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Determinants of governmental redistribution

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Determinants of governmental redistribution

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Abstract

This paper investigates the major drivers of governmental redistribution. We retest the Meltzer-Richard hypothesis and account for a plethora of political, institutional, and cultural forces that influence the scope of redistribution. Extended and harmonized data on *effective* redistribution recently provided by the SWIID version 5.0 allows for the assessment of the origins of governmental redistribution for a broad sample of countries. Our results confirm the Meltzer-Richard hypothesis, indicating that the link between market inequality and redistribution is even stronger when using perceived inequality measures. We support the decisive role of the median voter, though also approving a crucial role of top incomes. Political and institutional conditions as well as cultural aspects significantly influence governments in their decisions regarding the amount of redistribution.

Keywords: Redistribution, Inequality, Economic Policy, Dynamic Panel Data

JEL No.: C23, D31, D72, H11

1 Introduction

What determines the extent of redistribution? The well-known [Meltzer and Richard \(1981\)](#) model predicts that a higher level of inequality leads to higher redistributive efforts in a majority-voting model. An increase in mean incomes relative to the income of the decisive voter yields a larger mean-to-median ratio, which raises the demand for redistribution. Although the theoretical link is profound and broadly accepted, the empirical results regarding the relationship between inequality and redistribution are rather ambiguous. Some studies, for instance [Milanovic \(2000\)](#) and [Scervini \(2012\)](#), support the theoretical predictions, while others find no significant relationship ([Kenworthy and McCall, 2008](#) and [Gouveia and Masia, 1998](#)) or even a negative link between the two variables ([Georgiadis and Manning, 2007](#)). If we are not willing to assume that the extent of redistribution is purely random, but rather relies on rational decisions of governments, then this ambiguity gives rise to the implication that there are other determinants not yet identified in the literature.

So far, two main problems have impeded research on these determinants. First, earlier studies often rely on rough measures of redistribution. However, the extent to which specific fiscal policy instruments are actually redistributive often remains unclear. The size of taxes and transfers may say little about their redistributive impact, while their progressivity is difficult to measure and to compare across countries. Second, truly comparable data on income inequality and particularly that on redistribution has long been rather scarce.

Although comparability and quality of the Luxembourg Income Study (LIS) are unparalleled among cross-nationally comparable inequality data, the calculations which use a uniform set of assumptions and definitions on the basis of harmonized microdata result in a limited data coverage of only 232 country-years. While this limitation impedes the investigation of the determinants of redistribution based on a broad panel of countries, the incorporation of a larger set of observations typically comes at the cost of sacrificing the benefits of comparability and harmonization. Fortunately, some major progress has been made in cross-national inequality datasets in recent years, particularly with regard to the WIID 3.0b and the SWIID 5.0. The latest update of the Standardized World Income Inequality Database (SWIID) to version 5.0 in October 2014 now enables acquisition of observations for 174 countries from 1960 to present. Particularly the maximization of comparability for the broadest possible sample of countries and the clear distinction between market and net inequality for roughly 4,600 country-years comparable to those obtained from the LIS provide an unprecedented potential for exploring the origins of governmental redistribution across the globe. This rich dataset further allows for compilation of a sample that also includes a large number of developing economies, thereby enabling assessment of differences in the average causation of redistribution across different income levels. Due to limitations in data availability, little progress has thus far been made

in this direction.

We make use of the recent advancement in data availability by examining the empirical determinants of redistribution on a broad basis. As a result, the contribution of the paper is threefold. First, we provide profound empirical support for the Meltzer-Richard hypothesis, which rests upon a widely extended and cross-nationally comparable dataset. Second, we analyze the determinants of redistribution more generally by investigating the political economy channels influencing the amount of governmental redistribution. Finally, we elucidate the role of institutional design, cultural forces, and differences in the development level.

As for the Meltzer-Richard hypothesis, we find a positive and significant link between market inequality and redistribution. The results are robust to several model specifications as well as different measures of income inequality. Whereas the baseline estimations study the effect of officially reported market inequality, perceived inequality measures highlight an even larger impact. Perceived inequality is calculated using data on self-assessment by individuals concerning their position on the income scale as reported by the World Value Survey (WVS) and the International Social Survey Programme (ISSP).

It turns out that the Meltzer-Richard effect—while prevalent in the whole sample estimations—cannot be observed in developing countries. In fact, the robust positive effect of market inequality on redistribution stems mainly from advanced economies. This implies that market inequality hardly influences redistributive issues when democratic structures have not been evolved. An increase in the level of development typically coincides with greater democratic rights, leading to a significant impact of market inequality on redistribution. As a consequence, the Meltzer-Richard effect becomes incrementally important with an increasing development level.

We further account for the impact of different socio-economic groups on the extent of redistribution. Our paper provides robust evidence that the middle class exerts a significant influence on the amount of redistribution. Additionally, we do not find any such impact with regard to individuals at the bottom of the income distribution. Instead, our results reveal that top incomes in a society impede redistribution. These findings indicate that it is not the poor, but rather the rich, who play a crucial role in redistributive activities of the government.

In a second step, we re-estimate our baseline regression, taking account of different political institutions. The results imply that more stable governments redistribute less. Our data further provides evidence that governments with a religious background exhibit a lower level of redistribution. Interestingly, when splitting the sample according to voter turnout and religious background, different socio-economic groups become influential in redistributive questions. Moreover, we obtain a positive and significant impact on redistribution for the case that a government has not legally come into office, indicating that these governments may fear political uprisings of the population and therefore redistribute more to moderate respective sentiments.

Additionally, we find that the Meltzer-Richard effect depends to some extent on cultural forces, particularly the general acceptance of inequality in a country.

Methodologically, the large data coverage in the time-dimension of the SWIID allows for the application of system GMM estimations, which require sufficient lags of the dependent variable and the regressors. The benefit of using system GMM is that it retains some of the information of the equation in levels when accounting for unobserved heterogeneity. Maintaining this information is of great importance, as redistribution time-series are highly persistent. To exclude the possibility that our results are primarily driven by the selected estimation strategy, we provide an extensive sensitivity analysis, which includes several alterations of the baseline technique.

The paper is structured as follows. Section 2 gives an overview of important political economy channels which influence the extent of redistribution. Section 3 offers a description of the data and discusses the underlying empirical strategy. Section 4 outlines the main results and extends the analysis by accounting for varying institutional designs, cultural aspects, different development levels, and perceptions. The final chapter concludes.

2 Theoretical determinants of redistribution

The relationship between income inequality and redistribution is complex. Focusing on theoretical links from a perspective of political economy, this section intends to shed light on the major drivers of governmental redistribution identified in recent literature.

Meltzer-Richard hypothesis

A seminal paper of [Downs \(1957\)](#) extends the model of [Hotelling \(1929\)](#) to political economy, concluding that under some assumptions the median voter of the income distribution is the decisive agent in a democracy. As political parties have to gain votes, they determine policy strictly by majority vote. In a crucial work by [Meltzer and Richard \(1981\)](#) the median voter theorem is applied to the field of inequality and redistribution. The findings imply that higher income inequality leads to a rising demand for redistribution in a majority-voting equilibrium. Assuming an income distribution which is skewed to the right, higher inequality—measured by the mean-to-median ratio—increases possible gains from higher redistribution because of a relatively poorer median voter.

Although the theoretical fundament of the Meltzer-Richard hypothesis has been applied for decades, the empirical findings are far from consistent. A significant and positive relationship between overall inequality and overall redistribution is found by [Milanovic \(2000\)](#) and [Scervini \(2012\)](#). Other studies obtain a negative

link (Georgiadis and Manning, 2007), or even no significant relationship (Kenworthy and McCall, 2008 and Gouveia and Masia, 1998). Likewise, the decisive role of the median voter has been empirically questioned several times. Milanovic (2000) points out that the middle class is always a net loser in the process of redistribution as higher taxes are not fully compensated through transfers. Similarly, Scervini (2012) concludes that gains from redistribution are fairly small for the middle class.

