. The WDI database is a source of initial income, government consumption expenditure to GDP, trade openness to GDP, GDP per capita growth rates, and real interest rates of loans. The financial openness indicator is downloaded from the Chinn and Ito indicator website[17]. Intensity of redistribution is measured by the absolute reduction of Gini

[14]See Solt (2016) for a description and comparison of the SWIID with other sources on the Gini index.

[15]SeeAlvaredo et al. (2016) and Alvaredo et al. (2017) for a characterisation of the respective methodology for constructing this data set and a discussion of some new findings building on it, respectively. I thank Stylianos Karagiannis for bringing the availability of the WID into my consideration.

[16]The External Wealth of Nations dataset (see Lane and Milesi-Ferretti, 2007) is not employed due to missing data for later years.

[17]http://web.pdx.edu/ ito/Chinn-Ito_website.htm

index from market to the net Gini using the respective SWIID data. The data on human and real capital stem from the Penn World Table[18]. Appendix A contains more details of the variables and data sources that we used.

The logarithmic transformation is applied to most of the variables, except for the interest rate, growth rates, capital openness, and inflation. The inverse hyperbolic sign transform of CPI-based inflation is used due to the presence of negative values of inflation in some cases.

For the empirical estimations that are presented hereafter, all of the available data will be employed. However, the resulting panels are highly unbalanced: for a few countries and variables the series begin as early as 1965 but in most of the cases the data are only available from much later periods. Therefore, the effective number of data varies substantially both with the sets of countries under consideration (OECD, EU, and EMU1999) and in the particular set of (control) variables. In the tables that will follow both the effective number of observations and the countries under consideration will be reported.

Given that most of control variables were insignificant and quite restricting to the number of observations, the main estimations will be presented in Subsection 5.1 only with the main variables of interest in the regression functions. The sensitivity analysis with additional specifications and control variables will be discussed in Subsection 5.2 and reported in Appendix D.

4.2 Econometric specifications

In this section we will present the econometric models that were applied for the analysis of the impact of financial deepening on total inequality measured by the Gini index and the top-income shares, respectively. A standard dynamic panel model is employed to model the former one. In the case of the top-income shares, there is only data available for a few countries (e.g. only seven from the EU). Therefore, only the OECD case is considered because it comprises the largest set of thirteen countries. Since the number of countries is still small even in this case, a special framework is developed that overcomes the issue of a small number of observations by jointly estimating the underlying parameters of financial

[18]See Feenstra et al., 2015, available for download at www.ggdc.net/pwt.

deepening impact on the top-income shares by relying on certain properties that are implied by the Pareto distribution, which is well known to reasonably characterize the actual income data (see, for example, Saez, 2001, Atkinson et al., 2011).

The next subsection will describe how the model was applied in the case of the Gini index and Subsection 4.2.2 will present the methodology that was applied in the case of the top-income shares.

4.2.1 Models of the Gini index

Let $i \in \{1, 2, \dots, N\}$ and $t \in \{1, 2, \dots, T\}$ stand for the country and period indices, respectively. Relying on the insights from the previous sections, the following econometric model underlies the evaluation of the impact of financial deepening on total inequality of income in countries as measured by the Gini index:

$$\alpha(L)G_{i,t} = \beta_0 B_{i,t} + \beta_1 h(r_{i,t}, g_{i,t}) + \beta_2 B_{i,t} h(r_{i,t}, g_{i,t}) + \boldsymbol{\theta}' \boldsymbol{x}_{i,t} + \lambda_i + \varepsilon_{i,t}, \tag{11}$$

where:

$\alpha(L) = 1 - \alpha_1 L - \cdots - \alpha_k L^k$ is a lag polynomial of order $k \in N$ with real-valued parameters;

$G_{i,t}$ stands for the (natural) logarithm of the Gini index;

$B_{i,t}$ denotes the logarithm of private bank credit to GDP;

$h(r_{i,t}, g_{i,t})$ signifies either $\frac{r_{i,t} - g_{i,t}}{1 + g_{i,t}}$ or $r_{i,t} - g_{i,t}$, where $r_{i,t}$ represents the real bank lending interest rates and $g_{i,t}$ denotes the real growth rate;

$\boldsymbol{x}_{i,t}$ comprises various other control variables;

λ_i stands for the real valued country fixed effects;

$\boldsymbol{\beta} = (\beta_0, \beta_1, \beta_2)'$ and $\boldsymbol{\theta}$ are real valued vectors of parameters of proper lengths;

$\varepsilon_{i,t}$ denotes the usual zero mean error term.

Specification (11) is informative about the direction of the impact of $r_{i,t} - g_{i,t}$ on inequality. It is clear that its impact will be determined by $(\beta_1 + \beta_2 B_{i,t})$. In connection with the Piketty prediction of $r - g$ impact on inequality, the expected sign condition is $(\beta_1 + \beta_2 B_{i,t}) > 0$, whereas the alternatives that were considered, for instance, by Krusell and Smith (2015) or Acemoglu and Robinson (2015) the opposite would be the case.

Given that model (11) is a dynamic panel model, the usual fixed effects estimator is inconsistent for fixed T due to the presence of incidental parameters (Nickell, 1981). Furthermore, inequality is also highly likely to be endogenous with financial deepening, growth rate and/or interest rates. Therefore, we employ the generalised method of moments (GMM) based estimator originated for the dynamic panels by Arellano and Bond (1991) and extended by Arellano and Bover (1995) and Blundell and Bond (1998). In particular, we apply system GMM conditioning on both lags of differences and levels.

It should be noted that we use yearly data for the estimation of the models while avoiding pre-aggregation of initial data (e.g. into periods of 5 or 10 years). Although such an aggregation aims to capture the longer-term impact and the removal of business cycle effects, it is rather questionable because the business cycles can differ across time and countries both in terms of length and phases, whereas it can lead to pre-aggregation biases and result in a substantial reduction of number of observations. However, the use of yearly data might require us to consider more lags of the dependent variable in order to capture longer-term developments. Therefore, the lag order of the polynomial $\alpha(L)$ is selected based on the significance of the autoregressive terms.

4.2.2 Modeling of top-income shares

The Pareto distribution is known to well-characterise the top-tails of the income or wealth distribution (see e.g. Atkinson et al., 2011, Blanchet et al., 2017) and, therefore, the top-incomes can be properly characterised with a few parameters that, potentially, are time and country varying. Furthermore, it follows that the respective top-income shares depend only on a straightforward function of the shape parameter of the Pareto Type I distribution besides the considered share itself (see, for example, Blanchet et al., 2017, Jones, 2015, Jones and Kim, 2017). Hence, allowing for some random zero-mean deviation $\zeta_{i,t}$ from the Pareto distribution-implied shares[19], for any quantile p, the share of top-income is given by

$$s_{i,t}^{(p)} = (100/p)^{\eta_{i,t}-1} \exp\left(\zeta_{i,t}^{(p)}\right), \tag{12}$$

where $\eta_{i,t}$ is an inverse of the Pareto distribution scale parameter. Here, it is allowed to be period and country-specific and is governed by some process

$$\alpha_p(L)\eta_{i,t} = f(\boldsymbol{z}_{i,t}; \boldsymbol{\psi}) + \varepsilon_{i,t}^{(p)}, \tag{13}$$

where, potentially, the p-specific lag polynomial $\alpha_p(L) = 1 - \alpha_{1,p}L - \quad - \alpha_{k_p,p}L^{k_p},\ k_p \in \mathbb{N}$, $f(z_{i,t}; \boldsymbol{\psi})$ is a regression function with $\boldsymbol{z}_{i,t}$ containing the explanatory variables and $\boldsymbol{\psi}$ is the respective real-valued vector of parameters, while $\varepsilon_{i,t}^{(p)}$ is assumed to be independently and identically distributed zero mean error independent from the regression function terms. In a special case where the variance of $\varepsilon_{i,t}^{(p)}$ is zero, eq. (13) can also be deterministic.

It can be seen that the following normalised logarithms of income shares have the same from of the conditional expectation as that of $\eta_{i,t}$. Namely,

$$\begin{aligned} \tilde{s}_{i,t}^{(p)} :=& \quad \frac{\ln\left(s_{i,t}^{(p)}\right)}{\ln(100/p)} + 1 \\ =& \quad \eta_{i,t} + c\zeta_{i,t}^{(p)} \\ =& \quad \alpha_p^{-1}(L) f(\boldsymbol{z}_{i,t}; \boldsymbol{\psi}) + \xi_{i,t}^{(p)}, \end{aligned} \tag{14}$$

where the error term $\xi_{i,t}^{(p)} = \alpha_p^{-1}(L)\varepsilon_{i,t}^{(p)} + c\zeta_{i,t}^{(p)}$, $c^{-1} = \ln(100/p)$.

