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Income Inequality, Economic Growth, and the Effect of Redistribution

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Abstract

Evidence from a current panel of harmonized worldwide data highlights a robust negative effect of income inequality on economic growth that we trace back to its transmission channels. Less equal societies tend to have less educated populations and higher fertility rates, but not necessarily lower investment shares. The first two effects are harmful for growth and reinforced by limited credit availability. Higher public spending on education attenuates the negative effects of inequality. In addition to the inequality-growth relationship, we examine the direct influence of effective redistribution. When net inequality is held constant, public redistribution negatively affects economic growth. Redistribution hampers investment and raises fertility rates. Combining the negative direct growth effect and the indirect positive effect operating through lower net inequality, the overall impact of redistribution is insignificant. Whereas this result stems mainly from advanced economies, redistribution is beneficial for growth in low and middle-income countries.

Keywords: Economic Growth, Redistribution, Inequality, Panel Data
JEL No.: O11, O15, O47, H23

1 Introduction

In his famous book *"Equity and Efficiency: The Big Tradeoff"*, Okun (1975) points out that the trade-off between social justice and economic efficiency "plagues us in dozens of dimensions of social policy". Okun's notion led to the widespread belief that income inequality is beneficial for growth and that public redistribution via taxes and transfers creates disincentives and inefficiencies that Okun compares to a "leaky bucket", with money lost whenever transfers are made from the rich to the poor. However, empirical evidence on the existence of such a trade-off is rather ambiguous.

The literature at hand can be divided into two distinct groups. One branch examines the link between inequality and growth, while the other studies the growth effects of redistributive taxes and social transfers. This paper follows a novel approach by simultaneously exploring the growth effects of both income inequality and effective public redistribution. We find that a high level of inequality reduces GDP growth, but its remedy—redistribution via taxes and transfers—is detrimental to growth alike. Thus the direct negative effect of redistribution is offsetting its indirect positive growth effect from reduced net inequality. Taken together, at a given level of market inequality the impact of redistribution on economic growth is insignificant. However, both the growth effects of inequality and redistribution depend on the development level of the economies.

Whereas early cross-country studies tend to find a negative relationship between income inequality and economic growth, the results have become ambiguous since the advent of panel data methods.[1] Particularly Li and Zou (1998) and Forbes (2000) contradict previous findings by detecting a positive impact of inequality on economic growth. In contrast, Barro (2000) yields little indication of a distinct relationship between inequality and growth in a diverse panel of countries. However, the results are dependent on the development level, where inequality exerts a negative influence in developing countries and a positive effect in advanced economies. Castelló-Climent (2010) confirms the dependency on the development level, but finds an overall negative growth effect of income and human capital inequality. Voitchovsky (2005) enriches the debate by focusing on the shape of income distribution. The study concludes that growth is promoted by inequality at the top end of income distribution, but weakened by inequality at the bottom-end. Finally, Halter et al. (2014) emphasize the time dimension of the inequality-growth relationship by showing that higher inequality fosters growth in the short term, but hampers growth in the medium to long-run. Hence, one explanation for the inconclusiveness of the literature is that estimates based on time-series variations pick up positive short-run effects of inequality, whereas methods which also exploit cross-country variations capture its negative impact in the medium to long-run.

With regard to the growth effects of redistributive fiscal policy the empirical evidence is divided. Based on different fiscal policy instruments to proxy the extent of redistribution—such as marginal tax rates or social spending—earlier studies tend to find a negligible or

[1]The empirical growth literature of the 1990s is comprehensively reviewed in Aghion et al. (1999).

slightly positive impact on growth (see, e.g., Perotti, 1996). In light of these findings, Lindert (2004) suggests that large welfare states have come up with methods to minimize the negative incentive effects and deadweight losses from social spending. In contrast, a recent study by Muinelo-Gallo and Roca-Sagalés (2013), which uses panel data of 21 high-income OECD countries, shows that distributive expenditures and direct taxes produce significant reductions in inequality but also in GDP growth.

So far, two main problems have restricted the exploration of the growth effects of inequality and redistribution. First, the extent to which specific fiscal policy instruments are actually redistributive often remains unclear. Since the size of taxes and transfers may be little indication of their redistributive impact, their progressivity is difficult to measure and to compare across countries. Second, comparable data on income inequality has also long been restricted to a limited scope of countries and years.

Whereas the Luxemburg Income Study (LIS) has earned a reputation as the gold standard of cross-nationally comparable inequality data, calculations on the basis of harmonized microdata strongly restrict data availability, resulting in a coverage of only 232 country-years. The incorporation of a larger number of observations, however, comes at the cost of impairing comparability. Only recently, a comprehensive data set has been provided by Solt (2009, 2015b), which maximizes comparability for the broadest possible sample of countries and years using model-based multiple imputation estimates. The Standardized World Income Inequality Database (SWIID) 5.0 covers estimates of both net and market income inequality comparable with those obtained from the LIS Key Figures for roughly 4,600 country-years. Due to the progress in data availability, our analysis draws on an extended number of observations compared to earlier studies on the link between inequality and growth. Covering data from 154 countries between 1965 and 2012, our sample also includes a large number of developing countries, thereby enabling investigation of the effect of inequality and redistribution in dependence on the income level.

Above all, a clear distinction between inequality before and after taxes and transfers in the SWIID enables measurement of redistribution by calculating the difference between market-income and net-income Gini indices. Thus we are able to regress growth on effective redistribution, rather than relying on rough proxies of redistributive fiscal policies. Although commonly applied in sociology and public policy (see, e.g., Van den Bosch and Cantillon (2008)), the "pre-post" approach for measuring redistribution via the difference between market and net inequality is thus far quite novel in the empirical growth literature. Berg et al. (2014) utilize a previous version of the SWIID to receive data on effective redistribution. Whereas the study finds little evidence for a significant growth effect of redistribution, it suggests that inequality is an impediment to economic growth. Thewissen (2013) calculates a measure of pre-post redistribution using data from the LIS and the OECD. Based on a panel of high-income countries, the study finds no robust influence of inequality and redistribution on economic performance, but indicates a positive relationship between top income shares and growth.

In this paper, our extended dataset allows for application of the system GMM estimator, which requires sufficient lags of the instruments. The benefit of system GMM is that it retains some of the cross-country variation when accounting for unobserved heterogeneity. Maintaining this information is important, as most of the variation in the inequality data stems from cross-country differences, rather than from the time dimension. Moreover, exploiting cross-country variations enables capture of long-run growth effects.

In addition to reduced form evidence, this paper focuses on the transmission channels through which inequality and redistribution exert their influence on growth. While subject to some studies based on cross-country data (e.g. Perotti, 1994, 1996), the transmission channels of inequality have been rather neglected in panel data studies, which is criticized by Galor (2009). Hence, we simultaneously explore the transmission channels of both inequality and redistribution. Our results reveal that income inequality mainly acts via human capital accumulation and the fertility rate, but not necessarily via physical investments. Public redistribution, in contrast, seems to deter investment and to boost the fertility rate. Holding constant these transmission variables, the negative effects of inequality and redistribution on growth vanish. Moreover, the negative impact of inequality on growth is reinforced by credit market imperfections, but attenuated by generous public spending on education. Finally, we provide evidence for the endogenous fiscal policy channel: An increase in market inequality enhances public redistribution, which is why a low level of market inequality is conducive for economic growth.

The paper is organized as follows: Section 2 reviews the main theories on inequality, redistribution and growth, laying the groundwork for the empirical investigations. Section 3 presents our empirical specification. Section 4 describes the data, focusing on our measures of inequality and redistribution. The chapter overviews the extent of redistribution across countries and highlights the empirical relation between inequality and redistribution. We report the baseline results in Section 5, followed by an extensive sensitivity analysis. Subsequently, we examine the aggregate effect of public redistribution and investigate the transmission channels. The empirical section closes with an examination of the effects of inequality and redistribution at different levels of development. Section 6 concludes.

2 The link between inequality, redistribution, and economic growth

Numerous explanations exist for the link between inequality and economic growth.[2] This section consolidates the theoretical approaches into five categories: differential saving rates, credit market imperfections, endogenous fertility, sociopolitical unrest, and the endogenous fiscal policy approach.

[2] A review of the perspective of the new growth theories can be found in Aghion et al. (1999). Voitchovsky (2009) and Neves and Silva (2014) provide surveys of the more recent theoretical and empirical literature on inequality and growth.

2.1 Differential Saving Rates versus Credit Market Imperfections

The classical approach postulates that inequality stimulates growth by fostering saving and investment. Given that the marginal propensity to save rises with the income level of individual households (see, e.g., Kaldor, 1955), a concentration of incomes at richer households increases aggregate saving, which is conducive to growth if channeled into investments (Bourguignon, 1981).

However, in the presence of credit constraints and investment indivisibilities, an unequal distribution of wealth or disposable income may just as well be detrimental to growth. The credit market imperfections approach, pioneered by Galor and Zeira (1993), suggests that inequality prevents some individuals from exploiting their intellectual potential whenever credit is not available to cover the direct costs of schooling or the opportunity costs of forgone income. As the maximum amount of human capital accumulation per person is limited and the returns to human capital are diminishing on an individual level, an increase in inequality reduces both the average quantity and productivity of human capital investments. Naturally, educational inequality and its negative growth effect can to some extent be mitigated by a public education system that provides free and high quality education to children from poor families.

Whereas the Galor-Zeira model focuses on human capital investment, a similar argument also applies to physical capital investment. Viewing people as potential entrepreneurs who face individual investment opportunities that are bound by decreasing marginal returns and credit market imperfections, the poor may not be able to realize their investment projects, while the wealthy overinvest. A more unequal distribution of wealth would thus reduce the average productivity of physical capital, whereas its quantity may be relatively unaffected.

Galor and Moav (2004) provide an intertemporal reconciliation between the *differential saving rates* and the *capital market imperfection* approaches in a unified growth theory. The theory draws on the assumption that the role of physical capital as an engine for growth decreases relative to human capital. Moreover, it assumes that inequality and credit market imperfections primarily affect human instead of physical capital accumulation. Thus the effect of inequality on growth depends on the relative return to physical and human capital. Whereas inequality supports growth by increasing aggregate saving and physical capital investment in the early stages of development, it is detrimental to growth after human capital accumulation becomes the dominant driver of growth in later stages. However, in light of international capital flows and technology transfers, human capital accumulation may already constitute the dominant engine for growth in many of the currently developing countries. Moreover, if credit constraints become less binding in advanced economies, the effect of inequality on growth might eventually diminish.

2.2 Endogenous Fertility

Initial inequality can also be detrimental to growth due to a positive link between inequality and the fertility rate. This transmission channel is closely related to the human capital argument as decisions concerning human capital investment and family size are interrelated. According to a prominent line of reasoning brought forward by Becker and Barro (1988), most families are facing a trade-off between the quantity and education of their children.

Poor parents may lack the resources to invest in the education of their children, particularly if they are excluded from capital markets. Thus their only chance to increase family income (or their old-age support) is to increase household size. In contrast, richer families may face relatively high opportunity costs of raising children. As a result it may be optimal for richer parents to have fewer children and to increasingly invest in their human capital, providing their offspring with the prospect of higher lifetime incomes.

Firstly, from this it follows that poor societies tend to have high fertility rates and low levels of education. Secondly, empirical evidence underlines that more inequality is associated with larger fertility differentials between educated and uneducated women (Kremer and Chen, 2002). Building upon this finding, De la Croix and Doepke (2003) emphasize the growth effects of fertility differentials between the rich and the poor. A mean-preserving spread in income distribution increases the number of poorly educated children from disadvantaged families relative to well-educated children from richer families. As the relative weight of the less educated increases, average human capital is diluted and economic growth in subsequent periods is depressed. Moreover, an increase in inequality also raises the total fertility rate, which imposes another negative effect on per capita income growth.[3]

2.3 Sociopolitical Unrest

A further channel, emphasized by Alesina and Perotti (1996) and Alesina et al. (1996), deals with the extent of socio-political stability. Political instability has negative effects on a variety of productive economic decisions, such as saving and investment. As income inequality tends to cause an increase in political instability, it may provoke a reduction in the growth rate. A high probability of a future government change increases uncertainty, initiating capital exports due to lower risks associated with investments abroad. Likewise, foreign investors will be discouraged from investing in countries where political and economic conditions are fragile.