Recent investigations emphasize that individuals often hold erroneous beliefs about income inequality. Niehues (2014) and Engelhardt and Wagener (2014) highlight that perceptions of the electorate may matter more than objective data. These studies provide evidence that the Meltzer-Richard effect is less pronounced when examining actual inequality, but increases substantially if perceived inequality measures are analyzed. If citizen-voters consider the income distribution to be highly unequal, there may be strong demand for redistribution, even if “real” market inequality is moderate or low. Conversely, if voters are not aware of the “true” extent of inequality, demand for redistribution may be lower than that induced by the actual distribution of incomes.

Role of top incomes

In practice, top incomes are net-payers of redistributive activities, implying a generally reluctant attitude towards redistribution. Top incomes might engage in rent-seeking behavior or examples of cronyism to lower the financial burden through redistribution. In democracies, instances of rent seeking should be relatively short-lived, since politicians have to gain a majority of votes in order to stay in office. Contrary to the median voter model, Scervini (2012) and Bassett et al. (1999) state that the *de facto* political power is at a higher level than the median since higher income levels devote additional resources towards political activity or campaign contributions. As noted by Acemoglu and Robinson (2006a), even if *de jure* political power changes, elites may still exert a disproportionate influence by increasing the intensity of their collective action. Rosenstone and Hansen (1993) provide a similar explanation by illustrating that political participation in the US is higher for individuals with higher incomes and for those who are better educated.

Downs (1957) points out that higher inequality may increase asymmetric political power due to asymmetric information between different income groups. He argues that it is irrational for most citizens to acquire political information for purposes of voting since voting produces an extraordinarily small individual gain. Hence, lack of information converts democratic governments into representative regimes, as they have to rely on persuaders who influence non-interested, highly uncertain voters. As a consequence, inequality of political influence is a necessary result of the asymmetric distribution of information. Some studies, e.g. Moffitt (1999) and Bourguignon and Verdier (2000), identify a positive relationship between top incomes and the scope of redistribution through altruism and efforts of the rich to promote an educated middle class in order

to minimize the risk of expropriation.

Role of low incomes

As redistribution operates from high to low incomes, the bottom quintile of the income distribution benefits from a higher level of redistribution. However, it is questionable to what extent individuals at the bottom of the income distribution exert influence on the scope of redistribution. According to the median voter model, political influence of the lowest quintile should be negligible since the median voter is the decisive agent. In addition, electoral engagement is positively correlated with income, elucidating why rationally-acting politicians have an incentive to refrain from focusing on bottom-income voters (Blais, 2000 and Norris, 2002). In contrast, redistribution via the unemployment system may benefit the lowest incomes disproportionately if labor market conditions affect redistributive activities of policymakers. Such an effect is identified by Scervini (2012).

Role of political institutions and cultural preferences

In democracies, the relationship between market income inequality and redistribution should be stronger than in authoritarian regimes (Perotti, 1996). As voting does not play a significant role in policy making in those regimes, governments can ignore preferences of poorer voters (Milanovic, 2000). Empirical evidence on the impact of democracy on redistribution is inconclusive. While Persson and Tabellini (1994) emphasize the importance of democratic institutions, Scervini (2012) confirms the findings of Alesina and Rodrik (1994) and Perotti (1996) indicating that democracy does not have a significant influence on redistribution.

Acemoglu et al. (2013) refer to the fact that varying institutional regimes yield different results concerning redistribution. Unlike policies, institutions are durable and difficult to reverse, with the result that they can considerably influence the allocation of *de jure* political power and the amount of redistribution. Consequently, an increase in the size of administration may reduce the extent of redistribution, since higher levels of bureaucracy exacerbate the implementation of redistributive activities. A related argument proposed by Alesina and Tabellini (2007) indicates that politicians usually do not prefer to delegate redistributive tasks, as these responsibilities increase their incumbency advantage. Instead, bureaucrats are primarily motivated by their own career concerns, making redistribution a less relevant parameter. Additionally, more stable governments may reallocate less, as redistribution is an instrument in gaining votes as advocated by Downs (1957). Thus, redistributive activities might play a substantial role for governments with a bare majority or in countries experiencing political instability (Annett, 2001).

Political institutions, and therefore redistribution, may additionally be shaped by religious or cultural preferences of a society as promoted by Luttmer and Singhal (2011) and Acemoglu et al. (2005). We suspect

an adverse impact of religious governments on redistribution since religion and welfare state spending might act as substitute mechanisms insuring individuals against life risks (Scheve and Stasavage, 2006). As a consequence, religious groups may oppose governmental redistribution as suggested by Stegmüller et al. (2012). Cultural forces that influence the Meltzer-Richard effect in particular include the acceptance of inequality within a society and collective preferences for redistribution. Employing macro data, we cannot differentiate between individual preferences, but we are able to account for existing cultural differences between nations.

3 Empirical strategy

3.1 Data on redistribution

For our analysis, we are particularly interested in data concerning inequality and redistribution. To measure inequality, we use the Gini coefficient, which gauges personal income inequality between households. Depending on the income concept used to build this measure, we can distinguish between the Gini of incomes before (“market Gini”) and after (“net Gini”) taxes and transfers. Differences between these variables are the result of governmental interventions. Thus, redistribution can be measured as the difference between market and net inequality, i.e.

$$\text{REDIST}_{it} = \text{GINI(M)}_{it} - \text{GINI(N)}_{it} \tag{1}$$

where GINI(M) and GINI(N) denote market and net Ginis, and REDIST is the amount of redistribution in country $i = 1, \dots, N$ at time $t = 1, \dots, T$. This measure is often referred to as the “pre-post-approach”.

Unlike other macroeconomic statistics where researchers may be reasonably confident that series are constructed consistently across national statistical offices, the definitions and assumptions used for compilation of inequality series often vary substantially across countries (Atkinson and Brandolini, 2001). Owing to inadequate official statistics of inequality, researchers and international institutions have compiled a number of secondary datasets that seek to provide comparable country-year estimates of summary measures of income distributions. The gold standard of these data collections is the “Luxembourg Income Study” (LIS).¹ While comparability and quality of the LIS data are unparalleled, the calculation of inequality measures based on harmonized microdata including a uniform set of assumptions and definitions, strongly restricts data availability. The LIS currently covers 232 country-year-combinations with data from 41 countries.² This

¹Note, however, that even the LIS has recently been subject to some criticism (see the dispute between Ravallion, 2015 and Gornick et al., 2015).

²Note that seven of these countries are only represented by one observation in the LIS.

limitation makes cross-country analysis based on broad panels an impossible task and is also an impediment to implication of panel data techniques, which typically require a sufficient lag structure. The incorporation of a larger number of country-years, however, typically comes at the cost of sacrificing the benefits of comparability and harmonization. [Atkinson and Brandolini \(2001\)](#) review the pitfalls encountered in the utilization of secondary datasets, concluding that simple adjustments for the differences in definitions are often not sufficient to ensure comparability.

Two secondary collections have particularly succeeded in providing cross-national data with global coverage for relatively long time spans. These are the “World Income Inequality Database” (WIID) provided by [UNO-WIDER \(2014\)](#) and the “Standardized World Income Inequality Database” (SWIID) compiled by [Solt \(2009, 2015b\)](#). An intense discussion has arisen on whether to use the WIID or the SWIID for cross-country analyses on inequality. As [Jenkins \(2014\)](#) argues, any researcher employing cross-national income inequality data needs to acknowledge the benefit-cost trade-off and has to ensure that any analytical conclusions drawn are in accordance with the underlying data concept. In our case, there are some strong arguments advocating for the utilization of the SWIID. First, in light of the divergence of the inequality datasets at hand, the data used must be appropriate for the underlying research topic ([Solt, 2015a](#) and [Atkinson and Brandolini, 2009](#)). The provision of both gross and net Gini indices based on comparable welfare definition enables calculation of redistribution according to Equation (1) that is consistent across countries. Second, while the revised version 3.0b of the WIID from September 2014 brought a substantial expansion in the coverage of Gini indices and therefore enables calculation of effective redistribution for some country-years, it does so with significantly reduced scope compared to the SWIID. This particularly applies to developing economies, where the extent and harmonization of any other existing dataset pale in comparison to those of the data covered by the SWIID.