Given that the observations for the top-incomes shares of 10%, 5%, and 1% of population with the highest income will be used next, the following system of equations will be under

[19]The term $\zeta_{i,t}$ is assumed to be independent of the remaining part of the process under consideration and, formally, a p-specific upper bound on the support can be introduced as a function of $\eta_{i,t}$ to ensure that the shares remain below one.

estimation:

$$\begin{cases} \alpha_1(L)\tilde{s}_{i,t}^{(1)} = & f(\boldsymbol{z}_{i,t};\boldsymbol{\psi}) + \tilde{\xi}_{i,t}^{(1)}, \\ \alpha_5(L)\tilde{s}_{i,t}^{(5)} = & f(\boldsymbol{z}_{i,t};\boldsymbol{\psi}) + \tilde{\xi}_{i,t}^{(5)}, \\ \alpha_{10}(L)\tilde{s}_{i,t}^{(10)} = & f(\boldsymbol{z}_{i,t};\boldsymbol{\psi}) + \tilde{\xi}_{i,t}^{(10)}, \end{cases} \tag{15}$$

where $\tilde{\xi}_{i,t}^{(p)} = \alpha_p(L)\xi_{i,t}^{(p)},\ p \in \{1, 5, 10\}$. It is clear that system (15) is featured by the cross-equation parameter restrictions.

To estimate the parameter vector $\boldsymbol{\psi}$ in such a dynamic system, we employ the GMM by assuming further that $f(\boldsymbol{z}_{i,t};\boldsymbol{\psi}) = \boldsymbol{z}_{i,t}'\boldsymbol{\psi}$. It should be pointed out that, in the general case of non-deterministic eq. (13), $\tilde{\xi}_{i,t}^{(p)}$ contains an autoregressive component $\alpha_p(L)\zeta_{i,t}^{(p)}$ that by the construction correlates with lags of $\tilde{s}_{i,t}^{(p)}$ for $\alpha_p(L) \neq 1$; hence we exclude lags of $\tilde{s}_{i,t}^{(p)}$ from the conditioning set when estimating with the GMM. On the other hand, if $\exists\ p$ s.t. $\alpha_p(L) \neq 1$, this specific feature would allow us to test the hypothesis that the Pareto distribution is empirically fit to describe the shares: in such a case $\zeta_{i,t}^{(p)} \equiv 0$ and errors of the system under consideration were uncorrelated. Therefore, the lags of $\tilde{s}_{i,t}^{(p)}$ would also be valid instruments and the over-identifying restrictions would not be rejected, for example, by the Sargan–Hansen test[20]. The empirical results that will be presented shortly are consistent with such a case.

5 Estimation results

5.1 Main findings

This subsection will first report the estimation results for the Gini index of market and net income. It will then present the findings for the joint estimation of the top-income system of equations. In either case, the dependent variable is logarithmically transformed to reduce the heteroscedasticity of the errors. As discussed in Subsection 4.1, both the GFDD and the BIS data sources of the private bank credit have relative advantages and shortcomings

[20]See Sargan (1958), Sargan (1975), Hansen (1982).

(larger number of countries versus potential structural breaks), consequently the results will be reported using each data source; that is, whenever the Gini and top-income inequality is being used as the dependent variable. In all of the cases, the robust inference relies on standard errors adjusted for clustering by countries while the number of instruments is approximately guided by the number of countries. To shrink the number of instruments, the collapsed instruments with a restricted number of lags were used by projecting only on the history of the dependent variable.

It should be noted that, aside from a few marginal cases, the instrument adequacy regarding the employed lags and admissibility of over-identifying restrictions is not rejected practically in all of the cases under consideration. In a few of the cases, lag shifts of dependent variable in the instrument set were used to achieve such an outcome, otherwise the hypothesis of the absence of the second order serial correlation[21] of errors was rejected at the 5% significance level.

Table 1 reports the results of estimation for the Gini indexes whenever only the significant variables are kept in the regressions. Namely, the almost uniformly insignificant logarithm of bank credit[22], which is highly correlated with the interaction term, was removed. Some case-specific insignificant lags of the dependent variable were dropped from the initial estimations that are presented in Table D1 (see Appendix D). It should be pointed out that the results are practically unchanged when, instead of $\frac{r_t - g_t}{1+g_t}$ appearing in Table 1 and motivated by the arguments presented in Section 3, the unscaled $r_t - g_t$ is used for the estimations in connection with the findings discussed in Section 2 (see Subsection 5.2 for this and various other sensitivity checks).

Although the point estimates vary when the GFDD and BIS data of private bank credit are used[23], the general tendency is to have a significant negative sign of $\frac{r_t - g_t}{1+g_t}$ while at the same time the significant positive impact of its interaction term with the (logarithm) of bank credit to GDP.

[21]Or more precisely, of the second order moving average term.

[22]It should be pointed that the same insignificance holds for the bank credit and capital openness interaction, which is likely to happen because of relatively similar capital openness level of countries under consideration.

[23]It should be pointed out that the difference can arise because the countries under consideration differ and also because the quality of the data sources differs.

	(1)	(2)	(3)	(4)	(5)	(6)
Type of income variable	Market	Market	Market	Net	Net	Net
Variables \ Country group	OECD	EU	EMU1999	OECD	EU	EMU1999
			Bank credit data source: GFDD			
(r-g) / (1+g)	**-1.440****	**-2.392*****	**-2.316*****	**-1.348***	**-1.316****	**-4.119**
	(0.619)	**(0.832)**	**(0.829)**	**(0.754)**	**(0.611)**	**(2.663)**
log(credit) * (r-g) / (1+g)	**0.406****	**0.604*****	**0.589*****	**0.304***	**0.362****	**0.943**
	(0.167)	**(0.207)**	**(0.189)**	**(0.178)**	**(0.166)**	**(0.623)**
P-val(AR2)	0.861	0.716	0.234	0.803	0.337	0.195
P-val(Sargan)	0.0902	0.765	0.777	0.00432	0.937	0.0191
P-val(Hansen)	0.388	0.435	0.925	0.609	0.813	0.761
Number of instruments	33	29	12	33	29	12
Number of countries	31	27	10	31	27	10
Observations	721	531	172	721	531	176
			Bank credit data source: BIS			
(r-g) / (1+g)	**-1.512****	**-5.004*****	**-4.238**	**-1.963****	**-7.196****	**-2.520**
	(0.596)	**(0.967)**	**(3.328)**	**(0.919)**	**(2.905)**	**(2.702)**
log(credit) * (r-g) / (1+g)	**0.422*****	**1.325*****	**1.084**	**0.497****	**1.843*****	**0.594**
	(0.161)	**(0.243)**	**(0.821)**	**(0.226)**	**(0.710)**	**(0.652)**
P-val(AR2)	0.979	0.0615	0.339	0.576	0.0494	0.709
P-val(Sargan)	0.110	0.354	0.696	0.153	0.798	0.160
P-val(Hansen)	0.707	0.977	0.722	0.688	1	0.310
Number of instruments	33	29	12	33	29	12
Number of countries	27	17	10	27	17	10
Observations	648	354	171	648	354	180

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Dependent variable: logarithm of Gini index of income

Table 1. Estimation results with the Gini index of income (line two indicates the type of income), and GFDD and BIS as private bank credit data sources.

For instance, taking the point estimates from column (1) of Table 1 when the GFDD data of bank credit are used (as in Figure 1), the prediction is that the inequality reducing impact of $\frac{r_t - g_t}{1+g_t}$, conditionally on $r_t > g_t$, is outweighed by the interaction term whenever the bank credit is grater than, approximately, 35 percent of GDP. Therefore, it might not be a mere coincidence that the median bank credit in the OECD countries plotted in Figure 1 (the top-right figure) also passes this threshold around the 1976–1979 period, when the inequality starts rising and it also becomes a norm for the real interest rates to be greater than the corresponding real GDP growth rates.

Qualitatively, the characterised features seem to be observable when using either the GFDD and BIS bank credit data, which also yield quite similar significance. However, looking at the market income and net income inequality, the significance of the impact of bank credit seems to be slightly more pronounced for the former.

Turning to the top income inequality, Table 2 reports the related estimation results. It should be recalled that the estimates rely on the GMM estimation of the system (15) using jointly the 1%, 5%, and 10% top-income shares. As in the case of regressions of Gini indexes, the significance of bank credit was low and Table 2 relies on the regression with solely persistently significant terms.

The same pattern of impact emerges as was found previously. However, the estimated levels of bank credit to GDP rendering the total impact of '$r-g$' inequality increasing (given $r > g$) is much lower (below even ten percent). In practical terms, this would suggest that whenever the real bank lending interest rates become greater than the GDP growth rate, inequality can be expected to rise with increasing values of $r - g$.