In addition, high rates of inequality may also produce social instability. Particularly if inequality is accompanied by low rates of social mobility, individuals may engage in criminal activities. The participation of these individuals in crime represents a direct waste, as their time and energy are not devoted to productive activities. Moreover, investments in education

[3] See Galor and Zang (1997), Morand (1999), and Kremer and Chen (2002) for models of endogenous fertility arguing along similar lines of reasoning.

may be abandoned, which yields further negative growth effects. By violating property rights, high crime rates may also be an impediment to investment in physical capital.

One related argument deals with the existence of crony capitalism and nepotism. In societies with a highly unequal distribution of incomes, an exorbitantly wealthy upper class may enjoy disproportionate political power. As a consequence, the rich may subvert political or legal institutions, such that they can freely engage in rent-seeking activities. These activities may hinder GDP growth (see, for instance, Glaeser et al., 2003).

2.4 Endogenous fiscal policy: market inequality and redistribution

The previously described growth models are directly related to the distribution of disposable incomes. However, there is another line of the literature focusing on the growth effects of market inequality and public redistribution. Perotti (1996) named the theory put forward by Bertola (1993), Alesina and Rodrik (1994), and Persson and Tabellini (1994) the *endogenous fiscal policy approach*, and divided it into two successive arguments: The first—called the *political mechanism*—states that an unequal distribution of market incomes creates a high demand for redistributive taxes and transfers via the political voting process (Meltzer and Richard, 1981). The second—the *economic mechanism*—stresses the negative incentive effects of redistribution: By lowering the return on investment, redistributive taxes discourage physical or human capital accumulation. Moreover, a generous welfare system discourages labor effort. Both may reduce economic growth.

However, a positive insurance effect of public redistribution might offset its negative incentive effects. The reason is that a generous social safety net could stimulate risk taking, entrepreneurship, and innovation, resulting in a positive impact on economic growth.[4]

Finally, governments also engage in *indirect redistribution* by providing the poor with free access to public goods. This may lead to an increase in social mobility and to an equalization of market incomes, which is not captured in standard measures of redistribution such as taxes and transfers.

2.5 Overview

In sum, the testable implications that we draw from theory are that the growth effect of inequality should depend on (i) the degree of credit market imperfection, (ii) the public provision of education, and (iii) the development level. Inequality should exert its influence primarily via human capital accumulation and the fertility rate, while its effect on physical capital accumulation might be small, unless the channel of sociopolitical unrest plays a decisive role. Finally, according to the endogenous fiscal policy channel, a high level of market inequality should be related to a high level of redistribution, which is most likely detrimental for growth. As many of the proposed transmission channels are offsetting,

[4] Yet, Sinn (1996) shows that redistribution does not necessarily result in a decrease in net inequality. We come back to this issue in our data description in Section 4.3.

the net effect of inequality and redistribution remains an empirical question, which will be examined in the following sections.

3 Empirical model and estimation technique

We use a standard approach in specifying our empirical model, considering the growth rate of real per capita GDP to be a function

$$\frac{\mathrm{d}}{\mathrm{d}t}(y) = F(y_{t-1}, h_t, \mathbf{X}_t, \Psi_t, R_t) \tag{1}$$

where y_{t-1} denotes the log of initial production per capita, h_t is human capital endowment per person, and $\mathbf{X}_t$ comprises an array of control and environment variables. When holding constant these country specific potentials for economic growth, we study to what extent inequality Ψ_t and redistribution R_t contribute to income increases.

It is crucial to specify the basic system accurately, as the disregard of covariates could lead to inconsistency in the estimated coefficients, particularly as redistribution and inequality may depend on the political and institutional environment of the countries. For this reason, we apply the basic system specification of Barro (2000, 2003, 2013), which has been proven to explain empirical growth patterns quite accurately in a number of studies. However, many of the standard control variables in growth regressions also reflect the transmission channels of inequality and redistribution that we have summarized in Section 2. Therefore, a fully specified growth model only captures the growth effect of inequality and redistribution *beyond* its effect via the standard transmission channels (Galor, 2009). Hence, we compare the results from the comprehensive growth model to reduced specifications that omit the transmission variables to identify the full growth effect of inequality and redistribution.

Our set of growth determinants does not directly include physical capital, as data concerning the capital stock of the economy depends on arbitrary assumptions with regard to the rate of depreciation and the initial value. Instead, we follow Barro (2003) by assuming that higher levels of y_{t-1} and h_t reflect a greater stock of physical capital. Initial production is measured by the logarithmic value of real per capita GDP, denoted by $\log(\mathrm{GDP}_{pc})$. Human capital is gauged by average years of schooling (SCHOOLING) and by the logarithm of life expectancy at birth (LIFEEX) to proxy education and health of the population, respectively. Yet, whereas higher life expectancy reflects better health, an increase in log(LIFEEX) simultaneously raises effective depreciation. In order to disentangle these effects, we also include the logarithm of the fertility rate log(FERT) in the empirical system, thereby isolating the negative effect of population growth predicted by the standard growth model. The model also includes investments in physical capital, gauged by the investment share (INVS).

To capture the effect of political stability, we include an index of rule of law and democracy, denoted by POLRIGHT. Our analysis further includes government consumption (GOVC), which is assumed to decrease the steady state level of output due to distortions caused in the private sector. We also control for the extent of international openness (OPEN) by incorporating exports plus imports divided by GDP. Openness may simultaneously boost growth and inequality due to technological spillovers and increased competition. Finally, the inflation rate INFL serves as a proxy for economic uncertainty.

Controlling for the variables described above, we examine whether inequality Ψ_t and the amount of redistribution R_t affect the growth rate. Both variables are strongly interwoven: when only including redistribution in the model, the estimated parameter captures both the effect from a lower level of inequality (which we expect to be positive) and the incentive effects from the redistributional measures employed to achieve the reduction in inequality (which we expect to be negative). Thus, including both variables is the only way to isolate these contradicting effects.

Our estimation strategy uses 5-year averages of all variables. This standard approach in empirical growth studies is determined by the long-term perspective of growth theory, the need to smooth short-term fluctuations, and the occurrence of gaps in the data. Following Equation (1) and using the model structure developed in a number of recent empirical investigations (Bond et al., 2001, Voitchovsky, 2005, Halter et al., 2014), the 5-year growth rate evolves as

$$y_{it} - y_{it-1} = (\theta - 1)y_{it-1} + \lambda h_{it} + \gamma \Psi_{it} + \delta R_{it} + \beta \mathbf{X}_{it} + \eta_i + \xi_t + v_{it} \tag{2}$$

where a necessary assumption is that the variables in Equation (1) are linked additively. The term $(y_{it} - y_{it-1})$ proxies per capita GDP growth in i at 5-year period t, η_i denotes country-specific effects, ξ_t is a time effect of period t, and $v_{it} \equiv u_{it} - \xi_t - \eta_i$ is the error term of the estimation. The marginal effects of our variables of interest—inequality and redistribution—are captured in the coefficients γ and δ. The control variables are included in $\mathbf{X}_{it}$.

Equation 2 can easily be rewritten as

$$y_{it} = \theta y_{it-1} + \lambda h_{it} + \gamma \Psi_{it} + \delta R_{it} + \beta \mathbf{X}_{it} + \eta_i + \xi_t + v_{it} \tag{3}$$

When working with macroeconomic data, unobserved heterogeneity η_i often yields biases if not accounted accurately for. A simple way to overcome this problem would be to use a within-group estimator or a first-difference approach such as Anderson and Hsiao (1982). However, whereas the former suffers from a Nickell (1981) bias when conducting dynamic panel estimations, first-difference transformations neglect the cross-sectional information in the data and magnify gaps in unbalanced panels. As a result, efficiency gains are possible when estimating the model in a Generalized Method of Moments (GMM) context.

A common approach to account for both unobserved heterogeneity and endogeneity in models with lagged dependent variables is the GMM estimator proposed by Arellano and

Bond (1991).[5] Define that $\Delta k \equiv (k_{it} - k_{it-1})$ and $\Delta_2 k \equiv (k_{it-1} - k_{it-2})$, the basic idea of this approach is to adjust (3) to

$$\Delta y = \theta \Delta_2 y + \lambda \Delta h + \gamma \Delta \Psi + \delta \Delta R + \beta \Delta \mathbf{X} + \Delta \xi + \Delta v \tag{4}$$

and then to use sufficiently lagged values of y_{it}, h_{it}, Ψ_{it}, R_{it}, and $\mathbf{X}_{it}$ as instruments for the first-differences. However, differencing Equation (3) discards the information in the equation in levels. This drawback is particularly severe in the context of inequality studies, as most of the variation in inequality data stems from the cross section rather than the time-dimension. Moreover, Blundell and Bond (1998) and Bond et al. (2001) show that the difference GMM estimator can be poorly behaved if time-series are persistent or if the relative variance of the fixed effects η_i is high. The reason is that lagged levels in these cases provide only weak instruments for subsequent first-differences, resulting in a large finite sample bias.

System GMM proposed by Arellano and Bover (1995) and Blundell and Bond (1998) provides a tool to circumvent this bias if one is willing to assume a mild stationary restriction on the initial conditions of the underlying data generating process.[6] In this case, additional orthogonality conditions for the level equation in (3) can be exploited, using lagged values of Δk and $\Delta_2 k$ as instruments. In doing so, system GMM maintains some of the cross-sectional information in levels and exploits the information in the data more efficiently. Satisfying the Arellano and Bover (1995) assumptions, system GMM has been shown to have better finite sample properties (see Blundell et al., 2000). To detect possible violations of these assumptions, we conduct Difference-in-Hansen tests to assess the validity of the additional moment restrictions for each of the system GMM regressions.[7]

Let $\tilde{\mathbf{X}}'_{it} \equiv [\Psi_{it}\ R_{it}\ \mathbf{X}'_{it}]$ and $\mathbf{\Xi}'_{it} \equiv [y_{it}\ \tilde{\mathbf{X}}'_{it}]$, the moment conditions in our analysis used for the regression in first-differences are

$$\mathrm{E}[(v_{it} - v_{it-1})\mathbf{\Xi}_{it-2}] = 0 \text{ for } t \geq 3,$$

and the additional moment conditions for the regression in levels are given by

$$\mathrm{E}[(v_{it} + \eta_i)(\mathbf{\Xi}_{it-1} - \mathbf{\Xi}_{it-2})] = 0 \text{ for } t \geq 3.$$

We restrict the instrument matrix to lag 2, using second lags of the variables in levels as instruments for Δk and $\Delta_2 k$, and first lags of Δk and $\Delta_2 k$ as instruments for the level equation. Roodman (2009a) illustrates the necessity of introducing such a restriction, as otherwise the problem of "instrument proliferation" may lead to severe biases and weak-

[5] In the case of the growth-inequality nexus, two examples are Forbes (2000) and Panizza (2002).

[6] The assumption on the initial condition is $\mathrm{E}(\eta_i \Delta y_{i2}) = 0$, which holds when the process is mean stationary, i.e. $y_{i1} = \eta_i/(1-\theta) + v_i$ with $\mathrm{E}(v_i) = \mathrm{E}(v_i \eta_i) = 0$.

[7] A more detailed description of the estimator in the context of the empirical application can be found in Bond et al. (2001) and Roodman (2009b)

ened tests of instrument validity. Note that we treat each variable as endogenous to avoid arbitrary assumptions on exogeneity, predetermination, or endogeneity.

In principle, our specification can be estimated using one-step or two-step GMM. Whereas one-step GMM estimators use weight matrices independent of estimated parameters, the two-step variant weights the moment conditions by a consistent estimate of their covariance matrix. Bond et al. (2001) show that the two-step estimation is asymptotically more efficient. Yet it is well known that standard errors of two-step GMM are severely downward biased in small samples. We therefore rely on the Windmeijer (2005) finite sample corrected estimate of the variance which yields a more accurate inference.

4 Data description

4.1 Data on inequality and computation of redistribution measures

Our main variables of interest are inequality (Ψ) and redistribution (R). To measure inequality, we use the Gini coefficient, which gauges personal income inequality between households within a given country. In principle, the Gini can be calculated using market incomes ("market Gini") or disposable incomes ("net Gini"). Differences in these variables are the result of taxes and transfers. For this reason, our redistribution measure REDIST is calculated as

$$\text{REDIST}_{it} = \text{GINI(M)}_{it} - \text{GINI(N)}_{it} \tag{5}$$

where GINI(M) is market inequality, GINI(N) denotes inequality of disposable incomes, $i = 1, \ldots, N$ is the country index, and $t = 1, \ldots, T$ is the time index. This measure is often referred to as the "pre-post-approach" in the sociological and public policy literature.