As with any secondary inequality dataset, the SWIID represents a particular choice in the balance between comparability and coverage. While it may not be the most appropriate choice for all research on income inequality—especially if researchers are interested in changes in inequality over time in a single country—the maximization of comparability for the broadest possible coverage of country-years makes the SWIID ideal for redistribution studies based on broad panel estimation (see [Acemoglu et al., 2013](#)).³

Our analysis relies on data on market and net inequality from the SWIID version 5.0, which has only recently been made available.⁴ The SWIID seeks to maximize comparability by using the LIS series as baselines and filling in the missing observations via generation of model-based multiple imputation estimates

³Due to its frequent application in recent studies, we believe that the SWIID is on the verge to become the standard dataset in economic literature for obtaining redistribution measures via the pre-post approach (see, for instance, [Acemoglu et al., 2013](#) and [Ostry et al., 2014](#)).

⁴Version 5.0 of the SWIID was published in October 2014.

based on source data. Whereas earlier versions of the SWIID are entirely based on the WIID as source data, version 5.0 utilizes over ten thousand Gini coefficients from numerous cross-national inequality datasets, national statistical offices, and scholarly articles. Some concerns have been raised with regard to the multiple imputation procedure of version 4.0 of the SWIID (Jenkins, 2014). However, version 5.0 has addressed many of these objections.⁵ Both the coverage and comparability of the SWIID far exceed those of alternative inequality data collections.⁶ Since its introduction in 2008, the SWIID has expanded considerably over time. In version 5.0 it covers 174 countries from 1960 to 2013 with estimates of net income inequality comparable to those obtained from the LIS Key Figures for 4,631 country-years, and estimates of market income inequality for 4,629 country-years. The standardization process of the SWIID is described in Solt (2015b).

We calculate REDIST as the difference between market and net Ginis as they appear in the SWIID. While utilization of all possible information in the SWIID allows for acquisition of a large set of country-years, caution is advised when interpreting this measure. The SWIID algorithm uses estimates for some of the data on gross or net income inequality, which is why in some cases the difference between both measures contains little information about country specific redistribution. To address this problem, the SWIID reports a subsample of redistribution data which consists of only the most reliable observations. This sample discards observations from low-income countries before 1985 and from high-income countries before 1975. Coverage of this subsample—which we denote as REDIST(S)—includes 453 country-years.

While computation of redistribution in accordance with the pre-post approach has only recently found its way into the field of economics, it is very common in the sociological and public policy literature.⁷ The huge advantage of the method is that it yields a measure of *effective* redistribution, highlighting the *results* of redistributive activities by the government rather than the *effort* by which the result has been achieved. Owing to the limited availability of net and market Ginis in the past, some previous studies have employed indirect measures to proxy redistribution, such as average or marginal tax rates and different types of social spending. Yet such measures provide only a rough estimate of the extent of redistribution, as it remains unclear how far such fiscal policy instruments are indeed redistributive.

Three methodological notes shall be made: first, as a measure of effective redistribution via taxes and transfers, REDIST does not include in-kind provisions of public goods. Like most inequality databases, the SWIID is based on surveys covering household disposable income, which does not capture individual

⁵This particularly applies for the sorting of the source data into several categories, defined by the combination of welfare definition and equivalence scale used in their calculation. In addition, as Solt (2015a) emphasizes, most of the remaining arguments are hardly tenable with respect to version 5.0 of the SWIID.

⁶“All the Ginis” from Milanovic (2014) and the WIID3.0b cover less country-year observations than the SWIID, particularly with regard to the distinction between net and gross Gini indices. In addition, Milanovic (2014) stresses the incomparability of the observations included in his dataset and provides a series of dummy variables to account for the underlying income and household concept in order to calculate the Gini indices. Note also that the SWIID indices perform much better in replicating the LIS series than the WIID estimates (see Solt, 2015b).

⁷Van den Bosch and Cantillon (2008) provide an overview of the role of the pre-post approach in measuring the redistributive impact of taxes and transfers.

consumption of public goods. Second, the pre-post approach does not cover public attempts to equalize market inequality, neither by the promotion of equal opportunities nor by state intervention in private wage agreements. Third, GINI(M) in the SWIID includes incomes of all households, regardless of whether individuals are unemployed or out of the work force. Whereas market incomes in these cases are zero, the SWIID imposes a bottom-code at 1 percent of the mean income, which is assigned to each individual that reports a market income of less than 1 percent of the country-mean. The net Gini, however, neglects all individuals that do not report any incomes after taxes and transfers.

A potential weakness of the pre-post approach is that the level of gross inequality is not necessarily independent of the extent of public redistribution (see [Bergh, 2005](#)). On the upper end, taxes may reduce the labor supply of high-income earners, thus mitigating gross inequality. On the lower end, however, a generous welfare system may provide incentives for the poor to withdraw from the labor market and to live from transfers rather than relying on labor incomes. In line with [Ostry et al. \(2014\)](#), we suggest that the effect of redistribution on market inequality can safely be ignored, as both effects are—to some extent—offsetting.

3.2 Redistribution and inequality across countries

How much redistribution can be observed in the countries available in the SWIID? Figure 1 illustrates the histogram and the kernel density of REDIST using 5-year averages. Averaging the data is necessary to eliminate cyclical fluctuations and to estimate long-term rather than short-term effects. In addition, inequality turns out to be very persistent in the data, where the variation between countries is more than twice as high as the variation within countries.

The mean difference between the market and the net Gini in the sample is 6.56. However, the standard deviation of redistribution is high (6.44), indicating a substantial variation in the amount of redistribution across countries. Some nations with a generous social security system redistribute more than 20 Gini points, while other policies even yield increases in inequality. D’Agostino’s K-squared test rejects the assumption of a normal distribution.⁸ In fact, the kernel density suggests a bimodal distribution, where the largest part of the data is located around a moderate redistribution level of 2.94 Gini points. A second mode is located at a substantially higher level of REDIST.

The data also reveals that countries tend to redistribute more if the average income level is higher. When classifying the countries according to the World Bank, the mean value of redistribution in advanced economies is 12.08 percentage points, which substantially exceeds the mean redistribution level of developing countries (3.62). In addition, we observe a significantly higher amount of redistribution in democracies (6.35)

⁸We apply the version of D’Agostino’s K-squared test published in [D’Agostino et al. \(1990\)](#) which corrects standard errors by the sample size.

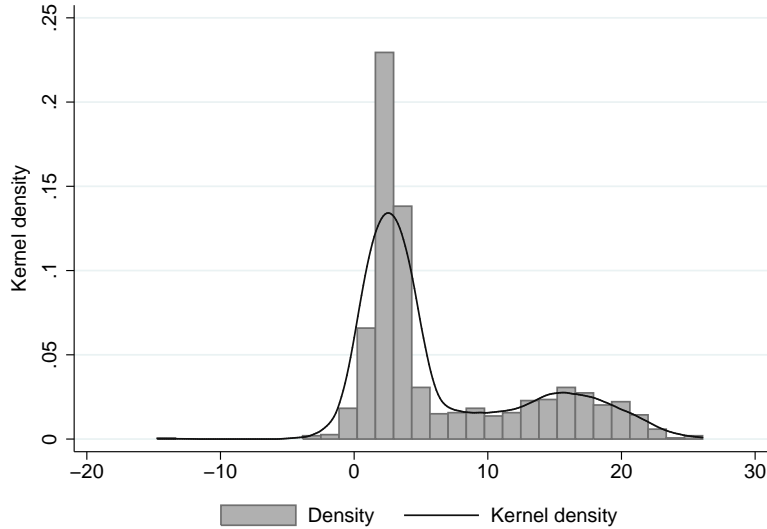


Figure 1 The distribution of the amount of redistribution across countries, REDIST ($N = 1,128$, skewness= 1.043, kurtosis= 2.847). Kernel is Epanechnikov.

compared to countries with a non-democratic government (3.22). However, there are major differences in the extent of redistribution which are dependent on the political attitude of the ruling party. Figure 2 plots the kernel density of redistribution for countries led by left-wing and right-wing parties separately.⁹ The figure indicates that right-wing governments on average tend to redistribute more (mean: 6.28 percentage points) than left-wing governments (mean: 5.18 percentage points). Most of the redistribution data in countries led by left-wing parties is concentrated around the first mode, whereas the difference in the height of the two modes is considerably lower in right-wing led nations.