The results that rely on the GFDD data seem to be slightly more robust. However, the use of an exponential (as in columns (5)-(8) of Table 2) and not a linear impact function (as in columns (1)–(4)) of $r - g$-linked terms and relying on that, up to the first order approximation $\exp(x-y)\big|_{x=y} \simeq 1 + x - y$, also leads to persistent significance with the BIS data[24]. This might suggest that the influence of the interest and GDP growth rates might be much more costly in terms of top-income inequality increase whenever larger positive gaps

[24]For the Gini index of market income such an improvement was not that clear.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bank credit data source	GFDD	GFDD	BIS	BIS	GFDD	GFDD	BIS	BIS
Variables \ Presence of AR instrum.	No	Yes	No	Yes	No	Yes	No	Yes
(r-g) / (1+g)	**-0.771*** **	**-1.807*** **	**-0.528*** **	**-0.317**				
	(0.0717)	**(0.476)**	**(0.0595)**	**(0.279)**				
log(credit) * (r-g) / (1+g)	**0.134*** **	**0.377*** **	**0.0792*** **	**0.0257**				
	(0.0171)	**(0.117)**	**(0.0134)**	**(0.0638)**				
exp{ (r-g) / (1+g) }					**-1.046*** **	**-1.181*** **	**-0.494*** **	**-0.616*** **
					(0.131)	**(0.251)**	**(0.0532)**	**(0.233)**
log(credit) * [exp{ (r-g) / (1+g) } - 1]					**0.200*** **	**0.231*** **	**0.0731*** **	**0.0987***
					(0.0317)	(0.0613)	(0.0121)	(0.0534)
P-val(Hansen)	0.192	0.768	0.405	0.540	0.698	0.782	0.422	0.340
Number of instruments	15	18	15	18	15	18	15	18
Number of countries	13	13	13	13	13	13	13	13
Observations	352	352	374	359	352	352	374	359

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Dependent variable: transformation of top-income shares as defined in eq. (15).

Table 2. Estimation results for the top-income shares with the GFDD and BIS private bank credit data.

emerge between the real lending and GDP growth rates.

5.2 Some further checks

In this subsection we will check the sensitivity of the main findings reported in the previous subsection and will present the results of the projection of $r - g$ term on the financial structure. The latter is important in order to understand whether the expansion of bank credit, which is especially important in the European countries due to the central role of banks in their financial systems, did not itself affect the gap between real interest rates and GDP growth rates.

The sensitivity analysis is concentrated on the case of the Gini indexes because of the larger number of observations, at least, for the OECD and EU groups of countries. Although the outcome for the EMU1999 is also presented for completeness, it should be kept in mind that the estimation precision for this group is less accurate.

In the previous section the results were obtained by omitting insignificant bank credit variable. The initial regression from which they were obtained is presented in Table D1 of Appendix D. It can be seen that, apart from a single marginally significant case out of twelve considered ones, the bank credit variable is insignificant. If it were significant, then one could suspect that, for some (constant) $\kappa \in \mathbb{R}$, not the 'r-g', but 'r-g-κ' is of importance for inequality; that is, that the gap starts hurting even before or after the $r = g$ threshold is passed.

Table D2 reveals next that the use of the $r - g$ term instead of $\frac{r-g}{1+g}$ yields practically the same results, as was already expected in Subsection 3.2. Apart from a single case (with the BIS credit data and Net income) whenever the significance level of the interaction term changes from 1% to 5%, even the point estimates of coefficients are barely affected.

Tables D3 – D5 investigate the sensitivity of the results to the inclusion of other control variables. The main issue with such an exercise is the potentially insufficient number of degrees of freedom for precise estimation of many additional parameters. We proceeded in two way to soften this aspect.

First, in Table 3 the model is augmented with the first two principal components out of the seven variables under consideration (i.e., capital openness, initial income per capita, government consumption expenditure to GDP, trade openness to GDP, human capital, intensity of redistribution, and inflation). As can be seen, apart from a single case (column (2)), the principal components are barely significant, if at all, while the significance of the other terms of interest is only moderately affected.

Second, using the GFDD-Market income case as a baseline having the largest number of observation and the strongest results, the significance of individual control variables is investigated in Tables D4 and D5 by step-wise inclusion of variables. The two tables are used here to make their size manageable. As can be seen, the significance of the two terms of primary interest is barely affected, while the other controls are mostly insignificant with probably the strongest significance revealed by government expenditure, trade openness, and capital openness. However, their significance varies and is not uniform across different country groups; even the signs of coefficients change. These results would suggest that, as expected in the introduction, the countries under consideration are indeed quite similar in terms of inequality patterns after the conditioning on the financial deepening and $r - g$ (as well as time-invariant factors), thus rendering the further controls under consideration less informative.

Table D6 presents some further robustness checks of the inclusion of period effects in the main specifications. It should be pointed out that this drastically increases the number of parameters under estimation and even increases the minimum number of instruments required for the identification of the model. The latter aspect makes the inference about the empirical acceptability of the over-identifying restrictions less feasible. Nevertheless, keeping these shortcomings in mind, one can see that the outcome with the market income Gini index is quite similar to the main findings, whereas the significance of the results with the Gini index of net income vanishes.

Finally, Table D7 investigates, whether the bank credit and the finance composition (bank credit to stock market capitalisation and bank credit to outstanding debt securities[25]) has any influence on[26] the $\frac{r-g}{1+g}$, which now becomes the dependent variable. It is clear that this is very tentative because many other factors can be connected with the riskiness of the environment and so can play a role, and would be worth studying further[27]. However, even such a simple projection reveals that bank credit (to GDP) itself is not significant, whereas its ratio to the stock market capitalisation turns out to be highly significant. Consequently, it looks like the gap between the interest rates and GDP growth rates is influenced by the finance composition.

[25]It should be pointed out that the logarithms of these ratios are used together with the logarithm of bank credit level in order to insure that there is no bias due to the usage of the ratios.

[26]The results with $r - g$ are again almost equivalent.

[27]Although a preliminary examination of bank concentration and riskiness measures did not yield the expected results.

6 Concluding remarks

Our analysis of both the Gini indexes of market and net income, and also the top-income shares points to that the impact of the financial deepening as measured in terms of private bank credit on income inequality, which is conditional on the sign and size of the gap between the real (bank lending) interest rates and the real GDP growth rates. Our estimates show that the bank credit expansion under $r > g$ increases inequality as measured by all indicators, which is consistent with the prediction derived from the Kunieda et al. (2014) model.

From the policy perspective, this implies that, in principle, inequality can be reduced by either shrinking the amounts of bank credit under the positive gap or seeking for some structural policies that, even under the same amount of bank credit, would ensure that the real GDP growth rates are above the real lending rates. The latter alternative seems to be very attractive because 'bad credit' might soon become inequality reducing under $r < g$.

Therefore, further understanding of the '$r - g$' gap drivers is needed. A preliminary attempt in this paper that looked only at the contribution of relative financing sources suggests that fostering stock markets can be a desirable solution because a larger stock market capitalisation relative to bank credit was shown to be $r - g$ reducing. At the same time, the dependence of $r - g$ on the structure of finance means that the total impact of expansion/reduction of bank credit on inequality ceteris paribus can be even stronger than revealed by the estimated equations due to the presence of indirect impact (through $r - g$).

The presence of the established interaction term of bank credit with the gap also has some implications for the discussion about the sign of the $r - g$ impact on income inequality. Whenever $r < g$, the sign of $r - g$ impact on inequality as measured by both the Gini index and top-income shares is negative. Given that $r > g$, which was the predominant case during the latest few decades, the impact of $r - g$ on inequality is conditional on credit penetration. For instance, the impact of $r - g$ on the Gini index of market income, as estimated from the OECD MC sample, is negative until bank credit to GDP reaches approximately 35% of GDP. Afterwards, the interaction-driven term dominates and larger $r - g$ leads to increasing inequality. For the top-income shares, this bank credit share in GDP threshold seems to be even lower.

In the case of the top-income inequality, some statistical evidence would indicate that the difference between the real interest and GDP growth rates can have a stronger than linear impact. Therefore, the increasing $r - g$ might be more costly in terms of inequality; at least, as measured by the top-income shares.

The dependence of bank credit impact on income inequality on the $r - g$ is fascinating because it implies that countries with the same path of credit can reach very different outcomes. For instance, if some Southern European countries faced additional risk premiums that increased this gap, then their inequality would be expected to reach higher levels than in countries with lower risk premiums[28], given similar or even lower bank credit penetration. At the same time, this suggests that the financial integration of some Central and Eastern European countries into the EU could have softened the increase of inequality that was associated with the quick increase of bank credit penetration in these countries.

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7 Appendices

7.1 Appendix A: Variables and data sources.

Variable	Definition	Transformation	Source
Initial income	GDP per capita (constant local currency).	Logarithmic	WB World Development Indicators
Real GDP growth rate	Annual percentage growth rate of GDP at market prices based on constant local currency.	None	WB World Development Indicators
Real interest rate	Real interest rate: the lending interest rate adjusted for inflation.	None	WB World Development Indicators
Government consumption	General government final consumption expenditure as a percentage of GDP.	Logarithmic	WB World Development Indicators
Trade openness	Trade openness (calculated as exports plus imports divided by GDP).	Logarithmic	WB World Development Indicators
Inflation	Inflation, measured by the consumer price index (annual %).	Inverse hyperbolic sign transform	WB World Development Indicators
Stock market	Market capitalization of listed domestic companies as a percentage of GDP (SMC).	Logarithmic	WB World Development Indicators
Bank credit	Total credit received by non-financial sector (adjusted for breaks).	Logarithmic	BIS, Credit to the Non-financial Sector.
	The financial resources provided to the private sector by domestic money banks as a share of GDP.	Logarithmic	WB Global Financial Development Database
Debt securities	Total amount of domestic private debt securities (amount outstanding) issued in domestic markets as a share of GDP.	Logarithmic	WB Global Financial Development Database
Human capital	Human capital index, based on years of schooling and returns to education; see Human capital in PWT9.	Logarithmic	Penn World Table (Version 9)
Capital openness	The Chinn-Ito index of capital account openness.	None	http://web.pdx.edu/~ito/Chinn-Ito_website.htm
Absolute redistribution	The absolute difference between the market and net income.	Logarithmic	Standardized World Income Inequality Database (Version 5.1)
Gini indexes of income	Gini index of market and net income.	Logarithmic	Standardized World Income Inequality Database (Version 5.1)
Top-income shares	Top 1%, 5%, and 10% income shares.	Logarithmic	World Wealth and Income Database (Version of 18-08-2016)

Table A1. Variables, transformations and data sources.