When working with cross-national income inequality data, researchers are confronted with a trade-off between the comparability and the coverage of observations (for a detailed discussion, see Solt, 2015a). The Luxemburg Income Study (LIS) has earned a reputation as the gold standard of cross-nationally comparable inequality data, but the calculation of inequality measures using a uniform set of assumptions and definitions strongly restricts data availability. The LIS currently covers observations of 232 country-years with data from 41 countries. The limited scope of countries and years included in the LIS impedes the application of system GMM and does not allow for the investigation of the effect of redistribution based on a large panel of countries. The incorporation of a larger number of observations, however, typically comes at the cost of sacrificing the benefits of comparability and harmonization. Atkinson and Brandolini (2001) review the pitfalls inherent in the use of secondary datasets and conclude that simple adjustments are often not sufficient to generate comparable inequality measures that rest on common income definitions and reference units.

To overcome this problem, the Standardized World Income Inequality Database (SWIID) compiled by Solt (2009, 2015b) employs model-based multiple imputation estimates of the missing country-years in the LIS series based on various source data. Initially consisting of only the UN World Income Inequality Database (WIID), the latest version of the SWIID employs source data provided by a large number of cross-national inequality databases, national statistical offices, and scholarly articles, thereby making use of a maximum of possible information. Hence, the coverage of country-years in the SWIID far exceeds those of alternative cross-national inequality datasets, particularly with regard to the scope of countries included. The maximization of comparability for the broadest possible coverage of countries-years provides a strong argument for application of the SWIID in cross-national analyses (Solt, 2015a). This particularly applies with regard to the empirical analysis of this paper, as we explicitly intend to investigate the effect of inequality and redistribution across different development levels. We use data of version 5.0 of the SWIID, which was published in October 2014. Introduced in 2008, the SWIID has expanded considerably over time, currently covering 174 countries from 1960 to present with estimates of net income inequality comparable with those obtained from the LIS Key Figures for 4,631 country-years, and estimates of market income inequality for 4,629 country-years. By calculating 5-year averages, we obtain a total of 1,128 country-years with regard to REDIST.

Our standard redistribution variable REDIST is the difference between market and net Ginis for all available information in the SWIID. While this calculation allows for acquisition of a large sample of data, caution is advised when interpreting this measure. Some of the data on gross or net income inequality are estimates based on data from other countries, which means that the difference between both measures of inequality contains little information about country specific redistribution. To address this problem, the SWIID reports a sample of the most reliable redistribution data, which we refer to as REDIST(S). This sample is solely based on observations for which survey data on net and gross incomes is available. REDIST(S) also neglects observations from developing countries before 1985 and from advanced economies before 1975, as historical data is often less reliable. REDIST(S) is available for 453 country-years.

The pre-post approach of Equation (5) yields a measure of effective redistribution, illustrating the overall result of governmental redistribution via taxes and transfers, rather than the effort by which the result is achieved. Compared to earlier studies, this provides two advantages: First, our analysis does not rely on rough redistribution measures, as the actual redistributive impact of specific components of the public transfer system—e.g. marginal tax rates or the size of social subsidies—vary from country to country. Second, our analyses rest on a considerably expanded number of country-years, since cross-national data on Gini indices is more widely available than comparable data on redistributive fiscal policies.[8] A potential drawback of the pre-post approach is that market inequality is not independent from the extent of public redistribution (Bergh, 2005). On the lower end of the income scale,

[8]Note that the SWIID—like most inequality databases—comprises household disposable income, excluding the in-kind provision of public goods. Thus the pre-post approach does not cover public attempts to equalize market inequality, neither by the promotion of equal opportunities nor by governmental interventions in private wage agreements.

a generous welfare system may boost gross inequality by encouraging low income earners to withdraw from the labor market and to live from transfers instead of market income. On the upper end, high income earners may be discouraged by taxes and thus reduce their labor supply, which lowers gross inequality. In our analysis, we follow Berg et al. (2014) by suggesting that the effects of redistribution on gross inequality can be neglected as its effects on the lower and on the upper scale of the income distribution are offsetting.

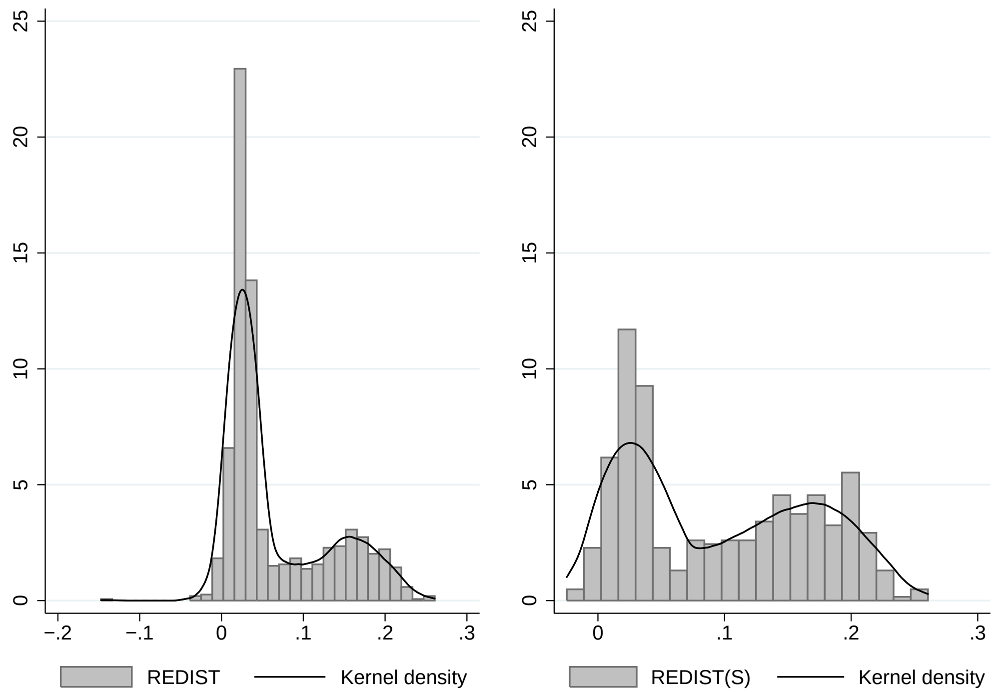

Figure 1 The distribution of REDIST and REDIST(S) across countries. REDIST: N=1,128, skewness=1.043, kurtosis=2.847. REDIST(S): N=453, skewness=0.268, kurtosis=1.627. Kernel is Epanechnikov.

Figure (1) illustrates the histogram of REDIST and REDIST(S) using 5-year averages, as in our empirical specification. When considering all country-years available in the SWIID, the mean value of redistribution is 6.56 percentage points. The standard deviation of 6.44, however, indicates that there are some major differences in the extent of redistribution across countries. The most expansive social system in the sample reduces market inequality by 26.07 percentage points, whereas some policies even yield an increase in inequality. The most extreme example of negative redistribution is Guatemala in the late 1970s (-14.73), followed by Macedonia (-2.62) in the early 1990s and Kenya (-2.55) in the early 1970s.

The data also highlights that there are substantial differences in the amount of redistribution between countries at different stages of development. Using the classification of the World Bank, the mean value of redistribution in the sample of high-income countries is 12.09 percentage points and substantially exceeds the mean redistribution level in low-income countries (3.62). As REDIST(S) is composed of a larger fraction of advanced economies, the picture changes slightly when considering the subsample of redistribution data that includes only the most reliable observations. The mean value increases to 9.64, but the bimodal distribution is preserved. Whereas the sample now includes a higher frequency of observations with high levels of redistribution, REDIST(S) contains less data points in which inequality is enhanced by political intervention.

4.2 Covariates and their relation to inequality and redistribution

The rest of the data concerning our dependent and control variables stems from commonly used data sets. The growth rate of real per capita GDP as well as the initial level of GDP, the investment share (INVS), the degree of openness (OPEN), and government consumption (GOVC) are from PWT 8.0 as published by Feenstra et al. (2013). The average years of schooling (SCHOOLING) is from Barro and Lee (2013) and includes the years of primary, secondary, and tertiary education that individuals of age 25 and older have received during their educational training. POLRIGHT is proxied using data from Freedom House (2014), which provides an index of democracy and rule of law d with $d \in (1, 7)$. As the variable is coded inversely—i.e. lower numbers are associated with higher rates of democracy—we recode the variable to obtain POLRIGHT $= 8 - d$ to make sure that the coefficient in the estimation illustrates the impact of an increase in democracy on growth, rather than the reverse. We further use fertility rates (FERT), inflation rates (INFL) and data on life expectancy at birth (LIFEEX) as reported by World Bank (2014). Table (1) provides an overview of the data used in our empirical models, their means, maxima, minima, and standard deviations.

Theory suggests that REDIST and GINI(N) are strongly interwoven with the covariates, as inequality does not *directly* affect growth, but exerts its influence through various transmission variables. Indeed, we observe a strong relationship between the Gini coefficient net of taxes and transfers and the fertility rate (correlation: 52 percent). Likewise, inequality and schooling are negatively related (correlation: -59 percent). One interpretation of this relationship concerns educational returns that may be lower in economies where the average human capital level is higher, leading to a reduction in wage inequality. Another interpretation runs from inequality to human capital, as stressed by the credit market imperfections channel. There is also a strong link between fertility and schooling (-51 percent), which seems to support the endogenous fertility argument. A variety of theoretical channels—such as credit-market imperfections and sociopolitical unrest—imply that inequality and investment are negatively related. In fact, the data exposes a moderate negative correlation of -13 percent.

It is important to emphasize that redistribution cannot be reasonably proxied with gov-

Table 1 Descriptive statistics of variables used in the regression

Variable	N	Mean	Std. Dev.	Min	Max
GROWTH	1624	.022	.041	-.303	.321
log(GDP$_{pc}$)	1626	8.388	1.303	5.317	11.802
GINI(N)	1128	.374	.1	.169	.676
GINI(M)	1128	.44	.086	.188	.713
REDIST	1128	.066	.064	-.147	.261
REDIST(S)	453	.096	.073	-.025	.261
INVS	1625	.206	.111	-.013	.986
SCHOOLING	1584	5.9	3.063	.04	13.09
log(LIFEEX)	2027	4.127	.2	3.081	4.422
GOVC	1626	.205	.118	-.024	.934
INFL	1656	.361	2.624	-.066	69.628
OPEN	1822	.76	.486	.02	4.378
POLRIGHT	1624	4.084	2.195	1	8
log(FERT)	2029	1.283	.55	-.137	2.213
CREDIT	1521	.383	.377	.009	2.951
PSEDUC	1018	.045	.02	.006	.264

ernment consumption. Several earlier empirical studies found a negative relationship between government consumption and economic growth (see, for instance, Barro, 2000, 2003, 2013). One may conclude that this result predicts the link between redistribution and growth, as redistributive expenditures—such as, for instance, social transfer payments—are classified as government consumption. Yet the correlation between REDIST and GOVC is surprisingly small in our sample and exhibits a *negative* sign (-3.62 percent). One reason for this is that redistributional measures represent only a small fraction of government consumption. If there is no systematic correlation between the remaining expenditures and transfer payments, GOVC is a poor indicator for mirroring the extent of redistribution. In addition, GOVC does not directly contain the redistributional impact of the tax system. The lack of correlation between GOVC and REDIST may also hint that the progressivity of the social system is more important for redistribution than its size.

4.3 The relationship between inequality and redistribution

The political economy mechanism of the endogenous fiscal policy channel suggests a strong relation between inequality of market incomes and redistribution. Empirical evidence on this channel, however, is rather ambiguous. Whereas earlier studies (e.g. Perotti, 1994, 1996) find a negative relationship between initial inequality and different proxies for redistribution, more recent studies conclude that societies with an unequal distribution of market incomes tend to redistribute more than others (see, for instance, Milanovic, 2000). One explanation for these contradicting results may be the lack of adequate measures for inequality and redistribution. Although the endogenous fiscal policy channel is triggered by the extent of market inequality, some earlier studies use net inequality to explain demand for redistribution. In addition, many studies rely on imperfect measures of redistribution, as the size of public transfers and taxes may be little indication of their redistributive impact.