Figure 3 illustrates the kernel density of the Gini coefficients before and after taxes and transfers. The mean value of the market Gini is 43.94 and is reduced to 38.91 after redistribution. However, the standard deviation of inequality after taxes and transfers is higher (11.14) than before the redistributive intervention of the government (9.46). D’Agostino’s K-squared test rejects the hypothesis that the net Gini is normally distributed, but it does not reject the null of normality of the market Gini. Redistribution policies apparently differ substantially across countries, transforming the unimodal distribution of the market Gini into a bimodal distribution with respect to the net Gini. Notably, whereas there are substantial deviations in net inequality between democracies and non-democracies, a similar pattern cannot be observed concerning market inequality. In fact, the Gini coefficients of democracies (43.92) and non-democracies (43.22) are nearly equal. This remarkable fact implies that governmental activities yield differences in inequality across countries, whereas market forces lead to a similar amount of inequality, irrespective of the form of government.

⁹Data on political parties is provided by the World Bank’s Database of Political Institutions, see [World Bank \(2012\)](#).

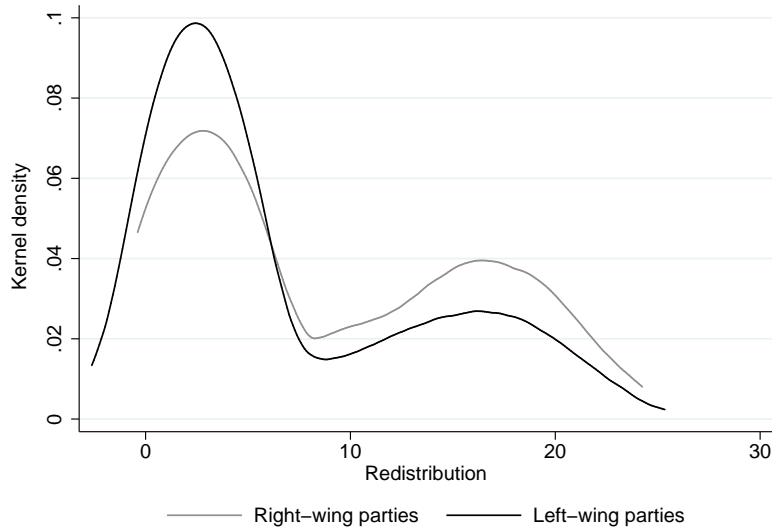


Figure 2 Kernel density of redistribution (REDIST) for different political parties. Kernel is Epanechnikov.

However, there are substantial deviations in market inequality across different levels of development, where low-income countries (46.03) tend to have a much higher level of market inequality than advanced economies (39.97).

Figure 4 illustrates the relationship between the Gini before and after taxes and transfers in the periods 1980-1984 and 2010-2013, respectively. In the early 1980s, we observe a strong positive relationship between inequality of net and market incomes (correlation: 83.30 percent). Although the Ginis of disposable and gross incomes are still positively related in the early 2010s, the strength of the correlation has substantially weakened (48.39). The reason for this development is the huge increase in the extent of redistribution in advanced economies, from an average of 9.78 in 1980-1984 to 14.75 in 2010-2013. At the same time, redistributive efforts have undergone little changes in developing economies, where we even observe a slight decline in REDIST (3.84 to 3.05). On average, countries with a high level of market inequality also reveal a high net inequality, which indicates that there is little change of inequality rankings across countries, at least within the respective development group.

In fact, it is crucial to consider the development level. At first glance, a bivariate analysis of the link between the market Gini and the amount of redistribution reveals no robust relationship, as suggested by Figure 5. However, when taking the level of economic development into account, the analysis reveals a positive relationship between market inequality and redistribution in both the sample of low-income countries (correlation: 55.22 percent) and the sample of advanced economies (39.87). However, what distinguishes these groups is that high levels of market inequality in developing economies are accompanied by a much lower extent of redistribution compared to developed countries. The most extreme example in the sample is Kenya,

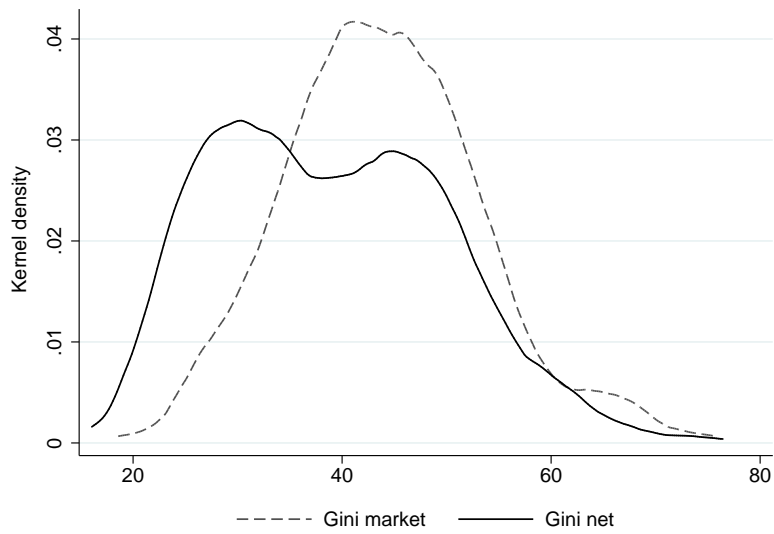


Figure 3 Kernel density of Gini coefficients before and after taxes and transfers, whole sample period. Kernels are Epanechnikov.

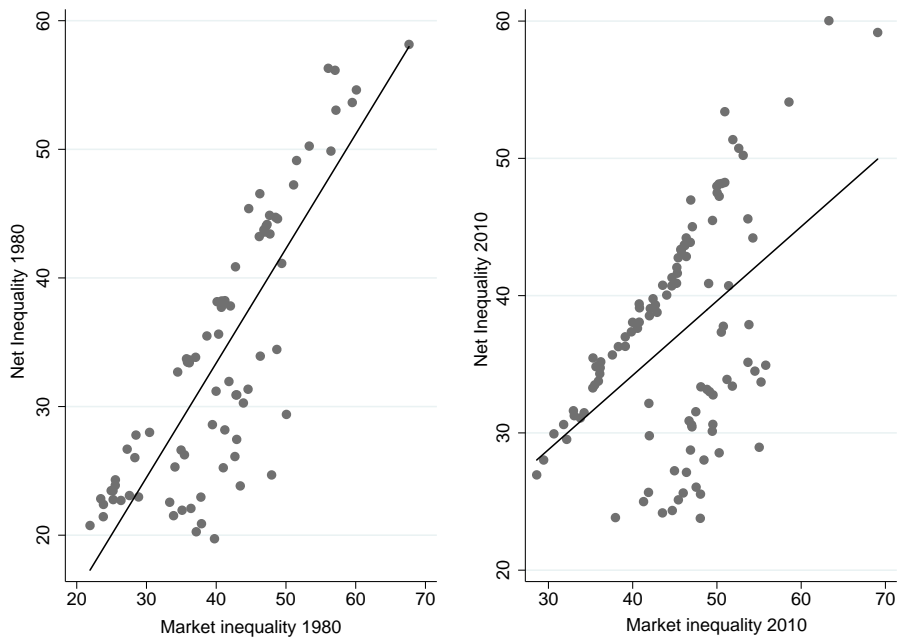


Figure 4 The relationship between Gini of disposable incomes and Gini of market incomes. Periods are 1980-1984 and 2010-2013.