7.2 Appendix B: Inequality–interest rates and inequality–bank credit scatter-plots.

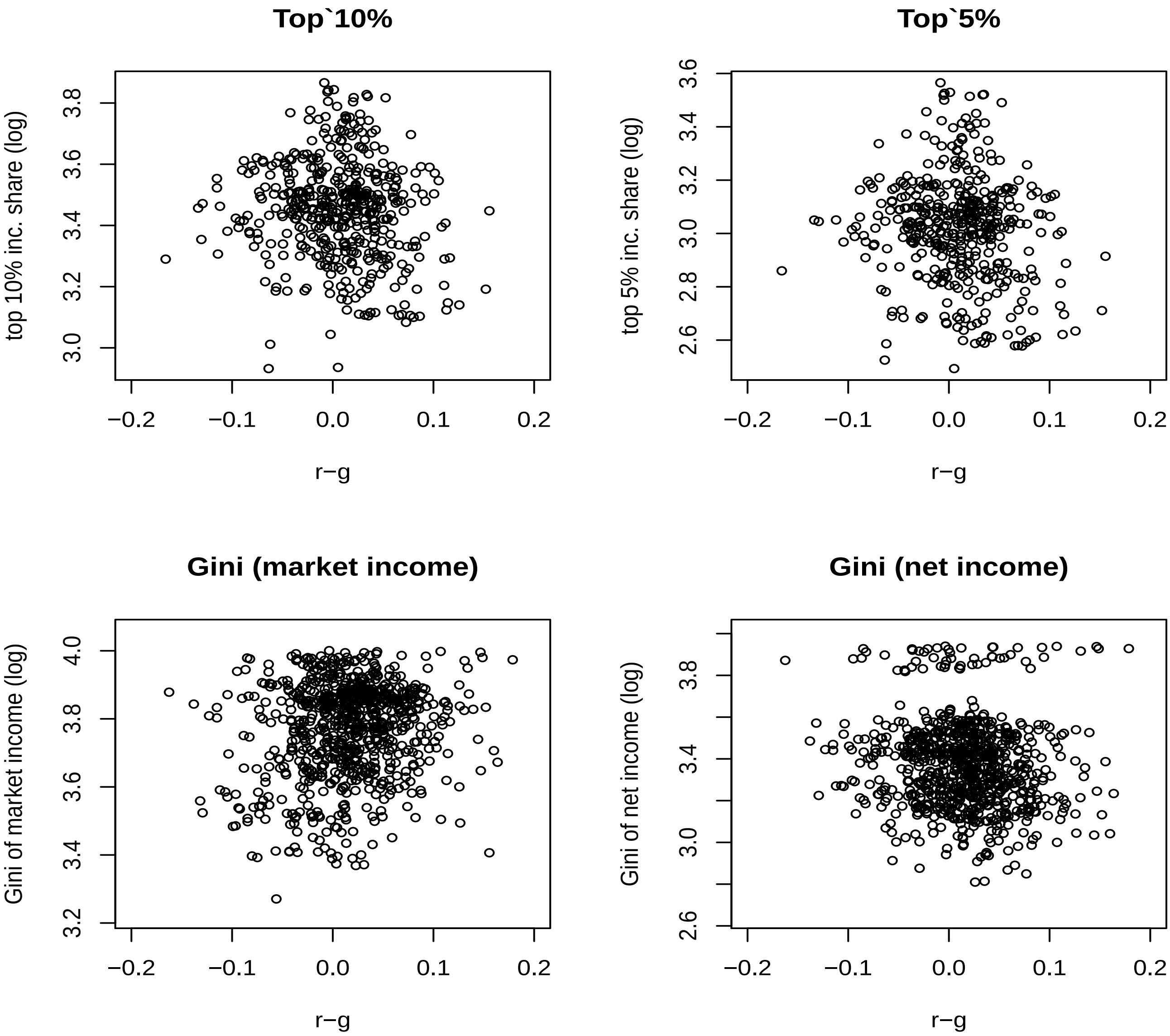

Figure 4: Inequality—interest rates scatter-plot.

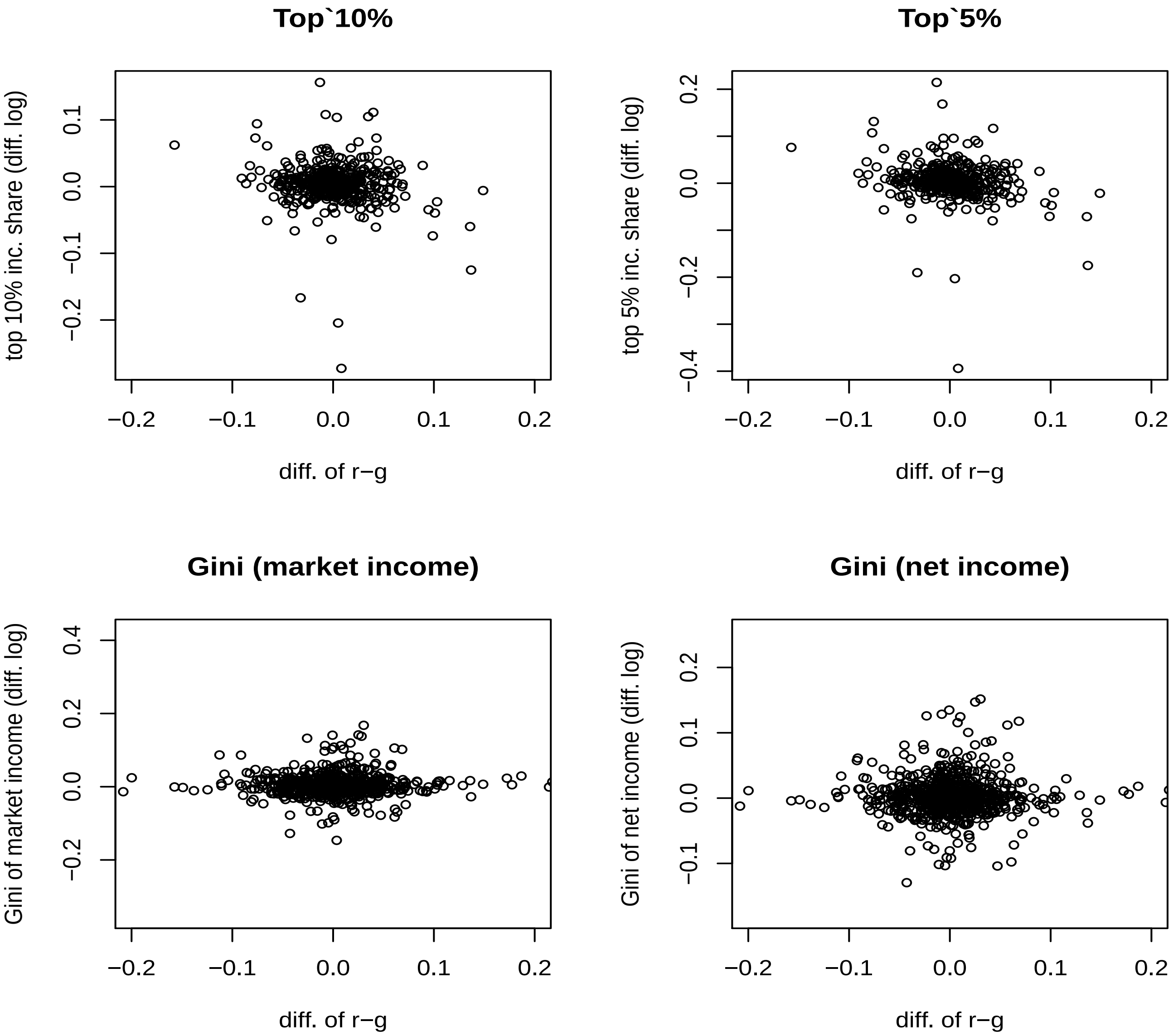

Figure 5: Inequality—interest rates scatter-plot (first differences).