Our dataset allows us to reconsider the endogenous fiscal policy channel by using market inequality and effective redistribution based on a large panel of countries. The data implies that lower levels of net inequality in many economies are the result of redistributional activities of the government, as the level of redistribution is strongly correlated with the extent of net inequality (correlation: -65 percent). These redistributional efforts, however, only slightly influence inequality rankings of the countries. Figure (2) illustrates the relationship between net inequality and market inequality in all countries for which reliable data is available in the 2005-2009 period. It turns out that countries with a high level of gross inequality in general also tend to have a high level of inequality of disposable incomes.[9] Yet the figure illustrates that some countries reduce market inequality to a substantially greater extent than implied by the average correlation. This group entirely consists of high-income economies, where the strongest deviations can be observed in Belgium, Denmark, Germany, Finland, the Netherlands, Norway, and Sweden.

According to the endogenous fiscal policy channel, we would expect more redistribution in countries that feature a higher level of market inequality. However, a bivariate analysis of the variables in Figure (3) reveals only a weak correlation of 21 percent. It turns out that high levels of market inequality in many developing economies are not necessarily accompanied by large redistributional efforts made by the government.[10] Thus the effect of market inequality on redistribution must be examined while holding constant the development level of the economies. Consider the simple reduced model

$$\text{REDIST(S)}_{it} = \alpha + \delta \text{GINI(M)}_{it} + \beta \log(\text{GDP}_{pc})_{it-1} + \eta_i + \xi_t + v_{it}$$

where the denotation of the variable is the same as in the previous section. Table (2) presents the results of the estimation of the model using Pooled OLS (POLS), Within-Group (WG), and 2SLS estimations. Whereas Column (1) neglects both η_i and ξ_t, Column (2) includes country fixed effects and Column (3) additionally incorporates period fixed-effects. Column (4) conducts 2SLS regressions with fixed-effects, where GINI(M) is instrumented with its lagged values in order to ensure that we are capturing the effect of market inequality on redistribution, rather than the reverse.

The results strongly support the political mechanism of the endogenous fiscal policy channel, as a higher level of market inequality results in a higher amount of redistribution

[9]When we split the data into advanced and developing economies according to the definition of the World Bank, we find that the correlation is 91 percent in the developing sample. In the group of advanced economies the correlation is weaker (61 percent), but still strongly significant.

[10]Observations in the restricted sample REDIST(S) where high levels of market inequality trigger only little redistribution entirely stem from developing economies. These countries include Kenya in 1985 (GINI(M): 57.54, REDIST(S): 5.71), India in 2010 (51.89, 0.53), Honduras in 2010 (54.60, 2.90), Guatemala in 2010 (50.93, 2.69), and South Africa in 2000 (64.75, 4.45). Note that the selection rule of the REDIST(S) sample to exclude observations of developing economies before the year 1985 yields exclusion of the high rates of negative redistribution observed in Guatemala and Kenya during the 1970s.

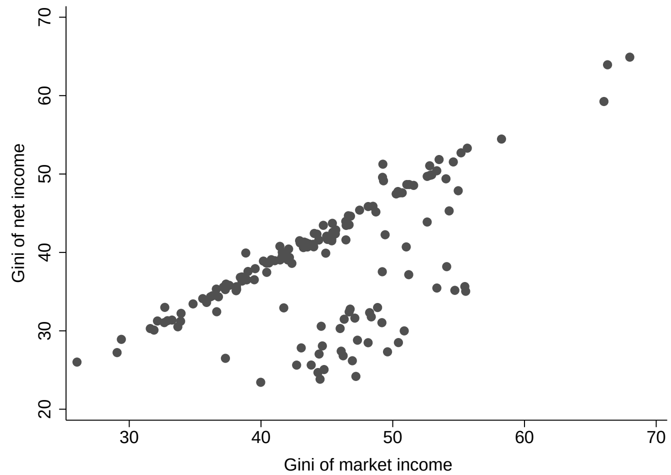

Figure 2 The relationship between inequality of net incomes and inequality of market incomes. The figure plots observations for each country in the 2005-2009 period. Data is from the restricted sample containing the most reliable data.

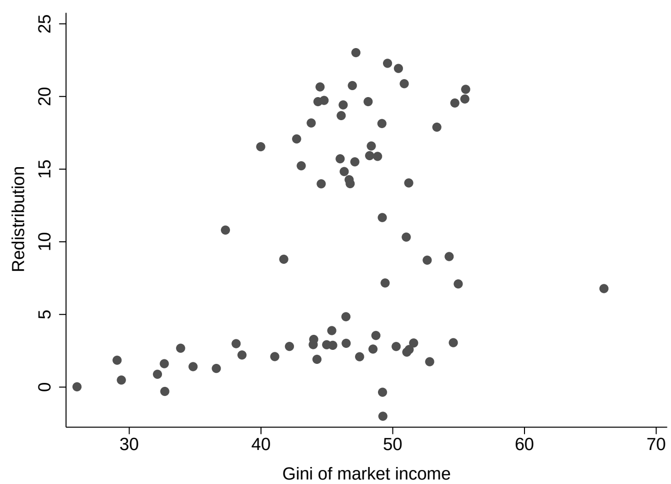

Figure 3 The relationship between market inequality and redistribution. The figure plots observations for each country in the 2005-2009 period. Data is from the restricted sample containing the most reliable data.

Table 2 Regressions of REDIST(S) on market inequality

	(1) POLS	(2) Within-Group	(3) Within-Group (time-dummies)	(4) Within-Group (2SLS)
GINI(M)	0.249***	0.427***	0.397***	0.401***
	(0.0694)	(0.0588)	(0.0699)	(0.0741)
log(GDP$_{pc}$)	0.0496***	-0.00106	-0.0199*	-0.000163
	(0.00613)	(0.00646)	(0.0104)	(0.00640)
Constant	-0.473***	-0.0833	0.0842	
	(0.0586)	(0.0628)	(0.101)	
Observations	434	434	434	411
R-squared	0.519	0.473	0.531	0.465

Notes: Table reports regressions of REDIST(S) on GINI(M) using Pooled OLS (Column 1) Within-Group without and with time-dummies (Columns 2 and 3), and 2SLS with country fixed effects (Column 4) estimations. Robust standard errors in parantheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

in each of the estimations. Whereas the development level is positively related to the extent of redistribution when neglecting country-fixed effects, this influence vanishes when using time-demeaning transformations in Columns (2)—(4). One interpretation is that the income level may be a proxy of the deeper institutional causes that distinguish the countries in their level of redistribution. Due to higher transparency, more efficient institutions and less corruption, the opportunities of rent-seeking and crony capitalism decline during the development process. Likewise, less-developed countries tend to be less-democratic. If the voter cannot influence the political process, a higher level of inequality most likely does not yield a higher amount of redistribution.

5 Regression results

5.1 Baseline regressions

We now turn to the investigation of the growth effect of inequality and redistribution. Table (3) reports the results of our baseline system GMM growth estimations when the full sample of available data from the SWIID is used. Our regression sample covers a maximum of 955 observations from 154 countries. The time dimension includes 5-year averages from the initial period 1965-1969 to the period 2010-2012.

Column (1) shows a reduced specification of our growth model in which—aside from time dummies and country fixed-effects—the lagged level of per capita income is the only control variable. As mentioned previously, theory suggests that inequality exerts its influence on growth via several transmission channels. These channels involve standard growth determinants such as physical and human capital accumulation, fertility rates, and political stability. Excluding some of the usual controls is thus the only way to identify the full growth effect of income inequality, although it involves the risk of an omitted variable bias.

The results in Column (1) suggest that both high net inequality, but also its cure in the form of public redistribution, are similarly bad for growth. The point estimate of the net Gini is negative and highly significant, suggesting that an increase of the Gini by one standard deviation, which is roughly 10 percentage points, lowers the annual growth rate on average by 2.5 percentage points. The estimated parameter of redistribution is significantly negative as well and roughly about the same size as the effect of inequality.

In Column (2) the investment share and the average years of school attainment are introduced into the model. Both variables are standard components of empirical growth models but—according to the theories of differential saving rates, credit-market imperfections, sociopolitical unrest, and endogenous fiscal policy—are also part of the transmission process from inequality to growth. Holding these transmission variables constant, we would expect this model to reveal a smaller impact of inequality on growth. Indeed, the estimated coefficient of the Gini declines to -0.102, which is less than half of the marginal effect detected in Column (1). In line with theory and previous empirical studies, the newly introduced controls are positive and significant.

When we introduce a number of additional control variables in Column (3), the effect of inequality shrinks further, but still remains significant. Among the new covariates, only the log of life expectancy—our health variable—is positively related to economic growth, whereas government consumption, inflation, international openness, and political rights are all insignificant.

Some theoretical models suggest that fertility is endogenous to income inequality. Holding constant the fertility rate could thus eliminate another transmission channel. Indeed, in Column (4) the estimated effect of the Gini diminishes and becomes insignificant when fertility is held constant, which resembles the findings by Barro (2000) and De la Croix and Doepke (2003).[11] As in these studies, the direct effect of fertility is negative and highly significant in our growth regression.

So far we have focused on inequality but devoted little attention to redistribution. In fact, the estimated coefficient of REDIST in Table (3) should be interpreted with caution. Whereas the maximum number of available observations is utilized here, the redistribution variable may be measured imprecisely in certain cases where estimates rest entirely on information from other countries. Hence, Table (4) applies REDIST(S), which is calculated from a subsample consisting of only the most reliable observations. The rest of the specifications in each column of Table (4) exactly follow the specifications shown in the corresponding columns of Table (3). However, our regression sample is now restricted to a maximum of 434 observations from 73 countries.

Regarding the reduced model of Column (1), the estimated parameters of redistribution

[11] Our sample composition does not change from Column (3) to Column (4), which strengthens the evidence for the endogenous fertility channel.

Table 3 Baseline regressions, full sample. Dependent variable is real per capita GDP growth.

	(1)	(2)	(3)	(4)
L.log(GDP$_{pc}$)	0.00117	-0.00948**	-0.0159***	-0.0195***
	(0.00570)	(0.00371)	(0.00389)	(0.00267)
GINI(N)	-0.248***	-0.102***	-0.0654***	-0.0283
	(0.0714)	(0.0359)	(0.0244)	(0.0296)
REDIST	-0.238***	-0.0966**	-0.0374	-0.0130
	(0.0789)	(0.0464)	(0.0439)	(0.0490)
INVS		0.111***	0.0670**	0.0694***
		(0.0306)	(0.0275)	(0.0237)
SCHOOLING		0.00414**	0.00153	0.0000341
		(0.00168)	(0.00144)	(0.00117)
log(LIFEEX)			0.0940***	0.0611***
			(0.0199)	(0.0173)
GOVC			-0.0314	-0.0380
			(0.0262)	(0.0264)
INFL			-0.000316	-0.0000738
			(0.000588)	(0.000529)
OPEN			0.00475	0.00289
			(0.00355)	(0.00356)
POLRIGHT			-0.000199	-0.000626
			(0.00116)	(0.00115)
log(FERT)				-0.0292***
				(0.00786)
Observations	955	865	740	740
Countries	154	126	125	125
Hansen p-val	0.00355	0.226	0.998	1.000
Diff-Hansen	0.187	0.854	1.000	1.000
AR(1) p-val	0.0000345	0.0000273	0.000107	0.000117
AR(2) p-val	0.651	0.658	0.463	0.609
Instruments	62	98	175	192

Notes: Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. All regressions include period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. Diff-Hansen gives the Difference-in-Hansen statistic of the instrument subset for the level equation. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. Instruments are the second lag of the explanatory variables in levels for the difference equation and the first lag in differences for the level equation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4 Baseline regressions, restricted sample. Dependent variable is real per capita GDP growth

	(1)	(2)	(3)	(4)
L.log(GDP$_{pc}$)	-0.00870	-0.0172***	-0.0214***	-0.0257***
	(0.00688)	(0.00524)	(0.00713)	(0.00770)
GINI(N)	-0.258***	-0.0631	-0.0562	-0.00829
	(0.0739)	(0.0585)	(0.0383)	(0.0551)
REDIST(S)	-0.229**	-0.0734	0.0138	0.0268
	(0.0929)	(0.0646)	(0.0569)	(0.0624)
INVS		0.176***	0.165***	0.126***
		(0.0362)	(0.0372)	(0.0454)
SCHOOLING		0.00539**	0.00580**	0.00513**
		(0.00266)	(0.00226)	(0.00242)
log(LIFEEX)			-0.0275	0.0210
			(0.0654)	(0.0541)
GOVC			-0.0846***	-0.0991***
			(0.0279)	(0.0311)
INFL			-0.0000163	-0.000434
			(0.00119)	(0.00115)
OPEN			0.00362	0.00254
			(0.00421)	(0.00411)
POLRIGHT			-0.00189	-0.00226
			(0.00213)	(0.00184)
log(FERT)				-0.0240*
				(0.0132)
Observations	434	418	374	374
Countries	73	68	67	67
Hansen p-val	0.0405	0.740	1.000	1.000
Diff-Hansen	0.441	0.990	1.000	1.000
AR(1) p-val	0.000287	0.0000544	0.0000349	0.0000360
AR(2) p-val	0.447	0.325	0.119	0.146
Instruments	50	80	154	169

Notes: Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. All regressions include period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. Diff-Hansen gives the Difference-in-Hansen statistic of the instrument subset for the level equation. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. The instrument matrix is restricted to lag 2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

and net inequality are very similar to the results obtained from the full sample estimations. A high level of net inequality is harmful for growth; yet, holding net inequality constant, public redistribution is also negatively related to economic performance. Quantitatively the results imply that reducing the Gini by ten percentage points lowers economic growth by roughly 2.3 percentage points because of the direct effect of taxes and transfers. On the other hand, growth accelerates by 2.6 percentage points due to the positive effect of the resulting lower level of net inequality.[12] This simple comparison suggests that the positive growth effect from a lower level of net inequality is on average almost fully offset when the decline in inequality is achieved via taxes and transfers.