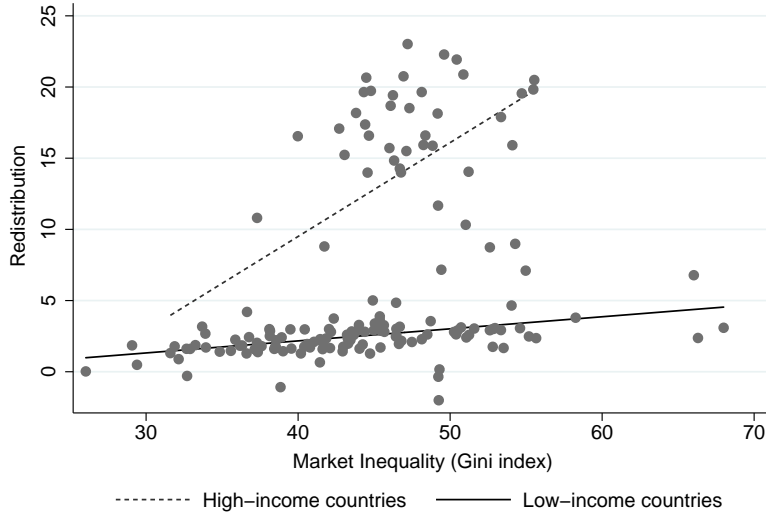


Figure 5 The relationship between market inequality and redistribution, period 2010-2013. “High-income countries” and “Low-income countries” illustrate the regression line between market inequality and redistribution in the subsamples of developing and advanced economies, respectively. Country classification refers to the World Bank.

where the market Gini was roughly 65 percent in the early 1970s and *increased* by 2.5 percentage points after taxes and transfers. Further examples stem entirely from developing economies, such as Angola (market Gini: 0.62 and REDIST: 0.025), Lesotho (.64 and .035), and Sierra Leone (.67 and .033). In more recent periods, Namibia (.63 and .033) and South Africa (.69 and .099) stand out. These examples underline that the relationship between inequality and redistribution has to be examined by holding constant some crucial variables that distinguish the countries.

3.3 Empirical model and estimation technique

To estimate the determinants of redistribution and to achieve a more in-depth understanding of the relationship between inequality and redistribution, we assume REDIST to be a function

$$\text{REDIST}_{it} = F(\text{REDIST}_{it-1}, \text{GINI}(M)_{it}, \mathbf{X}_{it}, \eta_i, \xi_t), \quad (2)$$

where $i = 1, \dots, N$ denotes countries, $t = 1, \dots, T$ is the time index with t and $t - 1$ five years apart, ξ_t is a specific effect of period ξ_t , and η_i is a country specific-effect which accounts for unobserved heterogeneity. \mathbf{X}_{it} captures a variety of control and environment variables and includes a number of determinants that we assume to have an effect on the level of redistribution. These determinants comprise the development level of the economy, which we include via the logarithmic value of real per capita GDP, denoted by $\log(\text{GDP}_{pc})$. We further incorporate an index of political rights (POLRIGHT) to account for the differences in redistribution

among democracies and non-democracies. The analysis also includes the logarithm of the fertility rate, denoted by $\log(\text{FERT})$. With the income level held constant, higher fertility rates imply a more binding budget constraint for the household, which may influence the redistributive efforts of the government. The labor market enters into the regression using the unemployment rate (UNEMP). In a further step, we analyze the impact of different socio-economic groups on the extent of redistribution, dependent on their income level. This includes the income shares of the richest 1 percent (TOP-1), the lowest decile of the income distribution (DECI₁₀), and the middle class. We model the middle class by employing two different concepts: the first (broader) concept MIDDLECLASS sums the income shares of the lower middle, middle, and upper middle quintiles of the income distribution, whereas the second (narrower) concept QUINT₃ only incorporates the middle quintile. Additionally, we enlarge the basic system in later sections by utilizing a number of political, cultural and institutional determinants, as well as measures of perceived inequality.

Data concerning the development level, fertility, unemployment, and the quintiles and deciles of the income distribution are extracted from [World Bank \(2014\)](#), POLRIGHT stems from [Freedom House \(2014\)](#), and TOP-1 is taken from SWIID v4.0, which is the latest version covering data on the income share of the top 1 percent.

We consider the variables to be linked additively and transform (2) into a 5-year panel data model to capture the long-term determinants of redistribution, which yields

$$\text{REDIST}_{it} = \vartheta \text{REDIST}_{it-1} + \alpha \text{GINI(M)}_{it} + \boldsymbol{\delta}' \Delta \mathbf{X}_{it} + (\eta_i + \xi_t + v_{it}), \quad (3)$$

where $v_{it} \equiv u_{it} - \xi_t - \eta_i$ is the idiosyncratic error term of the estimation and u_{it} is the error including time- and country-specific effects.

Using Within Group (WG) or Random effects (RE) estimations to account for unobserved heterogeneity in Equation (3) would yield a bias in the estimates, as RE requires by construction that $\text{Cov}[\eta_i, \text{REDIST}_{it-1}] = 0$ and $\text{Cov}[\eta_i, \mathbf{X}_{it-1}] = 0$, whereas the application of WG would lead to a correlation of the transformed error term and the time-demeaning transformation of REDIST_{it-1} . This bias, named after [Nickell \(1981\)](#), is not mitigated by an increase in cross-sectional observations. In order to circumvent these problems, the econometric literature has developed more reliable estimators which introduce a lagged dependent variable.

A common and widely-used approach to account for both unobserved heterogeneity and endogeneity is the estimator proposed by [Arellano and Bond \(1991\)](#). Introduce for reasons of lucidity $\Delta k \equiv (k_{it} - k_{it-1})$ and $\Delta_2 k \equiv (k_{it-1} - k_{it-2})$, the basic idea of this approach is to adjust (3) to

$$\Delta \text{REDIST} = \vartheta \Delta_2 \text{REDIST} + \alpha \Delta \text{GINI(M)} + \boldsymbol{\delta}' \Delta \mathbf{X} + \Delta \xi + \Delta v \quad (4)$$

and to use sufficiently lagged values of REDIST, GINI(M), and \mathbf{X} as instruments for Δk and $\Delta_2 \text{REDIST}$. These instruments are valid provided that the error term is serially uncorrelated. However, first differencing Equation (3) discards the information in the equation in levels. This drawback is particularly severe with regard to the purpose of this paper, as most of the variation in our data stems from the cross-section rather than the time-dimension. [Blundell and Bond \(1998\)](#) and [Bond et al. \(2001\)](#) show that the standard first-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.¹⁰ 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 \(1995\)](#) conditions, system GMM has proven to have better finite sample properties (see [Blundell et al., 2000](#)). To detect possible violations of these assumptions, we conduct Difference-in-Hansen tests for each of the system GMM regressions.¹¹

Define the vectors $\tilde{\mathbf{X}}'_{it} \equiv [\text{GINI(M)}_{it} \ \mathbf{X}'_{it}]$ and $\mathbf{A}'_{it} \equiv [\text{REDIST}_{it} \ \tilde{\mathbf{X}}'_{it}]$. The moment conditions used in the estimation of the first-difference GMM method considered in this paper can then be expressed as

$$\text{E}\{(v_{it} - v_{it-1})\mathbf{A}_{i,t-2}\} = 0 \text{ for } t \geq 3, \quad (5)$$

implying that the set of instruments is restricted to lag 2. Such a restriction is necessary, as otherwise the problem of “instrument proliferation” may lead to severe biases ([Roodman, 2009](#)). System GMM additionally uses moment conditions based on the regression equations in levels, which in our case are

$$\text{E}\{(v_{it} + \eta_i)(\mathbf{A}_{i,t-1} - \mathbf{A}_{i,t-2})\} = 0 \text{ for } t \geq 3. \quad (6)$$

In principle, the equations 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

¹⁰The assumption regarding the initial condition is $\text{E}(\eta_i \Delta \text{REDIST}_{i2}) = 0$, which holds when the process is mean stationary, i.e. $\text{REDIST}_{i1} = \eta_i / (1 - \vartheta) + v_i$ with $\text{E}(v_i) = \text{E}(v_i \eta_i) = 0$.

¹¹A more detailed description of the estimator in the context of the empirical application can be found in [Bond et al. \(2001\)](#) and [Roodman \(2009\)](#).

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 Results

4.1 Baseline results

Table 1 displays the results of our baseline estimates. Column (1) presents a reduced model which only incorporates the effect of market inequality, the development level, and the lagged dependent variable. As hypothesized by [Meltzer and Richard \(1981\)](#), we find a positive and highly significant impact of market inequality on the extent of redistribution, confirming that a poorer median voter has a higher demand for redistribution. Additionally, we observe a significantly positive effect of the development level, which is in line with implications of the descriptive statistics indicating that countries with a higher GDP redistribute more. The lagged endogenous variable is highly significant and close to one suggesting that REDIST is highly persistent over time. Period-specific effects rarely exert a significant influence on redistribution.