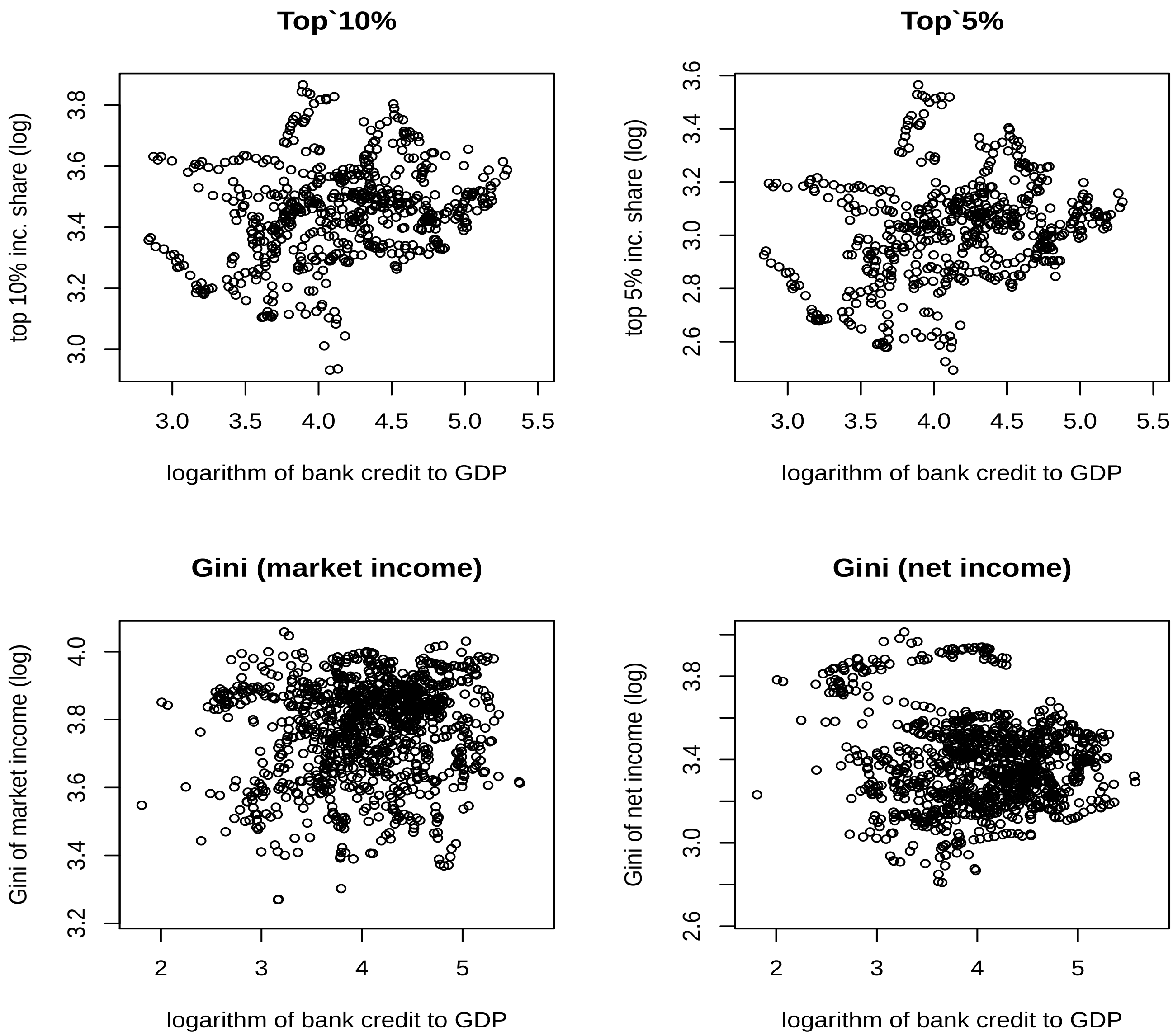

Figure 6: Inequality—bank credit scatter-plot (log-level).

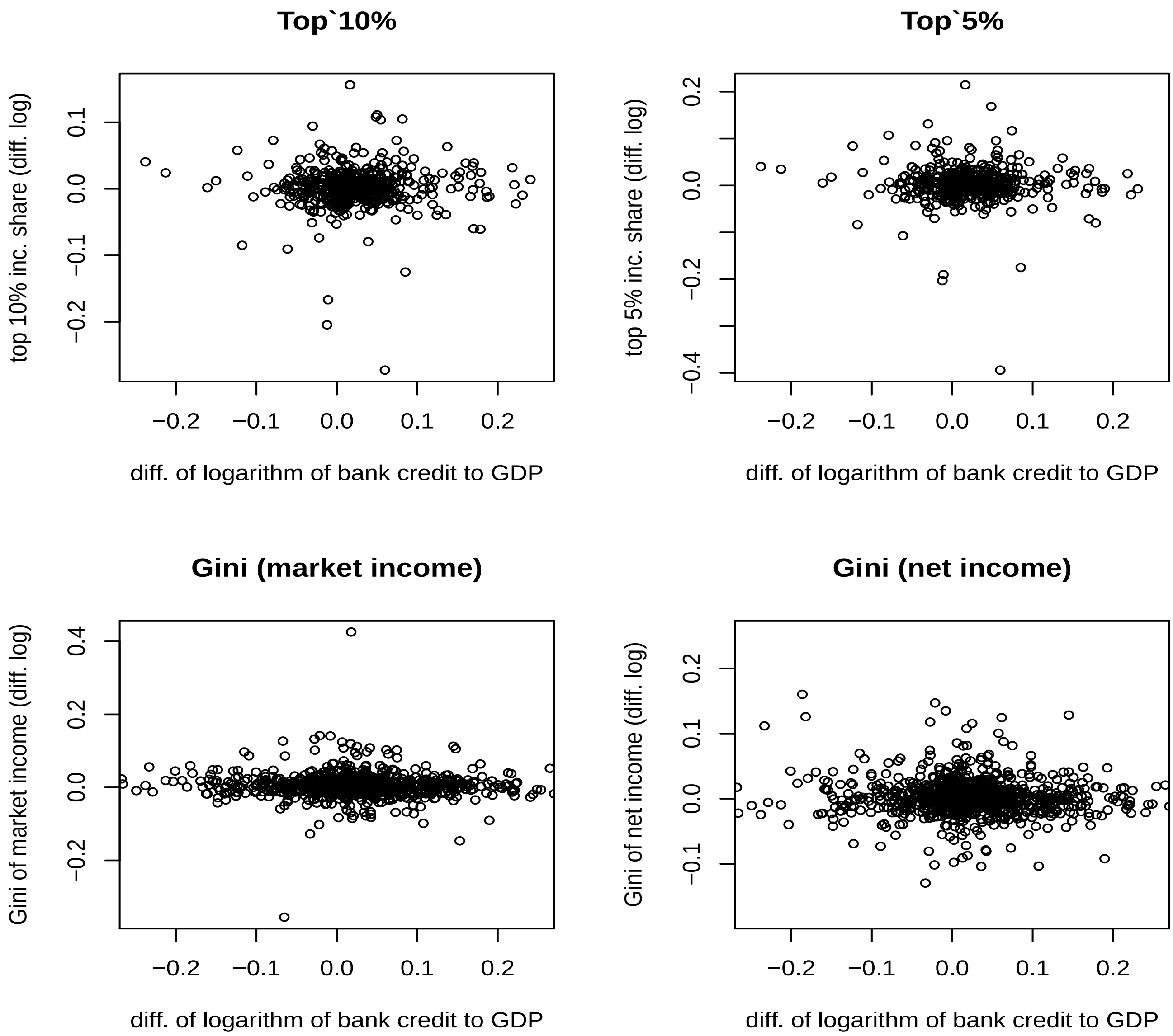

Figure 7: Inequality—bank credit scatter-plot (first differences of log-level).

7.3 Appendix C: Proof of Proposition 1.

Given that the analysis is performed for each fixed period t separately, hereafter the time index is dropped for simplicity of presentation. Consider first the consumption of "investors-borrowers" relative to that of "lenders" using eqs. (2) and (1), respectively:

$$\frac{c(\phi)}{c} = \frac{\frac{\phi-\mu\bar{\phi}}{1-\mu}\cdot\alpha A^{\frac{1}{\alpha}}w}{\bar{\phi}\alpha A^{\frac{1}{\alpha}}w} = \frac{\frac{\phi}{\bar{\phi}}-\mu}{1-\mu} =: b(\phi) \;\Rightarrow\; c(\phi) = b(\phi)c. \tag{16}$$

Hence, given that productivity is uniformly distributed with the mass L and consumption is linear in productivity for $\phi > \bar{\phi}$, the total consumption of population belonging to the $1-p$ share of largest consumers is given by

$$\begin{aligned} C_p &= L\int_p^1 c(\phi)\ \mathrm{d}\phi \\ &= Lc\int_p^1 b(\phi)\ \mathrm{d}\phi \\ &= Lc\int_p^1 \tfrac{\frac{\phi}{\bar{\phi}}-\mu}{1-\mu}\ \mathrm{d}\phi \\ &= Lc\left(\tfrac{1-p^2}{2\bar{\phi}(1-\mu)} - \tfrac{\mu(1-p)}{1-\mu}\right) \\ &= Lc\tfrac{1-p}{1-\mu}\left(\tfrac{1+p}{2\bar{\phi}} - \mu\right) \\ &= \tfrac{Lc(1-p)}{1-\mu}\tfrac{1+p-2\mu\bar{\phi}}{2\bar{\phi}}, \end{aligned}$$

assuming that $p > \bar{\phi}$ is under consideration and, therefore, eq. (16) is functional.