To an even greater extent than the full sample estimations, the regressions based on the restricted sample illustrate how inequality exerts its influence via the transmission channels: when investment and schooling are controlled for in Column (2), the estimated coefficient of inequality shrinks by roughly three quarters from -0.26 to -0.06 and loses significance. Likewise, the effect of redistribution becomes considerably smaller and insignificant. In Column (3), the Gini remains roughly unchanged when additional controls are introduced, all of which are insignificant aside from a negative effect of government consumption. In Column (4)—when the fertility rate is incorporated—the effect of inequality virtually disappears, resembling the corresponding estimation based on the full sample. The main transmission variables of inequality on growth—investment, schooling and fertility—are significant with the expected sign in all estimations.

Regarding the validity of our results we refer to the test statistics given in the lower part of Tables (3) and (4). The first requirement is the absence of second-order serial correlation in the residuals, which does not pose any problem as the AR(2) p-value is greater than 0.1 in all regressions. In addition, the p-values of Hansen's J-test reported in Columns (2)–(4) of both tables suggest that the null of joint validity of all instruments cannot be rejected. Yet there could be some doubt about the validity of our instruments in Column (1). However, since Hansen's J-test is also a general test of structural specification, the rejection of the null in the reduced model may point to an omitted variable problem rather than indicating general invailidity of the instruments (see, Roodman, 2009a). As we deliberately omit certain standard regressors to capture the full impact of inequality, a rejection of the specification in Column (1) is not surprising. Finally, the difference-in-Hansen test statistics emphasize superiority of system GMM over difference GMM by confirm the validity of the instrument subsets used for the level-equation in each model.

To avoid an overfitting problem, our set of instruments is restricted to only one lag per variable. Nevertheless, in our extended models reported in Columns (3)–(5) the number of instruments is relatively high because of the large number of presumably endogenous control variables. As a result, the potentially weakened Hansen tests yield unrealistically high p-

[12]Our calculation of the aggregate effect of redistribution rests on the assumption that market inequality is unaffected by redistribution. Given this assumption, an increase in redistribution by one percentage point lowers net inequality by exactly one percentage point.

values that are close to 1. In the light of the inevitable tradeoff between controlling for a large set of covariates and safely avoiding an overfitting problem, we show our full range of model specifications in each of the following sections.

5.2 Sensitivity analysis of the baseline results

To explore whether our baseline findings are sensitive to the estimation technique, Table (5) reports the results of three modifications of the baseline estimations. The first approach is a one-step variant of the baseline system GMM model. The two-step GMM estimator—which uses a consistent estimate of the covariance matrix to weight the moment conditions—can be severely downward biased in small samples. Although Windmeijer (2005) greatly reduces this problem, we verify unbiasedness of our baseline specification by comparing the results with a one-step variant that applies weight matrices independent of the estimated parameters. The second modification is an Arellano-Bond (first-difference GMM) version of the baseline model, which may be interesting to consider as it requires less assumptions on the initial condition. The last modification of the baseline model builds on the technique applied by Barro (2000, 2003, 2013) using 3SLS system estimations with each 5-year period serving as a separate equation. By jointly treating all equations, 3SLS accounts for possible correlations between the disturbances of the different equations. However, one major drawback is that country-specific errors are assumed to be randomly distributed. Conducting 3SLS allows us to compare our results based on new inequality and redistribution data more directly to some of the previous studies.

Table (5) reports three models for each of the alternate estimation techniques. The first model is the reduced specification that only captures the effect of inequality, redistribution, and convergence. The second and third models correspond to Columns 3 and 4 of the baseline table, illustrating the effect of inequality and redistribution when controlling for the suspected transmission variables and covariates. The results indicate that the negative effect of inequality on growth detected in the baseline estimations is remarkably stable. Likewise, redistribution tends to directly harm growth. However, its impact differs somewhat from the baseline model. 3SLS suggests a negative effect of redistribution that is greater in size and more stable over the various specifications than implied by system GMM. First-difference GMM, in contrast, yields some indication for a positive effect of redistribution on growth, which is most pronounced when all control variables are held constant. However, as discussed in Section 3, lagged levels of variables are weak instruments for subsequent changes if series exhibit a high degree of persistency. For this reason, the first-difference GMM estimator may be biased in this context. In addition, the application of first-difference GMM results in a decline of the number of observations from 740 to 602. The reason is that the estimator requires having at least three consecutive observations for each of the regressors, thereby magnifying gaps in our sample. Application of first-difference GMM may be advantageous if the restrictions on the initial conditions necessary for validity of the additional orthogonality

Table 5 Sensitivity analysis of the baseline results, full sample, Dependent variable is real per capita GDP growth.

	One-Step SGMM			Arellano-Bond (First-Difference GMM)			3SLS (Simultaneous Equation Model)		
	(1)	(3)	(4)	(1)	(3)	(4)	(1)	(3)	(4)
L.log(GDP$_{pc}$)	0.00193	-0.0166***	-0.0193***	-0.1240***	-0.0626***	-0.0532***	-0.0000305	-0.01439***	-0.01626***
	(0.00465)	(0.00326)	(0.0032)	(0.0293)	(0.0192)	(0.0118)	(0.0014)	(0.0020)	(0.00187)
GINI(N)	-0.270***	-0.0607***	-0.0252	-0.4480***	-0.1790**	-0.164**	-0.0831***	-0.0331*	-0.0158
	(0.0600)	(0.0235)	(0.0235)	(0.1640)	(0.0789)	(0.0659)	(0.0176)	(0.0174)	(0.0163)
REDIST	-0.276***	-0.0179	-0.000924	-0.1200	0.2800*	0.4380**	-0.1412***	-0.0550*	-0.0517*
	(0.0686)	(0.0375)	(0.0383)	(0.2230)	(0.1540)	(0.1700)	(0.0295)	(0.0302)	(0.0280)
INVS		0.0769***	0.0669***		0.1020**	0.0661		0.0466**	0.03734**
		(0.0245)	(0.023)		(0.0431)	(0.0429)		(0.0162)	(0.0153)
SCHOOLING		0.00222*	0.000314		-0.00202	0.00856**		0.00280***	0.0013**
		(0.00116)	(0.00109)		(0.0039)	(0.00404)		(0.00065)	(0.00063)
log(LIFEEX)		0.0822***	0.0547***		-0.000953	0.0498		0.0654***	0.0269**
		(0.0168)	(0.0163)		(0.0441)	(0.0492)		(0.0123)	(0.0123)
GOVC		-0.0312	-0.0375		0.00195	-0.00975		-0.0019	0.0062
		(0.0254)	(0.0272)		(0.0375)	(0.0354)		(0.0145)	(0.0138)
INFL		-0.000341	-0.0000966		-0.00042	-0.000917		-0.0015*	-0.00081
		(0.00059)	(0.000546)		(0.000643)	(0.000673)		(0.00091)	(0.00079)
OPEN		0.00527	0.00376		0.00157	-0.000897		0.0021	0.0089
		(0.00321)	(0.00312)		(0.00614)	(0.00642)		(0.0021)	(0.0019)
POLRIGHT		-0.000468	-0.000932		0.000401	0.00129		-0.00061	-0.00109
		(0.00117)	(0.00106)		(0.00256)	(0.00237)		(0.00088)	(0.00082)
log(FERT)			-0.0290***			-0.0514***			-0.0305***
			(0.00649)			(0.0194)			(0.00414)
Observations	955	740	740	776	602	602	776	602	602
Countries	154	125	125	144	119	119	144	119	119
Hansen p-val	0.00355	0.998	1.000	0.0245	0.291	0.317			
Diff-Hansen	0.187	1.000	1.000						
AR(1) p-val	0.000039	0.0000906	0.0001	0.017	0.000899	0.00123			
AR(2) p-val	0.608	0.453	0.605	0.0326	0.598	0.82			
Instruments	62	175	192	35	87	95	27	90	99
R-squared							0.08, 0.15, 0.06, -0.04, -0.10, -0.04, -0.02, -0.13, -0.08	0.07, 0.34, 0.19, 0.05, 0.33, 0.20, 0.26, 0.18, 0.00	0.00, 0.35, 0.39, 0.03, 0.25, 0.44, 0.38, 0.21, 0.00

Notes: Table reports sensitivity analyses of the baseline results. The first technique is a one-step system GMM variant of Table 3. The second technique is difference GMM (Arellano-Bond). The third approach is 3SLS in a simultaneous equation model using the same specification as the baseline model, but builds on a system of equations where each period t enters as a separate equation. Column numbers refer to the model of Table (3). (Robust) standard errors in parantheses. Hansen p-val gives the J-test for overidentifying restrictions. Diff-Hansen gives the Difference-in-Hansen statistic of the instrument subset for the level equation. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

conditions of system GMM are violated. Yet the Difference-in-Hanson statistics reported in Table (3) emphasize that the extra moment conditions are valid, resulting in substantial efficiency losses when using first-difference GMM.

Table (A3) in the appendix is concerned with two additional sets of sensitivity regressions. The first adjustment relaxes the restriction imposed on the moment conditions by enlarging the instrument matrix by one additional lag. The second model is designed similarly to the 3SLS regression but uses optimal systems GMM. The results strongly support the findings of the baseline system, suggesting that growth is negatively associated with both net inequality and public redistribution.

5.3 Overall effects of public redistribution and the endogenous fiscal policy channel

In accordance with the approach of Berg et al. (2014), our previous regressions examine the effect of redistribution when net inequality is held constant. In this case, the estimated parameter of redistribution captures the intrinsic effect of redistributive taxes and transfers, whereas the effect of net inequality is observed separately. The overall effect of redistribution can then be calculated by summing up the estimated parameters of redistribution and net inequality. Conducting this exercise, the aggregate effect of redistribution turns out to be small; however, its level of significance cannot be evaluated with this technique.

This section is concerned with an alternative approach that allows us to assess whether the aggregate effect of redistribution is statistically significant. Below, we directly estimate the aggregate growth effect of public redistribution in the restricted sample of high quality data. Leaving net inequality open, the estimated parameter of redistribution captures both the *direct* incentive effect of redistributive taxes and transfers plus the *indirect* effect resulting from the change in net inequality. The Gini of market inequality, GINI(M), which is possibly affected by some feedback effects of redistribution, is kept constant in this case. In other words, we examine the overall effect of redistribution for a given level of market inequality in Table (6). Aside from the application of a different measure of inequality, the rest of the specifications exactly follow the corresponding columns in Table (4). As there are virtually no changes in the effects of the covariates, we only report the variables of interest, in order to save space.