Column (2) introduces fertility, the degree of democratization, and unemployment in the model. The positive effect of inequality on redistribution remains significant, whereas the effect of the development level deviates from Column (1). The reason may be that richer economies typically tend to have lower fertility rates and enhanced political rights, implying that the positive effect of $\log(\text{GDP}_{pc})$ discovered in Column (1) may be the result of neglecting these variables. Fertility itself is negatively related to redistribution, providing clear indication that governments on average ignore stronger budget constraints of households with a higher number of children. In contrast, we find no significant impact of POLRIGHT and UNEMP on the extent of redistribution. Although we observe a strong correlation between POLRIGHT and REDIST, a robust relationship does not appear when controlling for a set of covariates. It is possible that political rights do not directly influence the amount of redistribution, but rather operate via other channels as suggested by [Acemoglu et al. \(2013\)](#). With regard to the unemployment rate, the result is striking as it implies that redistributive efforts of the government are not affected by the situation of the poorest, who are disproportionately hit by unemployment.

In Column (3) our baseline regression is extended by some variables controlling for the shape of the income distribution. The estimated parameter of MIDDLECLASS is positive and highly significant, suggesting that the middle class plays a decisive role in redistributive issues. The coefficient on TOP-1 is negative and significant, implying that top incomes reject a higher level of redistribution as they are net-payers. Contrary to the median voter theorem, the rich exert a significant impact on redistribution, fostering notions of their

Table 1 Baseline regressions, full sample. Dependent variable is redistribution REDIST.

	(1)	(2)	(3)	(4)	(5)	(6)
GINI(M)	0.0706*** (0.0160)	0.0712*** (0.0268)	0.232*** (0.0720)	0.195*** (0.0572)	0.208*** (0.0576)	0.203** (0.0985)
log(GDP _{pc})	0.710*** (0.0944)	-0.140 (0.216)	0.423 (0.258)	0.509** (0.236)	0.388 (0.256)	0.521 (0.368)
REDIST($t - 1$)	0.914*** (0.0255)	0.985*** (0.0309)	0.792*** (0.0793)	0.801*** (0.0694)	0.813*** (0.0712)	0.781*** (0.109)
UNEMP		0.0226 (0.0262)	-0.00741 (0.0256)	-0.0172 (0.0288)	-0.00188 (0.0240)	0.0182 (0.0179)
POLRIGHT		0.0392 (0.0683)	0.152* (0.0861)	0.186** (0.0933)	0.157* (0.0872)	0.0931 (0.1430)
log(FERT)		-1.260*** (0.373)	-0.381 (0.393)	-0.482 (0.444)	-0.353 (0.355)	0.1285 (0.4358)
MIDDLECLASS			0.182** (0.0785)		0.150** (0.0667)	0.2682*** (0.0929)
TOP-1			-0.146** (0.0640)	-0.175*** (0.0629)	-0.111** (0.0550)	-0.0646 (0.0758)
QUINT ₃				0.310* (0.167)		
DECI ₁₀					0.170 (0.204)	
POVERTY						-0.0056 (0.0055)
Observations	872	593	443	446	443	156
Countries	145	140	126	126	126	60
Hansen p-val	0.393	0.390	0.937	0.891	0.970	1.000
Diff-Hansen	0.240	0.538	0.998	0.994	1.000	1.000
AR(1) p-val	0.000341	0.0198	0.105	0.101	0.103	0.294
AR(2) p-val	0.253	0.711	0.440	0.430	0.438	0.134
Instruments	124	120	148	148	161	153

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-in-Hansen reports the p-value of the C statistic of the difference in the p-values of the restricted and the unrestricted model. The unrestricted model ignores the [Arellano and Bover \(1995\)](#) conditions. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

engagement in rent-seeking behaviour and cronyism. Adding measures of the income distribution in the regression elicits changes in some of the covariates. The effect of fertility becomes less pronounced when accounting for different income classes, whereas the impact of POLRIGHT increases.

Column (4) features the same regression as Column (3) but replaces MIDDLECLASS by $QUINT_3$, the income share held by the third quintile. $QUINT_3$ is a measure of the middle class in the narrow sense as it displays the influence of the median income. Similarly to MIDDLECLASS, we can observe a significantly positive impact on redistribution confirming the validity of the median voter hypothesis. As there is little difference in the results when comparing MIDDLECLASS and $QUINT_3$, we subsequently apply the broader definition MIDDLECLASS, commonly used in other studies (e.g. [Atkinson and Brandolini, 2011](#) and [Grabka and Frick, 2008](#)). Columns (5)–(6) include further measures of the income distribution with regard to the situation of the poor. $DECI_{10}$ comprises the income share held by the lowest decile of the distribution. As predicted by the median voter theorem, the estimated parameter of $DECI_{10}$ is positive, albeit insignificant. $DECI_{10}$ is a relative measure of poverty, which is dependent upon the average income level of the economy. Since our data contains a large number of developing countries, it may thus be advantageous to compare the results to a narrower indicator of absolute poverty. For this reason, the last column introduces a poverty headcount ratio depicting the share of the population living on less than 2 dollars a day (POVERTY). The results do not change notably as the effect of POVERTY is negative and insignificant. These findings are in line with the coefficient of UNEMP, implying that the poorest in a society do not affect the amount of redistribution. All other regressors remain unchanged, confirming the stability of our baseline model.

Regarding the validity of our results, we refer to the test statistics given in the lower part of the baseline table. The Hansen test of overidentifying restrictions indicates validity of the instruments in each of the regressions. Similarly, the Difference-in-Hansen test emphasizes the validity of the additional orthogonality conditions of system GMM, which suggests a potential loss in efficiency when estimating the baseline regression via first-difference GMM. In addition, the AR(2) p-value implies absence of second-order serial correlation in the residuals.

While application of REDIST enables assessment of the causes of governmental redistribution in the broadest possible sample of countries, one concern is that some data points may be less reliable, particularly if the SWIID uses estimates to achieve gross or net Ginis. To address this issue, Table [A2](#) in the appendix applies REDIST(S), which is a subset of REDIST that only consists of observations where survey data on gross and net incomes is available. The rest of the specifications in each column of Table [A2](#) exactly follow the specifications shown in the corresponding columns of Table [1](#).¹² The gain in accuracy, however, comes at

¹²Note that the reduced number of observations leads to a serious overfitting problem in the estimation. For this reason, we apply a collapsed instrument matrix as suggested by [Roodman \(2009\)](#).

a high cost: the regression sample in Table A2 is now restricted to a maximum of 434 observations from 73 countries, introducing the risk of a sample selection bias, as the sample now contains a substantially smaller share of poor economies. Despite the heavily reduced scope of data and countries included in the regression, the results depicted in Table A2 strongly resemble the findings of our baseline estimations. A higher extent of market inequality, increased political rights, and higher average incomes are associated with higher levels of redistribution. In addition, a broader middle class is positively related to REDIST(S), while top incomes tend to reduce redistributive activity of the government. As in the baseline estimates, we do not find any effect stemming from the poor in a society.

4.2 Sensitivity analysis

Table 2 reports the results of three modifications of the baseline estimations in order to investigate the stability of the baseline findings. The first approach maintains the system GMM specification but enlarges the instrument matrix by an additional lag. The second modification uses first-difference GMM as proposed by Arellano and Bond (1991). However, this technique discards the information in the equation in levels. Thus, caution is recommended when interpreting the results, especially as most of the variation in inequality data stems from the cross-sectional dimension rather than alterations over time. The last modification is a Within-Group (WG) estimation of the baseline model. As Nickell (1981) shows, the elimination of country fixed effects via time-demeaning in dynamic panel models results in a severe bias. For this reason, we exclude REDIST($t-1$) in the WG estimations. As WG techniques are widely used in empirical research on inequality, it may be advantageous to compare the system GMM results with those from the WG estimations.

Table 2 reports two versions of each of the modifications. The first model is the reduced specification from our baseline regression, which only includes the effect of gross inequality, different development levels, and redistributive efforts in the past. The second model is a more extensive specification which follows Column (5) of the baseline table, capturing additional determinants of redistribution.

The results strongly support the findings of our baseline estimations. The Meltzer-Richard effect emerges as a clear empirical pattern, as a higher level of market inequality significantly enhances the scope of redistribution in each of the estimations. In addition, all models suggest that an increase in the TOP-1's income share significantly lowers redistribution, whereas the amount of redistribution is higher if the economy is shaped by a broad middle class. As in the baseline estimations, we cannot find evidence that redistributive efforts are influenced by individuals at the lower end of the income distribution. Similarly to the results in Table 1, the extent of redistribution is very persistent over time.