Also taking into account eq. (1), from the average consumption ($\bar{c}$) expression provided in Kunieda et al. (2014), it easily follows that, in an open economy, the average consumption is given by

$$\bar{c} = \frac{c}{\bar{\phi}}\cdot\frac{\bar{\phi}^2 - 2\mu\bar{\phi} + 1}{2(1-\mu)}.$$

Hence, the consumption share of population belonging to the $1-p$ share of largest consumers is given by

$$S_p = \tfrac{C_p}{L\bar{c}} = (1-p)\frac{1+p-2\mu\bar{\phi}}{\bar{\phi}^2 - 2\mu\bar{\phi} + 1}.$$

7.4 Appendix D: Sensitivity analysis of estimations.

Table D1 — The initial regression of the main specification.

Table D2 — The estimation results with $r - g$ instead of $\frac{r-g}{1+g}$.

Table D3 — The estimation with the two principal components of the control variables.

Table D4 — The estimation results with the additional control variables (to be continued in Table D5).

Table D5 — The estimation results with additional control variables (second part as the continuation of Table D4).

Table D6 — The estimation results with period dummies.

Table D7 — The finance composition impact on (r-g)/(1+g).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Bank credit data source	GFDD	GFDD	GFDD	GFDD	GFDD	GFDD	BIS	BIS	BIS	BIS	BIS	BIS
Type of income variable	Market	Market	Market	Net	Net	Net	Market	Market	Market	Net	Net	Net
Variables \ Country group	OECD	EU	EMU1999	OECD	EU	EMU1999	OECD	EU	EMU1999	OECD	EU	EMU1999
(r-g) / (1+g)	**-1.412****	**-2.224*****	**-0.994**	**-1.063**	**-1.329****	**-1.426**	**-1.496****	**-5.316*****	**-5.992**	**-1.178****	**-6.515****	**-14.21**
	(0.604)	**(0.775)**	**(2.092)**	**(0.679)**	**(0.626)**	**(3.464)**	**(0.628)**	**(1.046)**	**(7.712)**	**(0.583)**	**(2.745)**	**(15.70)**
log(credit)	**0.0155**	**-0.0176**	**0.0348**	**0.00610**	**-0.0144***	**0.0803**	**0.0224**	**0.0235**	**0.0478**	**0.00652**	**0.00993**	**0.0812**
	(0.0174)	**(0.0261)**	**(0.0498)**	**(0.0165)**	**(0.00836)**	**(0.0744)**	**(0.0173)**	**(0.0260)**	**(0.0669)**	**(0.0122)**	**(0.0246)**	**(0.0865)**
log(credit) * (r-g) / (1+g)	**0.394****	**0.582*****	**0.290**	**0.226**	**0.381****	**0.332**	**0.415****	**1.403*****	**1.565**	**0.301****	**1.661****	**3.657**
	(0.162)	**(0.198)**	**(0.492)**	**(0.174)**	**(0.176)**	**(0.845)**	**(0.169)**	**(0.258)**	**(1.897)**	**(0.151)**	**(0.667)**	**(3.909)**
First lag of dependent	1.057***	1.209***	1.133***	1.391***	1.299***	0.686*	1.012***	0.858***	0.898***	1.443***	0.856***	0.498*
	(0.0865)	(0.135)	(0.208)	(0.0980)	(0.0890)	(0.391)	(0.0979)	(0.165)	(0.193)	(0.114)	(0.0844)	(0.295)
Second lag of dependent		-0.252***	-0.229*	-0.495***	-0.350***					-0.636***		
		(0.0693)	(0.127)	(0.181)	(0.0801)					(0.142)		
Third lag of dependent	-0.191***		-0.145***			-0.296*	-0.213***	-0.144***	-0.235***		-0.254***	
	(0.0469)		(0.0286)			(0.173)	(0.0494)	(0.0363)	(0.0759)		(0.0611)	
Constant	0.438	0.236	0.762**	0.330	0.225	1.691**	0.664*	0.987**	1.069***	0.628***	1.269***	1.305
	(0.356)	(0.565)	(0.379)	(0.329)	(0.233)	(0.784)	(0.355)	(0.473)	(0.413)	(0.154)	(0.304)	(1.129)
P-val(AR2)	0.880	0.944	0.298	0.0882	0.406	0.496	0.860	0.0264	0.205	0.0969	0.0663	0.438
P-val(Sargan)	0.0862	0.627	0.756	0.758	0.961	0.0531	0.162	0.514	0.791	0.859	0.591	4.98e-05
P-val(Hansen)	0.697	0.546	1	0.390	0.780	0.698	0.863	0.979	0.993	0.829	0.996	0.768
Number of instruments	33	29	12	33	29	12	33	29	12	33	29	12
Number of countries	31	27	10	31	27	10	26	16	9	26	16	9
Observations	721	531	172	734	531	176	628	346	167	638	346	183

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Dependent variable: logarithm of Gini index of income

Table D1. The initial estimation results with (logarithm of) bank credit included.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Bank credit data source	GFDD	GFDD	GFDD	GFDD	GFDD	GFDD	BIS	BIS	BIS	BIS	BIS	BIS
Type of income variable	Market	Market	Market	Net	Net	Net	Market	Market	Market	Net	Net	Net
Variables \ Country group	OECD	EU	EMU1999	OECD	EU	EMU1999	OECD	EU	EMU1999	OECD	EU	EMU1999
r-g	**-1.447****	**-2.430*****	**-2.306*****	**-1.368***	**-1.307****	**-4.152**	**-1.477****	**-4.869*****	**-3.608**	**-1.959****	**-6.918****	**-2.249**
	(0.617)	**(0.827)**	**(0.831)**	**(0.753)**	**(0.619)**	**(2.661)**	**(0.585)**	**(0.974)**	**(2.815)**	**(0.921)**	**(2.838)**	**(2.406)**
log(credit) * (r-g)	**0.410****	**0.620*****	**0.587*****	**0.310***	**0.367****	**0.953**	**0.412*****	**1.289*****	**0.925**	**0.495****	**1.770****	**0.526**
	(0.165)	**(0.208)**	**(0.190)**	**(0.178)**	**(0.171)**	**(0.623)**	**(0.158)**	**(0.244)**	**(0.696)**	**(0.227)**	**(0.693)**	**(0.579)**
First lag of dependent	1.066***	1.151***	1.186***	0.946***	1.292***	0.749***	1.029***	0.878***	1.189***	0.907***	0.853***	1.300***
	(0.0747)	(0.0842)	(0.149)	(0.0579)	(0.0826)	(0.282)	(0.0845)	(0.137)	(0.159)	(0.0732)	(0.0822)	(0.129)
Second lag of dependent		-0.269***	-0.258**		-0.366***				-0.277**			-0.461***
		(0.0530)	(0.120)		(0.0721)				(0.136)			(0.131)
Third lag of dependent	-0.173***		-0.143***	-0.119*		-0.274*	-0.197***	-0.118**	-0.137***	-0.242***	-0.242***	
	(0.0377)		(0.0333)	(0.0670)		(0.148)	(0.0427)	(0.0472)	(0.0378)	(0.0563)	(0.0645)	
Constant	0.402	0.452	0.821**	0.587**	0.249	1.758***	0.634**	0.909**	0.857**	1.132***	1.283***	0.541**
	(0.313)	(0.320)	(0.395)	(0.292)	(0.223)	(0.561)	(0.309)	(0.396)	(0.369)	(0.166)	(0.302)	(0.241)
P-val(AR2)	0.861	0.731	0.254	0.814	0.337	0.196	0.958	0.0827	0.315	0.570	0.0545	0.699
P-val(Sargan)	0.0911	0.757	0.766	0.00424	0.939	0.0215	0.101	0.317	0.647	0.150	0.735	0.163
P-val(Hansen)	0.393	0.447	0.913	0.599	0.802	0.749	0.698	0.974	0.585	0.631	0.990	0.318
Number of instruments	33	29	12	33	29	12	33	29	12	33	29	12
Number of countries	31	27	10	31	27	10	27	17	10	27	17	10
Observations	721	531	172	721	531	176	648	354	171	648	354	180

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Dependent variable: logarithm of Gini index of income