Holding market inequality constant, the coefficient of redistribution is positive in the reduced model of Column (1). It becomes negative when the investment share and schooling are controlled for in Column (2) and tends to be positive again when the remaining controls are introduced in Columns (3) and (4). However, the coefficient of redistribution is small and insignificant in every regression. Obviously the negative direct growth effect of redistribution and the indirect positive effect achieved via a lower level of net inequality are offsetting.[13]

[13] Surprisingly, market inequality is negatively correlated to economic growth in Column (1), although theory suggests that it is the distribution of *disposable* incomes that affects growth. Hence, the estimated coefficient of market inequality seems to capture the growth effect of net inequality, which vanishes when its

Table 6 Overall growth effects of redistribution, restricted sample. Dependent variable is real per capita GDP growth.

	(1)	(2)	(3)	(4)
GINI(M)	-0.259***	-0.0555	-0.0511	-0.00193
	(0.0674)	(0.0571)	(0.0405)	(0.0541)
REDIST(S)	0.0649	-0.0139	0.0822	0.0234
	(0.107)	(0.0724)	(0.0689)	(0.0717)
Observations	434	418	374	374
Countries	73	68	67	67
Hansen p-val	0.0478	0.741	1.000	1.000
Diff-Hansen	0.550	0.992	1.000	1.000
AR(1) p-val	0.000326	0.0000519	0.0000376	0.0000454
AR(2) p-val	0.518	0.363	0.112	0.135
Instruments	50	80	154	169

Notes: Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. All regressions include period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. Diff-Hansen gives the Difference-in-Hansen statistic of the instrument subset for the level equation. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. The instrument matrix is restricted to lag 2. Control variables are identical to the ones applied in the corresponding columns in Table (3). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

What do our results imply about the validity of the endogenous fiscal policy channel? Whereas Section 4.3 provides evidence for the political economy mechanism, the results in Table (6) at first glance seem to contradict the economic mechanism. A similarly negligible effect of redistribution is obtained in regression models that do not control for any measure of inequality and thus allow market inequality to act through redistribution (see, Appendix A2). Nonetheless, a more in-depth analysis reveals that the economic mechanism cannot be rejected. Such an exploration requires disentanglement of the causes of an equal distribution of incomes. There are two reasons why net inequality may be low: either because of government redistribution or because of a low level of market inequality. Our results from Section 5.1 indicates that societies with an equable distribution of net *and* market incomes experience higher growth rates compared to societies where a low level of net inequality is the result of public redistribution. This finding highlights negative incentive effects of redistribution, which is in line with the economic mechanism of the fiscal policy channel.

5.4 Empirical investigation of the transmission channels

In the previous regressions the effect of inequality and redistribution diminishes when we control for investment, schooling, and fertility. This could be evidence that inequality exerts its influence on growth via transmission channels that act specifically through these vari-

transmission variables are held constant. As shown in Section 4.3, the Ginis of market and net inequality are still closely correlated, despite varying extents of public redistribution.

ables. Holding constant the transmission variables would thus remove the growth effect of inequality, which means that the reduced model would be preferable. Yet the causality is thus far unclear. Whereas the theoretical models mentioned in Section 2 predict a causal effect of inequality or redistribution on the transmission variables, the reverse causation is plausible as well.

Taking this problem into account, Table (7) directly examines how inequality and redistribution affect the suspected transmission variables. Each transmission variable, that is investment, schooling and fertility, is regressed on the reduced empirical model that before was used to explain economic growth. This approach provides the advantage of good comparability among the transmission regressions and our main growth regressions.[14] Moreover, our estimation strategy allows us to assess the direction of causality, due to the instrumentation of the explanatory variables with their lagged levels and first differences. All regressions are based on the restricted instead of the full sample, as the former allows more reliable statements, particularly about the effects of redistribution.

The first column of Table (7) reports an estimation of the investment share, which is insignificantly related to the Gini of net incomes but negatively affected by redistribution. Since the positive investment effect of differential saving rates counteracts the negative impact of capital market imperfections or sociopolitical unrest, the undetermined effect of inequality is consistent with the theoretical ambiguity. In contrast, the incentive effects of redistribution seem to matter for investment decisions, which is not surprising as progressive taxes lower the return on investment.

The results from the schooling and fertility regressions in Columns (2) and (3) directly confirm our expectations from theory and the reduced-form estimates. Whereas inequality enhances the fertility rate, it causes a decline in school attainment. Redistribution is insignificantly related to schooling, but significantly increases fertility.

From theory it follows that credit constraints might reinforce the impact of inequality on its transmission variables. Empirically, such a conditional effect can be examined by the introduction of an interaction term into the model. Ideally, we would want to introduce an interaction term between the Gini and a moderator variable that directly measures the degree of imperfections in capital markets. As such a variable does not exist, the ratio of private credit to GDP (CREDIT) serves as a proxy for credit availability.[15]

Indeed, the results from Columns (4)—(6) reveal that the net Gini and its interaction term with CREDIT are individually and jointly significant in both the schooling and the fertility regression, but insignificant in the investment regression.[16] The estimated parameters imply that the negative effect of inequality on schooling as well as the positive effect of inequality on fertility are stronger the lower the availability of credit. Poor families seem to

[14] Although system GMM is designed for dynamic models, it does not require the dependent variable to appear on the right hand side (see, Roodman, 2009b).

[15] We instrument the credit ratio and the interaction term with their lagged values, as they are possibly endogenous to growth. The data source of CREDIT is World Bank (2014).

[16] See the p-values on the Wald tests of joint significance, given in the last line of Table (7).

Table 7 Transmission channels of inequality. Dependent variables are investment shares (INVS), fertility (FERT), and schooling (SCHOOLING).

	(1) INVS	(2) SCHOOLING	(3) FERT	(4) INVS	(5) SCHOOLING	(6) FERT
log(GDP$_{pc}$)	0.102***	0.133	-0.501**	0.0790***	0.613	-0.634***
	(0.0161)	(0.305)	(0.202)	(0.0165)	(0.438)	(0.162)
GINI(N)	-0.190	-11.62**	6.969***	-0.249	-15.43***	9.708***
	(0.196)	(4.618)	(2.355)	(0.210)	(4.779)	(1.905)
REDIST(S)	-1.004***	3.342	7.029***	-0.875***	-1.135	5.871***
	(0.328)	(5.021)	(2.585)	(0.264)	(4.333)	(1.785)
CREDIT				-0.0464	-2.556***	2.306***
				(0.0691)	(0.969)	(0.453)
GINIxCREDIT				0.236	5.764*	-6.141***
				(0.215)	(3.211)	(1.352)
Observations	434	418	426	408	395	408
Countries	73	68	72	71	67	71
Hansen p-val	0.227	0.135	0.165	0.641	0.780	0.596
Diff-Hansen	0.964	0.289	0.956	0.998	0.906	0.987
AR(1) p-val	0.139	0.0100	0.00322	0.0728	0.0508	0.00549
AR(2) p-val	0.0288	0.140	0.545	0.0724	0.905	0.0890
Instruments	50	50	50	80	80	80
Joint p-val				0.4762	0.0040	0.0000

Notes: Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. All regressions include period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. Diff-Hansen gives the Difference-in-Hansen statistic of the instrument subset for the level equation. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. The instrument matrix is restricted to lag 2. The last line shows the p-values of the Wald test for joint significance of GINI(N) and its product with CREDIT for all interaction models. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

choose a higher quantity of children if they are unable to finance their children's education because of credit market restrictions. Hence, the data supports the endogenous fertility and the credit market imperfection channel.

In Table (8) we test whether the conditional relationship between inequality and the transmission variables also applies to the effect of inequality on growth. Therefore, we introduce the interaction term between inequality and credit availability in the baseline models of Table (3). In the reduced model reported in Column (1), both the Gini and the interaction term with the credit to GDP ratio are highly significant, individually and jointly. Based on the results from this regression, the solid upwards-sloping line in Figure (4) plots the marginal growth effect of inequality across different levels of CREDIT.[17] As indicated by the dashed 90 percent confidence bands, the marginal effect of inequality is negative at low values of CREDIT, but becomes insignificant at a credit to GDP ratio of roughly 60 percent, which is located around the 75th percentile of our sample. However, only at very high levels of CREDIT the effect of inequality turns significantly positive. The critical value lies at a credit to GDP ratio of about 110 percent, which is located around the 90th percentile of the sample.

Our regressions of the transmission variables suggest that much of the negative influence of inequality on growth results from forgone investments in human capital. In addition, some of the most productive investment opportunities (in regard to human or physical capital) may be replaced by less productive alternatives. Yet we can only control for the quantity of investments, and not for their average productivity. This might be one reason why the interaction effect shrinks, but still remains significant when we control for the investment share and the average years of schooling in Columns (2) and (3). Similarly to the baseline regressions, inequality and its product with the credit to GDP ratio only become insignificant when the fertility rate is introduced in Column (4). By holding fertility constant, we eliminate another element of the credit market imperfections channel. As a result and in line with our previous findings, the growth effect of inequality vanishes.

Finally, the effect of inequality on growth is subject to another conditionality: a dissipation of intellectual potential occurs if inequality is high and education is expensive for poorer households. Thus the growth effect of inequality could depend on the volume of public spending on education, which could ease the access to education for the poor. Indeed, the negative marginal effect of inequality on growth seems to be stronger if public education spending is low. Figure (5) plots the marginal effect of inequality based on a regression model that includes an interaction term between the net Gini and the ratio of public education spending to GDP (PSEDUC).[18] When education spending increases, the negative effect of inequality diminishes, becoming insignificant once a level of roughly 6 percent is passed. Although the average effect of inequality becomes positive for extremely high

[17] The generation of the figures illustrating interaction effects with continuous modifying variables has been accomplished with the help of the algorithm suggested by Brambor et al. (2006).

[18] The data source of PSEDUC is World Bank (2014).

Table 8 Interaction between the Gini coefficient, credit, and public spending on education

	(1)	(2)	(3)	(4)	(5)	(6)
L.log(GDP$_{pc}$)	0.00440	-0.00642	-0.0131***	-0.0150***	0.00712	-0.00742**
	(0.00593)	(0.00425)	(0.00320)	(0.00365)	(0.00523)	(0.00362)
GINI(N)	-0.288***	-0.157***	-0.0805***	-0.0240	-0.209**	-0.113**
	(0.0697)	(0.0502)	(0.0290)	(0.0406)	(0.0916)	(0.0567)
CREDIT	-0.139***	-0.0839***	-0.0555***	-0.0296**		
	(0.0310)	(0.0204)	(0.0144)	(0.0150)		
PSEDUC					-1.028	-0.822*
					(0.869)	(0.484)
GINI×CREDIT	0.362***	0.192***	0.113***	0.0511		
	(0.0889)	(0.0557)	(0.0376)	(0.0420)		
GINI×PSEDUC					1.761	1.288
					(1.678)	(1.009)
REDIST	-0.0976	0.0277	0.0469	0.0156	-0.229***	-0.113**
	(0.0665)	(0.0537)	(0.0489)	(0.0520)	(0.0739)	(0.0544)
INVS		0.120***	0.0843***	0.0769***		0.0906***
		(0.0295)	(0.0225)	(0.0230)		(0.0243)
SCHOOLING		0.00297	0.000992	-0.000285		0.00595***
		(0.00187)	(0.00120)	(0.000991)		(0.00167)
log(LIFEEX)			0.0996***	0.0662***		
			(0.0199)	(0.0188)		
GOVC			-0.0276	-0.0292		
			(0.0237)	(0.0236)		
INFL			-0.000902	-0.000717		
			(0.000721)	(0.000648)		
OPEN			0.00270	0.00279		
			(0.00298)	(0.00315)		
POLRIGHT			-0.00120	-0.00148		
			(0.00127)	(0.00131)		
log(FERT)				-0.0279***		
				(0.00812)		
Observations	895	810	713	713	724	665
Countries	152	125	123	123	142	122
Hansen p-val	0.142	0.717	1.000	1.000	0.117	0.517
Diff-Hansen	0.789	0.999	1.000	1.000	0.917	0.834
AR(1) p-val	0.0000166	0.0000236	0.000108	0.000130	0.00000556	0.000000619
AR(2) p-val	0.623	0.585	0.447	0.656	0.531	0.639
Instruments	98	134	209	226	87	121
Joint p-val	0.0001	0.0013	0.0058	0.4375	0.0308	0.1102

Notes: Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. All regressions include time dummies. Hansen p-val gives the J-test for overidentifying restrictions. Diff-Hansen gives the Difference-in-Hansen statistic of the instrument subset for the level equation. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. The instrument matrix is restricted to lag 2. The final line shows the p-values on the Wald test for joint significance of GINI(N) and its product with the respective moderator variable.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

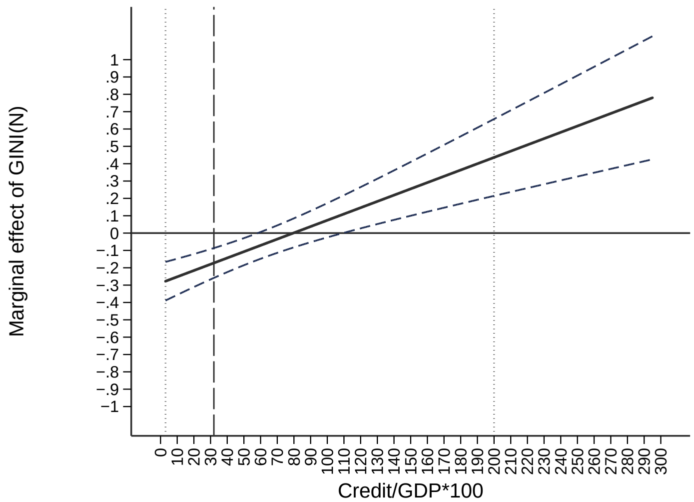

Figure 4 The marginal effect of inequality on growth across different levels of credit availability: values are calculated using the results of the growth regression in Column (1) of Table (8). The upwards sloping line plots the marginal effect of inequality across different levels of the credit to GDP ratio. Surrounding dashed lines represent the 90% confidence intervals. Vertical lines indicate the distribution of the credit to GDP ratio in the sample: dotted lines mark the first and 99th percentiles, the dashed line marks the median value.