The application of Arellano-Bond results in a decline of the number of observations, from 872 to 716. The

Table 2 Sensitivity analysis of the baseline results, different estimation techniques. Dependent variable is redistribution (REDIST).

	System GMM (additional lag in instrument matrix)		First-difference GMM (Arellano Bond)		Within-Group estimation (WG)	
	(1)	(2)	(1)	(2)	(1)	(2)
GINI(M)	0.0734*** (0.0182)	0.213*** (0.0575)	0.196*** (0.0425)	0.225*** (0.0860)	0.249*** (0.0320)	0.290*** (0.0517)
Log(GDP _{pc})	0.649*** (0.188)	0.322 (0.252)	-0.553 (0.898)	0.597 (0.803)	-0.601 (0.489)	0.0643 (0.739)
REDIST($t-1$)	0.916*** (0.0320)	0.803*** (0.0731)	0.249** (0.100)	-0.0433 (0.192)		
UNEMP		0.00278 (0.0244)		0.00180 (0.0788)		0.0836** (0.0398)
POLRIGHT		0.137 (0.0889)		-0.107 (0.217)		-0.0179 (0.0873)
Log(FERT)		-0.224 (0.339)		2.818* (1.620)		1.580*** (0.736)
TOP-1		-0.0874* (0.0470)		-0.436** (0.222)		-0.128* (0.0672)
MIDDLECLASS		0.201*** (0.0664)		0.175* (0.0947)		0.135** (0.0558)
DECI ₁₀		0.110 (0.191)		-0.619 (0.731)		0.344 (0.223)
Observations	872	443	716	294	1035	474
Countries	145	126	140	110	154	134
Hansen p-val	0.605	1.000	0.179	0.727		
AR(1) p-val	0.000350	0.104	0.0479	0.616		
AR(2) p-val	0.254	0.479	0.119	0.226		
Instruments	149	194	58	49		

Notes: Table reports system GMM, first-difference GMM, and Within-Group estimations. All models include period fixed effects. System GMM uses Windmeijer-corrections, robust standard errors in parentheses. The instrument matrix of the system GMM estimations is restricted to lag 3, the instrument matrix of the first-difference GMM estimations is restricted to lag 2. Hansen p-val gives the p-value of Hansen's J-test, AR(1) p-val and AR(2) p-val report the p-values of the AR(1) and AR(2) test. * $p < .10$, ** $p < .05$, *** $p < .01$.

reason for this is that the estimator requires at least three consecutive observations for each of the regressors, which magnifies gaps in our sample. Employing Arellano-Bond may be advantageous if the restrictions on the initial conditions necessary for validity of the additional orthogonality conditions of system GMM are violated. Yet the Difference-in-Hansen statistics reported in Table 1 show quite clearly that the extra moment conditions are valid, and therefore yield substantial efficiency losses when using first-difference GMM.

When accounting for unobserved heterogeneity via first-differences and time-demeaning, the impact of the development level vanishes. One interpretation of this is that the development level may be a proxy of deeper institutional conditions distinguishing the countries according to their level of redistribution. As economies develop, opportunities of rent-seeking and crony capitalism decline. Likewise, less-developed countries tend to be less democratic. If the voter cannot influence the political process, a higher level of inequality probably does not yield a higher amount of redistribution.

4.3 Different political institutions

As we intend to explain the driving forces in governmental redistribution we have to focus more intensively on the institutional conditions of countries. As already shown in Figure 2, differences in the political orientation of parties play a role in redistributive issues. Additionally, we expect that various political institutions may directly influence the amount of redistribution. To examine their effect on redistribution, we apply several political variables taken from the World Bank’s Database of Political Institutions.

Table 3 displays the impact of these indicators. In Column (1) we add a dummy variable FRAUD which is 1 if electoral fraud took place in a period, and 0 otherwise. The results indicate that FRAUD is positively related to redistribution, implying that governments which did not legally come into office redistribute more than others. These findings may reflect the fear of political uprisings by the population as put forward by [Acemoglu and Robinson \(2006b\)](#). All other regressors remain unchanged compared to our baseline regressions.

Columns (2)—(3) include two additional variables controlling for the size of political institutions and the stability of the government. NUMGOV represents the number of seats held by all government parties, which proxies the size of the political system within a country. NUMVOTE records the total vote share of all government parties and acts as a proxy of the stability of the government. Both coefficients exert a significantly negative influence on REDIST. With regard to NUMGOV a higher number of seats indicates larger political institutions, leading to higher bureaucracy and difficulty in realizing extensive redistributive activities, as numerous authorities are involved.¹³ In terms of NUMVOTE, a higher vote share of the government parties reduces the amount of redistribution. Since redistribution serves as an instrument in

¹³We test whether this result is driven by the population size. We apply the logarithmic value of population and find a positive, albeit insignificant impact on redistribution. The estimated parameter of NUMGOV, however, barely changes. Regression results are available upon request from the authors.

Table 3 The effect of political institutions. Dependent variable is redistribution (REDIST).

	Fraud	Government seats	Government votes (in %)	Religion
GINI(M)	0.211*** (0.0622)	0.219*** (0.0566)	0.210*** (0.0616)	0.207*** (0.0592)
Log(GDP _{pc})	0.330 (0.250)	0.399* (0.237)	0.363 (0.224)	0.381 (0.254)
REDIST($t - 1$)	0.817*** (0.0725)	0.805*** (0.0689)	0.816*** (0.0690)	0.819*** (0.0680)
UNEMP	-0.00923 (0.0212)	-0.0283 (0.0268)	-0.00262 (0.0275)	-0.00627 (0.0252)
POLRIGHT	0.181* (0.0959)	0.124 (0.0762)	0.156* (0.0851)	0.165** (0.0822)
Log(FERT)	-0.693** (0.325)	-0.559 (0.414)	-0.255 (0.394)	-0.309 (0.374)
TOP-1	-0.113** (0.0562)	-0.124** (0.0545)	-0.0877 (0.0551)	-0.0810 (0.0606)
MIDDLECLASS	0.150** (0.0681)	0.137** (0.0678)	0.171** (0.0708)	0.137** (0.0673)
DECI ₁₀	0.0787 (0.200)	0.308 (0.235)	0.212 (0.214)	0.304 (0.209)
FRAUD	0.686* (0.372)			
NUMGOV		-0.000846** (0.000429)		
NUMVOTE			-0.0104** (0.00502)	
RELIGION				-0.906** (0.438)
Observations	443	443	443	443
Countries	126	126	126	126
Hansen p-val	0.991	0.994	0.999	0.997
Diff-Hansen	1.000	1.000	1.000	1.000
AR(1) p-val	0.105	0.101	0.0959	0.0978
AR(2) p-val	0.415	0.397	0.456	0.394
Instruments	174	174	174	174

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-in-Hansen reports the p-value of the C statistic of the difference in the p-values of the restricted and the unrestricted model. The unrestricted model ignores the [Arellano and Bover \(1995\)](#) conditions. 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 4 Sample split, political participation and form of the government. Dependent variable is redistribution (REDIST).