Table D2. The estimation results with ‘r-g’ instead of (r-g)/(1+g).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Bank credit data source	GFDD	GFDD	GFDD	GFDD	GFDD	GFDD	BIS	BIS	BIS	BIS	BIS	BIS
Type of income variable	Market	Market	Market	Net	Net	Net	Market	Market	Market	Net	Net	Net
Variables \ Country group	OECD	EU	EMU1999	OECD	EU	EMU1999	OECD	EU	EMU1999	OECD	EU	EMU1999
(r-g) / (1+g)	**-0.897***	**-0.573**	**-2.613***	**-1.189****	**-1.343***	**-3.177**	**-1.102**	**-4.340******	**-10.99**	**-1.423****	**-4.547****	**-2.355**
	(0.526)	**(0.670)**	**(1.529)**	**(0.602)**	**(0.776)**	**(6.708)**	**(0.716)**	**(1.564)**	**(14.33)**	**(0.717)**	**(2.048)**	**(10.42)**
log(credit) * (r-g) / (1+g)	**0.255***	**0.0762**	**0.621***	**0.317****	**0.379***	**0.977**	**0.302**	**1.089******	**2.681**	**0.372****	**1.196****	**0.803**
	(0.141)	**(0.176)**	**(0.360)**	**(0.159)**	**(0.208)**	**(1.625)**	**(0.191)**	**(0.411)**	**(3.552)**	**(0.185)**	**(0.479)**	**(2.705)**
1st princ. component	0.0168	0.118*	0.0412	-0.0449	-0.0588	-0.201	0.0160	0.00457	0.0869	-0.0194	-0.0584	-0.195
	(0.0208)	(0.0616)	(0.0451)	(0.0294)	(0.0426)	(0.283)	(0.0242)	(0.0465)	(0.0712)	(0.0195)	(0.0524)	(0.139)
2nd princ. component	-0.00310	0.113**	0.0373	-0.0821*	-0.0849	-0.430	-0.00501	-0.0130	0.0805	-0.0453	-0.0966	-0.341
	(0.0149)	(0.0564)	(0.0441)	(0.0470)	(0.0552)	(0.473)	(0.0186)	(0.0501)	(0.0870)	(0.0283)	(0.0745)	(0.244)
First lag of dep. var.	0.941***	0.732***	0.702	0.945***	1.366***	0.153	0.953***	0.896***	0.118	0.974***	0.874***	0.958
	(0.194)	(0.255)	(0.550)	(0.0813)	(0.112)	(0.647)	(0.205)	(0.239)	(0.772)	(0.0476)	(0.0846)	(1.074)
Second lag of dep. var.		-0.230**	-0.0326		-0.490***				0.218			-0.471
		(0.105)	(0.261)		(0.0902)				(0.404)			(0.488)
Third lag of dep. var.	-0.216***		-0.176**	-0.299***		-0.278	-0.234***	-0.218***	-0.177	-0.316***	-0.303***	
	(0.0602)		(0.0738)	(0.0480)		(0.374)	(0.0592)	(0.0391)	(0.109)	(0.0398)	(0.0544)	
Constant	1.025	1.734**	1.881	1.245***	0.512*	4.117***	1.047	1.231	3.087**	1.180***	1.522***	2.034
	(0.654)	(0.820)	(1.247)	(0.235)	(0.310)	(0.977)	(0.700)	(0.865)	(1.555)	(0.143)	(0.232)	(2.045)
P-val(AR2)	0.702	0.416	0.128	0.507	0.213	0.403	0.838	0.0679	0.460	0.197	0.0372	0.131
P-val(Sargan)	0.105	0.960	0.683	0.770	0.913	0.817	0.116	0.274	0.991	0.786	0.211	0.427
P-val(Hansen)	0.801	0.734	0.980	0.696	0.745	0.987	0.883	0.988	0.992	0.801	0.997	0.939
Number of instruments	33	29	12	33	29	12	33	29	12	33	29	12
Number of countries	30	23	9	30	23	9	27	17	10	27	17	10
Observations	646	432	157	646	432	159	590	316	165	590	316	173

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Dependent variable: logarithm of Gini index of income

Table D3. The estimation with the two principal components of the control variables.

Variables \ Country group	(1) OECD	(2) EU	(3) EMU1999	(4) OECD	(5) EU	(6) EMU1999	(7) OECD	(8) EU	(9) EMU1999	(10) OECD	(11) EU	(12) EMU1999
(r-g) / (1+g)	**-1.289****	**-1.493****	**-2.376*****	**-1.004****	**-0.960****	**-2.019***	**-0.998****	**-0.672**	**-2.031***	**-0.979****	**-0.684**	**-2.832****
	(0.513)	**(0.623)**	**(0.920)**	**(0.468)**	**(0.449)**	**(1.202)**	**(0.486)**	**(0.433)**	**(1.229)**	**(0.488)**	**(0.436)**	**(1.297)**
log(credit) * (r-g) / (1+g)	**0.363*****	**0.423****	**0.580*****	**0.282****	**0.271****	**0.496***	**0.281****	**0.200***	**0.499***	**0.275****	**0.203***	**0.722****
	(0.132)	**(0.170)**	**(0.214)**	**(0.126)**	**(0.121)**	**(0.286)**	**(0.129)**	**(0.113)**	**(0.292)**	**(0.129)**	**(0.114)**	**(0.326)**
capital openness				0.0458	0.0481*	0.0145	0.0623	0.0970**	0.0122	0.0633	0.0953*	0.0242
				(0.0283)	(0.0271)	(0.0177)	(0.0416)	(0.0495)	(0.0287)	(0.0467)	(0.0562)	(0.0266)
initial income (lagged)							-0.00938	-0.0391	0.00537	-0.00901	-0.0382	0.0123
							(0.0236)	(0.0368)	(0.0321)	(0.0233)	(0.0368)	(0.0293)
government consumption										0.0113	0.0179	-0.217**
										(0.103)	(0.193)	(0.0970)
human capital												
trade openness												
absolute redistribution												
inflation												
First lag of dep. var.	1.098***	1.021***	1.252***	1.017***	1.030***	1.232***	0.973***	0.907***	1.224***	0.960***	0.915***	1.253***
	(0.135)	(0.111)	(0.109)	(0.104)	(0.110)	(0.139)	(0.107)	(0.149)	(0.104)	(0.180)	(0.163)	(0.197)
Second lag of dep. var.	-0.0650	-0.0608	-0.290**	-0.00966	-0.0766	-0.275**	-0.000695	-0.0328	-0.272**	0.00203	-0.0338	-0.271**
	(0.184)	(0.0755)	(0.115)	(0.101)	(0.0809)	(0.136)	(0.0915)	(0.0812)	(0.116)	(0.0860)	(0.0814)	(0.129)
Third lag of dep. var.	-0.151**	-0.125**	-0.132***	-0.228***	-0.198***	-0.143***	-0.218***	-0.177***	-0.142***	-0.216***	-0.176***	-0.168***
	(0.0689)	(0.0576)	(0.0340)	(0.0652)	(0.0625)	(0.0343)	(0.0772)	(0.0633)	(0.0367)	(0.0786)	(0.0650)	(0.0412)
Constant	0.443*	0.626*	0.653*	0.796*	0.895**	0.699**	0.989*	1.486**	0.660*	0.982**	1.393	1.204**
	(0.234)	(0.349)	(0.346)	(0.419)	(0.437)	(0.341)	(0.514)	(0.629)	(0.394)	(0.495)	(1.189)	(0.586)
P-val(AR2)	0.398	0.965	0.288	0.221	0.651	0.244	0.176	0.402	0.235	0.194	0.397	0.624
P-val(Sargan)	0.493	0.118	0.937	0.191	0.0645	0.935	0.139	0.0379	0.910	0.103	0.0331	0.988
P-val(Hansen)	0.984	0.749	1	0.774	0.834	1	0.939	0.893	1	0.926	0.861	1
Number of instruments	52	33	33	33	33	33	33	33	33	33	33	33
Number of countries	31	27	10	30	26	9	30	26	9	30	26	9
Observations	711	517	172	686	496	163	686	496	163	686	495	163

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Dependent variable: logarithm of Gini index of market income

Table D4. The estimation results with the additional control variables (to be continued in Table D5).