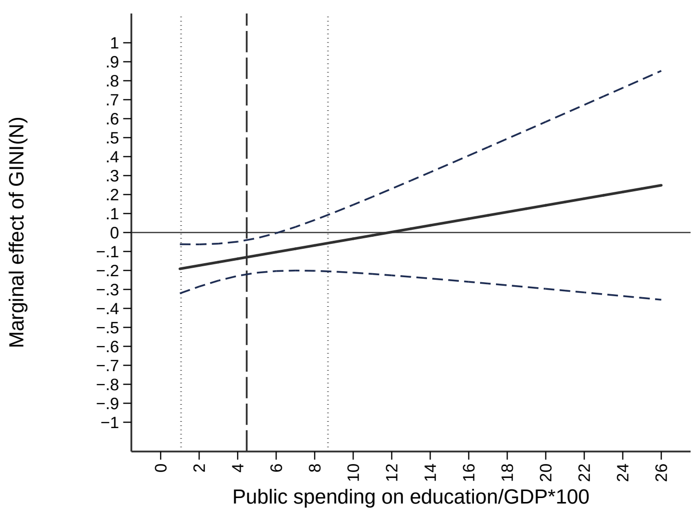

Figure 5 The marginal effect of inequality on growth across different levels of public education spending: values are calculated using the results of the growth regression in Column (5) of Table (8). The upwards sloping line plots the marginal effect of inequality across different levels of Public spending on education/GDP. Surrounding dashed lines represent the 90% confidence intervals. Vertical lines indicate the distribution of public spending on education/GDP in the sample: dotted lines mark the first and 99th percentiles, the dashed line marks the median value.

values of public education expenditure, it remains insignificant as long as public education expenditure is above the critical threshold.

In summary, this section shows that inequality exerts its influence on growth by reducing the average level of human capital and increasing the fertility rate, particularly in countries where credit availability is low. Physical capital investments, however, are relatively unaffected by inequality, but reduced by public redistribution via taxes and transfers. In addition, redistribution raises the fertility rate. Finally, a highly developed public education system seems to mitigate the negative effect of inequality on growth.

5.5 Different development levels

The basic regression results suggest that inequality and growth are negatively related. However, this conclusion is based on the whole sample, whereas we suspect that the effect of inequality on growth varies across different development levels (see, Barro, 2000 and Castelló-Climent, 2010).

Recently, unified growth theory brought forward a unitary explanation regarding the influence of inequality in the development process. As Galor and Moav (2004) emphasize, the effect of inequality on growth changes over the course of economic development due to variations in the prime engine of growth. In early stages of development, physical capital is the key source of income increases. In this phase, a higher level of inequality is benefitial for growth, as it channels ressources towards individuals with a higher propensity to save. Yet as the economies evolve, human capital becomes relatively more important than physical capital. Thus, a more equal distribution of disposable incomes promotes investment in human capital and exerts a positive influence on growth, especially in the presence of credit constraints. Finally, in later stages of development the credit constraints typically become less binding. As a result, the effect of inequality on growth may vanish.

Table (9) illustrates the results of our baseline estimations, conducted separately for high and low income countries. In order to distinguish between income groups, we rely on the classification of the World Bank.[19] The results obtained from the separation of the sample reveal substantial differences across development levels. Whereas net inequality exerts a strong and significantly negative influence on growth in less-developed countries, this effect turns insignificant in the group of advanced economies.

Figure (6) illustrates the marginal growth effect of the Gini coefficient for different development levels and the associated 90 percent confidence interval. The underlying model is Column (1) of Table (10), where we introduce an interaction term between the Gini coefficient and initial incomes, denoted by GINI$\times$L.log(GDP$_{pc}$). This inclusion allows for investigation of the impact of inequality without relying on fixed threshold values to distinguish between development levels. We conduct the analysis identically to the baseline

[19] According to the Atlas method used by the World Bank, high-income economies are defined to have per capita incomes greater than 12,746 USD.

Table 9 The impact of inequality on growth for different levels of development, baseline regression for high and low income countries. Dependent variable is per capita GDP growth.

	Low-Income Countries				High-Income Countries			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
L.log(GDPpc)	0.0105*	-0.00380	-0.0142***	-0.0171***	-0.0317***	-0.0264***	-0.0301***	-0.0301***
	(0.00584)	(0.00438)	(0.00405)	(0.00408)	(0.00489)	(0.00488)	(0.0115)	(0.0112)
GINI(N)	-0.151**	-0.126***	-0.0706**	-0.0326	-0.0640	0.0560	-0.0756	0.0103
	(0.0589)	(0.0335)	(0.0342)	(0.0338)	(0.0656)	(0.0526)	(0.160)	(0.219)
REDIST	0.0401	0.00961	0.106	0.0276	-0.0812**	-0.0572	-0.0230	-0.0337
	(0.0879)	(0.0732)	(0.0703)	(0.0725)	(0.0385)	(0.0395)	(0.0733)	(0.0687)
INVS		0.0736*	0.0562	0.0577		0.0690*	0.0138	0.0262
		(0.0401)	(0.0351)	(0.0407)		(0.0362)	(0.0468)	(0.0611)
SCHOOLING		0.00349**	0.000715	-0.000194		0.00125	0.00146	0.000638
		(0.00168)	(0.00104)	(0.00133)		(0.00192)	(0.00251)	(0.00234)
log(LIFEEX)			0.0919***	0.0581***			-0.0192	-0.0234
			(0.0188)	(0.0218)			(0.0861)	(0.0841)
GOVC			-0.0230	-0.0266			-0.0898	-0.0948
			(0.0231)	(0.0237)			(0.0865)	(0.0869)
INFL			-0.000307	-0.000327			0.00306	0.00791
			(0.000571)	(0.000556)			(0.0324)	(0.0283)
OPEN			0.00485	0.00678			-0.00193	-0.00183
			(0.00506)	(0.00571)			(0.0100)	(0.0113)
POLRIGHT			-0.000736	-0.000600			-0.00308	-0.000658
			(0.00138)	(0.00107)			(0.00621)	(0.00767)
log(FERT)				-0.0306***				-0.0186
				(0.00844)				(0.0230)
Observations	669	581	497	497	286	284	243	243
Countries	133	106	100	100	48	46	43	43
Hansen p-val	0.251	0.426	1.000	1.000	0.843	1.000	1	1
AR(1) p-val	0.000355	0.000347	0.000581	0.000770	0.000333	0.000339	0.00632	0.00438
AR(2) p-val	0.799	0.747	0.651	0.766	0.424	0.654	0.655	0.669
Instruments	62	98	175	192	62	98	175	192

Notes: Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. Column numbers refer to the model specification of Table (3) All regressions include period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. The instrument matrix is restricted to lag 2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10 The impact of inequality for different levels of development, estimated via interaction terms. Dependent variable is per capita GDP growth.

	(1)	(2)	(3)	(4)
L.log(GDP$_{pc}$)	-0.0557**	-0.0562***	-0.0393***	-0.0355***
	(0.0254)	(0.0176)	(0.0120)	(0.0113)
GINI(N)	-1.409***	-1.088***	-0.545**	-0.359
	(0.522)	(0.390)	(0.228)	(0.235)
GINI×L.log(GDP$_{pc}$)	0.145**	0.116**	0.0574**	0.0405
	(0.0630)	(0.0454)	(0.0274)	(0.0274)
Observations	955	865	740	740
Countries	154	126	125	125
Hansen p-val	0.0121	0.487	1.000	1.000
Diff-Hansen	0.677	0.974	1.000	1.000
AR(1) p-val	0.0000570	0.0000430	0.000131	0.000124
AR(2) p-val	0.455	0.459	0.382	0.524
Instruments	78	114	191	208
Joint p-val	0.0001	0.0003	0.0019	0.2856

Notes: Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. All regressions include period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. Diff-Hansen gives the Difference-in-Hansen statistic of the instrument subset for the level equation. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. The instrument matrix is restricted to lag 2. The final line shows the p-values on the Wald test for joint significance of GINI(N) and its product with L.log(GDP$_{pc}$). Covariates are identical to Table (3). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

specification; however, for reasons of lucidity, Table (10) only reports the interacting variables, as there are virtually no changes in the effects of the covariates.

It turns out that the marginal effect of net inequality on growth is significantly negative in poor economies. Yet the impact of an unequal distribution of incomes weakens as the economies develop and eventually turns insignificant. The null is reached at an income level of roughly 18,000 USD, but the effect of inequality already ceases to be significant once an average threshold of approximately 8,000 USD is exceeded. In economies with incomes larger than 18,000 USD, the effect of inequality tends to become positive, but the confidence interval indicates that this influence is far from significant.

Figure (7) illustrates the results from a similar analysis concerning the influence of redistribution across different levels of development. The underlying model uses the same specification as Column (1) of Table (6), where the effect of redistribution is examined while holding constant market inequality. In addition, we introduce an interation term between redistribution and the initial income level, denoted by REDIST×L.log(GDP$_{pc}$).[20] The figure highlights that redistribution contributes positively to economic growth in earlier stages of development. However, once the economies reach an average income level of approximately 13,000 USD, the negative incentive effects triggered by redistribution prevail, which is why

[20]The results of these estimations are reported in Table (A4) in the appendix.

the effect on growth tends to be negative.

Our findings strongly support the implications of the unified growth theory. Provided that human capital accumulation has already become the prime engine of growth in most developing countries, the effect of inequality and redistribution changes over the development process due to variations in the equality of opportunities. In early stages of development, opportunities for investments in human capital are unequally distributed among households. In the presence of underdeveloped financial markets, weak public education systems and high opportunity costs for education, budget constraints are binding and the initial wealth endowment of the family determines the education level of the children. In this case, redistribution as a policy measure to increase equality of opportunities exerts positive effects on growth. The development process of the economies is typically accompanied by a substantial expansion of the financial system, international capital inflows, and improvements in the public education systems. All of these effects lead to a decline in the influence of inequality by improving families' prospects of achieving a higher education level for their children, which is mirrored by a decline in intergenerational income elasticity (see Corak, 2013). Once the distribution of human capital endowment is due much more to preferences and individual skills rather than to initial wealth, high education rents may even lead to a growth-enhancing effect of inequality. In this case, redistribution may be an impediment to growth. The reason is that incentives for human capital investments, labor supply, and entrepreneurship rise if income gaps increase. Our results yield tentative implications in this direction, but the effects are far from significant.

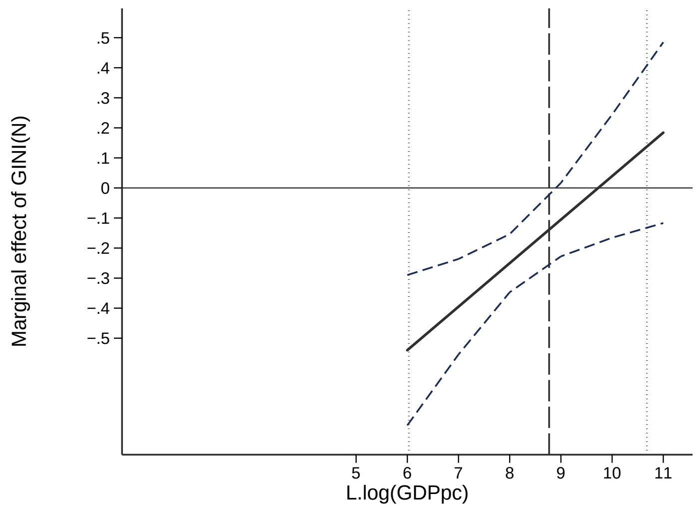

Figure 6 The marginal effect of inequality on growth at different levels of development: values are calculated using the results of the growth regression in Column (1) of Table (10). The upwards sloping line plots the marginal effect of inequality at various levels of development. Surrounding dashed lines represent the 90% confidence intervals. Vertical lines indicate the distribution of the development level in the sample: dotted lines mark the first and 99th percentiles, the dashed line marks the median value.

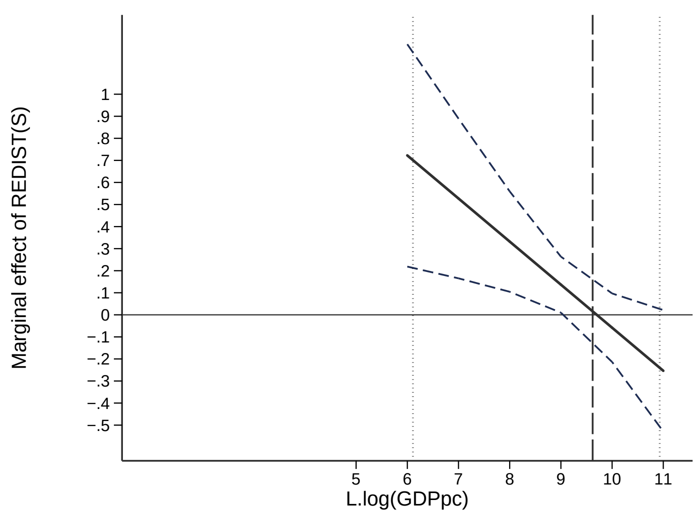

Figure 7 The marginal effect of redistribution on growth at different levels of development: values are calculated using the results of the growth regression in Column (1) of Table (A4) in the appendix. The upwards sloping line plots the marginal effect of redistribution at various levels of development. Surrounding dashed lines represent the 90% confidence intervals. Vertical lines indicate the distribution of the development level in the sample: dotted lines mark the first and 99th percentiles, the dashed line marks the median value.

6 Conclusions

Based on a current set of harmonized worldwide data, this paper finds a robust negative effect of income inequality on growth when the transmission variables of inequality are left open. By showing that less equal societies tend to have a less educated population and higher fertility rates, in particular when credit availability is low, the paper supports the credit market imperfections and the endogenous fertility channel. In contrast, the correlation between inequality and physical capital investment is rather weak.

In line with the political economy mechanism of the endogenous fiscal policy channel, this paper finds that a higher level of market inequality predicts more public redistribution. Moreover, redistribution by taxes and transfers seems to directly harm economic growth when net inequality is held constant. We find evidence that this may be due to an impairment of physical capital investment and an increase in the fertility rate.

When estimating the aggregate growth effect of redistribution—its direct negative effect combined with its indirect positive effect resulting from lower net inequality—our results suggest that both effects are offsetting. Thus, at a given level of market inequality, redistribution seems to be a free lunch. Nonetheless, the most growth friendly environment is a low level of net inequality that stems from an equable distribution of market incomes, but not from redistributive taxes and transfers.

Finally, this paper shows that the growth effects of inequality and redistribution vary with the development level. A negative impact of inequality prevails in developing and middle-income countries, where the negative potential of inequality is severe due to capital market imperfections and an insufficient provision of public goods. In high income countries, where opportunities are on average distributed more equally, no significant correlation between inequality and growth occurs. Likewise, the paper reveals that redistribution by taxes and transfers is beneficial for growth in poor countries, but rather harmful in rich economies.

For economic policy our results suggest some scope of action: a highly developed public education system seems to mitigate the negative growth effect of inequality. Hence, governments should be able to simultaneously promote equity *and* efficiency by working towards providing free and high quality education for poorer families.

Two paths for future research remain: First, it is still possible that a low level of education and a high fertility rate are the *cause* rather than the *effect* of inequality. Although we estimate a causal relation running from inequality to education and fertility, more research is necessary in order to fully rule out that results are driven by feedback effects. Second, as the pre-post approach measures effective redistribution, it does not provide insights on the growth effects of specific redistributive policies. Future research should identify and analyze the policy instruments by which redistribution is achieved, and in doing so determine how it can be accomplished most efficiently.

Appendix

Appendix A1: Standardization Procedure in the SWIID

Our preferred measures of income inequality and redistribution stem from the Standardized World Income Inequality Database (SWIID, Version 5.0, released in October 2014) generated by Solt (2009, 2015b). The SWIID is based on the UN World Income Inequality Database (WIID), and several other cross-country inequality datasets, data provided by national statistical offices, and scholarly articles. As the source data is not directly comparable, Solt (2015b) provides an algorithm to transform and adjust the original data, achieving estimates of net and market inequality comparable to those of the LIS Key Figures. A very rough overview of the standardization procedure can be given as follows: (1) The data is sorted into categories by welfare definitions and by equivalence scale. (2) Ginis of net and market inequality on the basis of household adult equivalent income from the Luxembourg Income Study (LIS) are added as a baseline, generating a dataset in which each country-year observation has data entries in at least one of thirteen categories. (3) Ratios between the variables in different categories are estimated as a function of country-decade, country, region and development status through various regression models. In further steps eleven series of estimates, comparable with the LIS net-income data, are calculated and combined into a single variable. (4) Possible measurement errors are corrected by using five-year weighted moving averages on all data points except those taken from the LIS and certain time periods.

Table A2 The aggregate impact of redistribution on growth

	(1)	(2)	(3)	(4)
L.log(GDPpc)	-0.00220	-0.0140***	-0.0215***	-0.0269***
	(0.00801)	(0.00534)	(0.00833)	(0.00682)
REDIST(S)	-0.0912	-0.0779	0.0496	0.0186
	(0.114)	(0.0646)	(0.0726)	(0.0544)
INVS		0.158***	0.168***	0.0975**
		(0.0411)	(0.0383)	(0.0439)
SCHOOLING		0.00711***	0.00710***	0.00504**
		(0.00245)	(0.00250)	(0.00198)
log(LIFEEX)			-0.00521	0.0381
			(0.0751)	(0.0520)
GOVC			-0.0863***	-0.118***
			(0.0300)	(0.0290)
INFL			0.0000335	-0.000877
			(0.00111)	(0.00111)
OPEN			0.00435	0.00264
			(0.00452)	(0.00471)
POLRIGHT			-0.00314	-0.00147
			(0.00242)	(0.00189)
log(FERT)				-0.0305***
				(0.0118)
Observations	434	418	374	374
Countries	73	68	67	67
Hansen p-val	0.00117	0.274	1.000	1.000
Diff-Hansen	0.323	0.699	1.000	1.000
AR(1) p-val	0.00114	0.0000653	0.0000432	0.0000460
AR(2) p-val	0.438	0.423	0.117	0.144
Instruments	35	65	139	154

Notes: Table reports two-step System GMM estimations with Windmeijer-corrected standard errors in parentheses. All regressions include period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. Diff-Hansen gives the Difference-in-Hansen statistic of the instrument subset for the level equation. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. The instrument matrix is restricted to lag 2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3 Sensitivity analysis, full sample, redistribution variable is REDIST

	Three Lags in Instrument Matrix			OSGMM (linear System of equations)		
	(1)	(3)	(4)	(1)	(3)	(4)
L.log(GDP$_{pc}$)	0.00297	-0.0162***	-0.0194***	0.5962***	-0.0142***	-0.0153***
	(0.00508)	(0.00302)	(0.00293)	(0.0128)	(0.0014)	(0.0011)
GINI(N)	-0.2370***	-0.0526**	-0.00452	-0.0817***	-0.0403***	-0.0124
	(0.0616)	(0.0233)	(0.0220)	(0.01638)	(0.0097)	(0.0096)
REDIST	-0.2700***	-0.0235	-0.00380	-0.1520***	-0.0460***	-0.0492***
	(0.0822)	(0.0432)	(0.0385)	(0.0262)	(0.0171)	(0.0105)
INVS		0.0886***	0.0661**		0.0533***	0.0421***
		(0.0261)	(0.0265)		(0.0127)	(0.0105)
SCHOOLING		0.00227*	0.000215		0.0027***	0.0010***
		(0.00116)	(0.00113)		(0.0005)	(0.0004)
log(LIFEEX)		0.0746***	0.0551***		0.0642***	0.0263***
		(0.0160)	(0.0173)		(0.0078)	(0.0072)
GOVC		-0.0306	-0.0372		0.0076	0.0148
		(0.0236)	(0.0268)		(0.0125)	(0.0106)
INFL		-0.000798	-0.000495		-0.0012***	-0.0007**
		(0.000611)	(0.000544)		(0.0005)	(0.0003)
OPEN		0.00589*	0.00419		0.0037***	0.0018
		(0.00338)	(0.00323)		(0.0013)	(0.0011)
POLRIGHT		-0.000461	-0.000704		-0.0006	-0.0010*
		(0.00119)	(0.00101)		(0.0007)	(0.0006)
log(FERT)			-0.0324***			-0.0307***
			(0.00615)			(0.0027)
Observations	955	740	740	776	602	602
Countries	154	125	125	144	119	119
Hansen p-val	0.0473	1.000	1.000			
Diff-Hansen	0.640	1.000	1.000			
AR(1) p-val	0.0000331	0.0000929	0.000118			
AR(2) p-val	0.645	0.427	0.574			
Instruments	85	252	277	27	90	99
R-squared				0.08, 0.14, 0.05, -0.03, -0.07, -0.04, -0.01, 0.12, -0.09	0.01, 0.29, 0.21, 0.08, 0.32, 0.21, 0.29, 0.17, 0.00	-0.02, 0.33, 0.39, 0.04, 0.26, 0.43, 0.40, 0.22, 0.00

Notes: Table reports sensitivity analyses of the baseline results. The first technique maintains system GMM including an additional lag in the instrument matrix. The second method uses optimal systems GMM (OSGMM) estimation in a linear IV system of equations where each period t enters as a separate equation. Robust standard errors are in parantheses. Hansen p-val gives the J-test for overidentifying restrictions. Diff-Hansen gives the Difference-in-Hansen statistic of the instrument subset for the level equation. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4 The impact of redistribution across different levels of development. Dependent variable is per capita GDP growth.

	(1)	(2)	(3)	(4)
L.log(GDP$_{pc}$)	0.00785	-0.00826	-0.0172	-0.0239**
	(0.0108)	(0.00915)	(0.0120)	(0.0116)
REDIST(S)	1.894**	1.304**	1.346*	0.527
	(0.840)	(0.579)	(0.784)	(0.712)
REDIST×L.log(GDP$_{pc}$)	-0.195**	-0.132**	-0.130	-0.0490
	(0.0898)	(0.0603)	(0.0823)	(0.0741)
GINI(M)	-0.226***	-0.0693	-0.0580	-0.0299
	(0.0759)	(0.0541)	(0.0517)	(0.0523)
Observations	434	418	374	374
Countries	73	68	67	67
Hansen p-val	0.141	0.938	1.000	1.000
Diff-Hansen	0.723	1.000	1.000	1.000
AR(1) p-val	0.000439	0.0000675	0.0000765	0.0000633
AR(2) p-val	0.273	0.279	0.125	0.124
Instruments	62	92	166	181
Joint p-val	0.0544	0.0737	0.0764	0.5711

Notes: Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. All regressions include period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. Diff-Hansen gives the Difference-in-Hansen statistic of the instrument subset for the level equation. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. The final line shows the p-values on the Wald test for joint significance of REDIST(S) and its product with L.log(GDP$_{pc}$). The instrument matrix is restricted to lag 2. Control variables are identical to those applied in the corresponding columns in Table (3). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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