Variables \ Country group	(1) OECD	(2) EU	(3) EMU1999	(4) OECD	(5) EU	(6) EMU1999	(7) OECD	(8) EU	(9) EMU1999	(10) OECD	(11) EU	(12) EMU1999
(r-g) / (1+g)	**-1.194****	**-0.575**	**-1.786***	**-1.224***	**-0.842***	**-1.506**	**-1.032**	**-0.995***	**-2.413***	**-0.440**	**-0.747**	**-2.992****
	(0.596)	**(0.410)**	**(1.048)**	**(0.701)**	**(0.480)**	**(1.178)**	**(0.653)**	**(0.540)**	**(1.381)**	**(0.767)**	**(0.555)**	**(1.343)**
log(credit) * (r-g) / (1+g)	**0.357****	**0.167**	**0.467***	**0.365****	**0.247***	**0.416**	**0.306***	**0.288****	**0.612****	**0.163**	**0.218**	**0.756*****
	(0.146)	**(0.108)**	**(0.261)**	**(0.178)**	**(0.128)**	**(0.287)**	**(0.161)**	**(0.139)**	**(0.292)**	**(0.181)**	**(0.140)**	**(0.282)**
capital openness	-0.0245	0.0781	0.0354	-0.0240	0.0881	0.0286	0.0154	0.127	0.0696	0.0198	0.145	0.0487
	(0.0921)	(0.0790)	(0.0415)	(0.0899)	(0.0858)	(0.0362)	(0.0732)	(0.0917)	(0.0588)	(0.103)	(0.0941)	(0.0574)
initial income (lagged)	-0.0779	-0.0688	-0.0534	-0.0801	-0.0721	-0.0707	-0.0490	-0.105	-0.0638	-0.116	-0.128	-0.0430
	(0.0755)	(0.0600)	(0.0698)	(0.0900)	(0.0645)	(0.0860)	(0.0753)	(0.0823)	(0.0910)	(0.115)	(0.0903)	(0.0769)
government consumption	-0.404	-0.0698	-0.214**	-0.406	-0.151	-0.238**	-0.134	-0.215	-0.264*	-0.0935	-0.0922	-0.319**
	(0.341)	(0.198)	(0.0967)	(0.355)	(0.204)	(0.105)	(0.242)	(0.181)	(0.155)	(0.286)	(0.170)	(0.160)
human capital	0.809	0.534**	0.217	0.798*	0.269	0.271	0.632	0.129	0.0635	0.722	0.0314	0.0560
	(0.527)	(0.249)	(0.226)	(0.442)	(0.399)	(0.290)	(0.490)	(0.338)	(0.459)	(0.700)	(0.399)	(0.412)
trade openness				0.00594	0.0917	0.0273	-0.0276	0.134	0.0883***	-0.00629	0.140	0.0673**
				(0.0712)	(0.124)	(0.0387)	(0.0375)	(0.143)	(0.0256)	(0.0648)	(0.149)	(0.0302)
absolute redistribution							-0.0141	0.0362	0.0724	-0.0315	0.0627	0.0566
							(0.0418)	(0.0454)	(0.0657)	(0.0531)	(0.0392)	(0.0602)
inflation										-0.218	-0.0201	-0.302
										(0.232)	(0.0961)	(0.311)
First lag of dep. var.	0.652***	0.526**	1.078***	0.658***	0.565***	1.105***	0.592***	0.502**	1.022***	0.468**	0.441**	0.990***
	(0.230)	(0.211)	(0.204)	(0.213)	(0.185)	(0.199)	(0.185)	(0.206)	(0.199)	(0.236)	(0.200)	(0.169)
Second lag of dep. var.	0.0703	0.0625	-0.189**	0.0685	0.0322	-0.207**	0.112	-0.000606	-0.242***	0.156	0.0212	-0.201***
	(0.103)	(0.0694)	(0.0954)	(0.102)	(0.0817)	(0.0932)	(0.108)	(0.104)	(0.0740)	(0.121)	(0.119)	(0.0769)
Third lag of dep. var.	-0.198***	-0.156***	-0.175***	-0.199**	-0.170***	-0.187***	-0.180***	-0.182**	-0.225***	-0.168***	-0.175**	-0.230***
	(0.0717)	(0.0508)	(0.0663)	(0.0790)	(0.0594)	(0.0701)	(0.0624)	(0.0749)	(0.0692)	(0.0588)	(0.0697)	(0.0749)
Constant	2.974**	2.438**	2.006	2.984**	2.618*	2.096	2.188*	3.380**	2.378*	2.981**	3.357**	2.492**
	(1.448)	(1.234)	(1.255)	(1.519)	(1.382)	(1.331)	(1.190)	(1.450)	(1.228)	(1.515)	(1.366)	(1.015)
P-val(AR2)	0.225	0.961	0.631	0.212	0.509	0.578	0.520	0.347	0.677	0.578	0.401	0.594
P-val(Sargan)	0.301	0.0171	0.963	0.264	0.0915	0.966	0.136	0.404	0.962	0.105	0.257	0.974
P-val(Hansen)	0.791	0.766	1	0.821	0.855	1	0.869	0.990	1	0.892	1	1
Number of instruments	33	33	33	33	33	33	33	33	33	33	33	33
Number of countries	30	26	9	30	26	9	30	23	9	30	23	9
Observations	686	495	163	686	495	163	660	442	163	640	422	157

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Dependent variable: logarithm of Gini index of market income

Table D5. The estimation results with additional control variables (second part as the continuation of Table D4).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Bank credit data source	GFDD	GFDD	GFDD	GFDD	GFDD	GFDD	BIS	BIS	BIS	BIS	BIS	BIS
Type of income variable	Market	Market	Market	Net	Net	Net	Market	Market	Market	Net	Net	Net
Variables \ Country group	OECD	EU	EMU1999	OECD	EU	EMU1999	OECD	EU	EMU1999	OECD	EU	EMU1999
(r-g) / (1+g)	**-1.370*** **	**-1.902** **	**-2.633**	**-1.128**	**-0.324**	**0.636**	**-1.324*** **	**-2.104** **	**-3.684* **	**-0.520**	**-1.445**	**0.764**
	(0.455)	**(0.887)**	**(1.623)**	**(0.743)**	**(0.721)**	**(1.783)**	**(0.417)**	**(1.034)**	**(1.981)**	**(0.425)**	**(1.375)**	**(2.210)**
log(credit) * (r-g) / (1+g)	**0.378*** **	**0.495** **	**0.649* **	**0.236**	**0.0854**	**-0.0955**	**0.365*** **	**0.540** **	**0.947** **	**0.129**	**0.369**	**-0.196**
	(0.120)	**(0.228)**	**(0.354)**	**(0.167)**	**(0.185)**	**(0.383)**	**(0.116)**	**(0.271)**	**(0.480)**	**(0.106)**	**(0.347)**	**(0.538)**
First lag of dep. var.	1.013***	1.145***	1.319***	1.025***	1.344***	0.851***	1.000***	0.986***	1.258***	1.011***	0.847***	1.241***
	(0.107)	(0.139)	(0.0850)	(0.0709)	(0.155)	(0.167)	(0.0893)	(0.137)	(0.128)	(0.0646)	(0.126)	(0.148)
Second lag of dep. var.		-0.256***	-0.355***		-0.347***				-0.342***			-0.487***
		(0.0565)	(0.0952)		(0.0719)				(0.104)			(0.108)
Third lag of dep. var.	-0.190***		-0.109**	-0.0732		-0.240**	-0.212***	-0.162***	-0.131***	-0.140**	-0.279***	
	(0.0417)		(0.0477)	(0.0533)		(0.111)	(0.0449)	(0.0425)	(0.0503)	(0.0554)	(0.0750)	
P-val(AR2)	0.707	0.701	0.462	0.613	0.0259	0.403	0.991	0.330	0.227	0.920	0.173	0.265
P-val(Sargan)	0.173	0.0569	4.76e-06	4.53e-05	0.133	0	0.258	0.0536	7.99e-07	2.91e-09	0.000108	0.0302
P-val(Hansen)	1	1	1	1	1	1	1	1	1	1	1	1
Number of instruments	82	76	62	82	76	62	82	76	62	82	76	63
Number of countries	31	27	10	31	27	10	27	17	10	27	17	10
Observations	721	531	172	721	531	176	648	354	171	648	354	180

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Dependent variable: logarithm of Gini index

Table D6. The estimation results with period dummies.

Bank credit data source Variables \ Country group	(1) GFDD OECD	(2) GFDD EU	(3) GFDD EMU1999	(4) BIS OECD	(5) BIS EU	(6) BIS EMU1999
log(bank credit)	**-0.0396**	**-0.000465**	**-0.0724**	**-0.0161**	**-0.0232**	**-0.0476**
	(0.0286)	**(0.0231)**	**(0.0540)**	**(0.0387)**	**(0.0290)**	**(0.0327)**
log(bank credit / stock market)	**0.0400****	**0.0211*****	**0.0194***	**0.0431****	**0.0273*****	**0.0162***
	(0.0186)	**(0.00672)**	**(0.0105)**	**(0.0189)**	**(0.00763)**	**(0.00918)**
log(bank credit / debt securities)	**0.00201**	**0.0110**	**0.000946**	**0.0176**	**0.00724**	**0.00196**
	(0.0144)	**(0.0127)**	**(0.0469)**	**(0.0208)**	**(0.0136)**	**(0.0317)**
First lag of dep. var.	0.430***	0.694***	0.743**	0.242**	0.667***	0.770***
	(0.133)	(0.0975)	(0.329)	(0.116)	(0.103)	(0.228)
Second lag of dep. var.	-0.140	-0.134*	-0.0946	-0.135	-0.116	-0.159
	(0.0895)	(0.0719)	(0.154)	(0.0919)	(0.0817)	(0.136)
Third lag of dep. var.	0.0846	0.0454	-0.0533	0.0816	0.00218	-0.115**
	(0.0701)	(0.0625)	(0.147)	(0.0610)	(0.0774)	(0.0582)
Constant	0.170	-0.0126	0.320	0.0593	0.0908	0.210
	(0.125)	(0.105)	(0.277)	(0.170)	(0.134)	(0.145)
P-val(AR2)	0.126	0.357	0.652	0.362	0.375	0.269
P-val(Sargan)	0.0607	0.174	0.205	0.00217	0.358	0.208
P-val(Hansen)	0.658	0.781	0.501	0.842	0.998	0.724
Number of instruments	33	29	12	32	29	12
Number of countries	405	238	122	400	204	121
Observations	28	22	10	25	16	9

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Dependent variable: (r-g) / (1+g)

Table D7. The finance composition impact on (r-g)/(1+g).

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