	Political participation		Form of the government	
	low	high	religious	secular
GINI(M)	0.366*** (0.0643)	0.116** (0.0519)	0.715* (0.367)	0.235*** (0.0584)
Log(GDP _{pc})	1.013** (0.468)	0.211 (0.243)	-0.649 (2.810)	0.419* (0.250)
REDIST($t - 1$)	0.639*** (0.0954)	0.938*** (0.0586)	-0.0204 (0.317)	0.783*** (0.0688)
UNEMP	0.00774 (0.0282)	0.00620 (0.0287)	-0.496 (0.451)	-0.000232 (0.0263)
POLRIGHT	0.121 (0.103)	0.0904 (0.0773)	-0.0746 (1.210)	0.148 (0.106)
Log(FERT)	-0.109 (0.728)	-0.117 (0.565)	-1.942 (3.890)	-0.362 (0.361)
Top-1	-0.223*** (0.0761)	-0.0118 (0.0380)	0.778 (0.674)	-0.135** (0.0634)
MIDDLECLASS	0.222** (0.0930)	0.126* (0.0765)	0.984** (0.442)	0.182*** (0.0666)
DECI ₁₀	0.364 (0.312)	0.284 (0.253)	3.167*** (0.737)	0.0252 (0.193)
Observations	246	195	30	413
Countries	87	84	15	123
Hansen p-val	1.000	1.000	1.000	0.979
Diff-Hansen	1.000	1.000	1.000	1.000
AR(1) p-val	0.163	0.0875	0.682	0.102
AR(2) p-val	0.390	0.376	0.867	0.399
Instruments	161	157	34	161

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-in-Hansen reports the p-value of the C statistic of the difference in the p-values of the restricted and the unrestricted model. The unrestricted model ignores the [Arellano and Bover \(1995\)](#) conditions. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

gaining votes in the political process, more stable governments do not necessarily have to incorporate a higher demand for redistribution in comparison to more volatile governments. In Column (4) we account for the religious background of the government by adding RELIGION as a regressor. Data on religion is taken from the Political Institutions Database and compiled to a religion dummy which is 1 if a government is dedicated to a religion, and 0 otherwise.¹⁴ Religious governments tend to redistribute less than non-religious governments, supporting the idea of a substitutive relationship between religion and the welfare state. Other controls remain unchanged, confirming the stability of our model.

Table 4 gives further insights into the redistributive effects of political participation and the religious background of a government by splitting the sample. Columns (1)—(2) display the regression estimates when splitting the sample according to voter turnout. Redistributive activities of the government are influenced by the relative political participation of different income groups as suggested by Franzese (1998). When voter turnout is low, bottom incomes participate little in the political process. Thus, the effective median voter has a higher income than the median income of the population, indicating that it is the politically relevant share of the population which matters in redistribution. Column (1) reports the results for the case that voter turnout is below the sample mean of 70.2 percent, while Column (2) shows the regression estimates when voter turnout is above average. MIDDLECLASS unequivocally exerts a significantly positive impact, confirming the decisive role of the median voter. However, when voter turnout is low MIDDLECLASS cedes its role as the primary influential group on redistribution. In this case, top incomes negatively affect governmental decisions on redistribution, as political participation is biased against the poor and informal channels of political influence (e.g. money contributions, influencing of others) become more important. In contrast, a high voter turnout impedes lobbying activities of the top incomes since government action focuses more intensively on the demands of the majority.

Columns (3)—(4) display the results of our baseline estimation according to the religious dedication of a government. The middle class still plays an important role in societies with religious governments. The lowest decile of the income distribution also exerts a positive and significant impact on the amount of redistribution. In contrast, secular governments do not incorporate issues of the bottom incomes, which is in line with findings from our baseline regression. Instead, top incomes negatively influence the extent of redistribution, reinforcing conjectures of cronyism in this group, which is not the case in religious administrations.

¹⁴The dummy variable takes a value of 1 irrespective of the confession of the particular regime. As a matter of course, there may be strong deviations between redistributive activities across different confessions. However, the number of observations is not sufficient to examine the effect of different religious regimes on redistribution. We observe 43 Christian governments, 37 Islamic regimes, 5 Hindu administrations, and even fewer Jewish or Buddhist governments in our data.

4.4 Different cultures and preferences for redistribution

One further aspect that is strongly related to the institutional framework of a country is culture. [Luttmer and Singhal \(2011\)](#) find that cultural forces play a crucial role in the generation of preferences for redistribution. When investigating the determinants of redistribution on the basis of macro data, preferences can hardly be included, as we cannot reasonably account for systematic differences in the preferences of households. However, as [Hofstede \(2001\)](#) argues, every person’s mental programming is partly unique, partly shared with others. The collective level of mental programming is common to people belonging to a certain group, but different for people from other groups. This comprises the whole area of subjective human culture, passed from one generation to the next. Contrary to preferences on the individual level, the effect of *collective* preferences that are common to individuals of a country but differ across nations can be included in our investigations.

To measure culture, we rely on the concept of [Hofstede \(2001\)](#), distinguishing between five dimensions of collective values. Power distance (PDI) reflects the extent to which less powerful individuals are willing to accept an unequal distribution of power. The degree of individualism (IND) indicates whether a society is shaped more by the individual or the collective. Masculinity (MAS) determines whether a society is characterized more by masculine or by feminine values. [Hofstede \(2001\)](#) considers values such as confidence and competitiveness to be masculine, while cooperation, tolerance, and humility are thought of as more feminine values. Uncertainty avoidance (UAI) reflects the degree of aversion to unpredictable situations. Finally, the extent of long-term orientation (LTO) describes a society’s time horizon and illustrates whether people attach more importance to the future or the present. Data on these dimensions stems from national surveys, where each dimension is calculated on the basis of several different questions. Overall, the survey consists of 60 “core” questions and 66 “recommended” questions.

Figure [A1](#) in the appendix illustrates the bivariate relationship between the cultural dimensions of [Hofstede \(2001\)](#) and the extent of redistribution. While there seems to be no robust relationship between redistribution and MAS (correlation: -9 percent) or UAI (22 percent), we observe that countries tend to redistribute less if power distance is high (-61 percent) or if the time horizon is on the long-run (-58 percent). In addition, a higher degree of individuality is associated with higher redistributive efforts (73 percent). Table [A3](#) in the appendix is concerned with a more detailed exploration of the effect of culture on redistribution. The table reports system GMM estimations of the reduced model

$$\text{REDIST}_{it} = \vartheta \text{REDIST}_{it-1} + \alpha \text{GINI}(M)_{it} + \beta C_i + \delta C_i \times \text{GINI}(M)_{it} + (\eta_i + \xi_t + v_{it}), \quad (7)$$

for each of the cultural dimensions $C = \{\text{PDI}, \text{IND}, \text{UAI}, \text{MAS}, \text{LTO}\}$. Note that the inherent nature

of collective programming requires that cultural time-series are strongly persistent, making them even time-invariant when exploring panel data in the “small T ” context. This underlines the need to exploit the [Arellano and Bover \(1995\)](#) orthogonality restrictions, as C_i would disappear completely when applying first-difference GMM. Asymptotically, the inclusion of time-invariant regressors in system GMM does not affect coefficient estimates for other regressors, as all instruments for Equations (3) and (7) are assumed to be orthogonal to fixed effects and other time-invariant regressors (see, e.g., [Roodman, 2009](#)). Note also that the number of countries included in the estimation declines from 145 in the baseline table to only 66 in Table A3 due to limited availability of cultural data.

The results suggest no influence of masculinity, uncertainty avoidance and long-term orientation. In contrast, we observe that the Meltzer-Richard effect depends on the degree of individuality and the power distance. The results of these estimations are illustrated in Figures 6 and 7. If a society is shaped by the highest possible value of collectivism (i.e. $IND = 0$), the effect of gross inequality on redistribution is insignificant. However, the more individualistic a society becomes, the more prevalent the Meltzer-Richard effect. This may reflect the character of collectivistic societies as a substitute for social security systems. Gregariousness differs considerably between societies and has its origins in history and tradition. People living in patrilineal or matrilineal extended families or in tribal units based on kinship ties typically developed a broad sense of responsibility for the members of their group. In this case, there is no need for public redistribution. In contrast, societies shaped by a high degree of individualism lack such a safety net. As a consequence, higher inequality enhances demand for public redistribution.

Quite similarly, power distance plays an important role for redistribution. The results emphasize that low levels of PDI are accompanied by a strong prevalence of the Meltzer-Richard effect, whereas we observe no impact of inequality on redistribution in societies where less powerful individuals are willing to accept an unequal distribution of power. These findings imply that the acceptance of inequality is important for redistribution. Moreover, what we might observe with these results is—to some extent—a kind of societal preference for redistribution. Individuals in countries with low PDI values such as Austria (11), Denmark (18), Ireland (28) and Sweden (31) have high preferences for an equal distribution of power. As a consequence, if there are imbalances in the distribution of power, they may increase the demand for redistribution. In contrast, individuals at the bottom of the income distribution living in nations with a high degree of PDI such as Malaysia (104), Guatemala (95), Russia (93), and China (80) accept their position on the income ladder, resulting in a particularly less pronounced Meltzer-Richard effect in those countries.

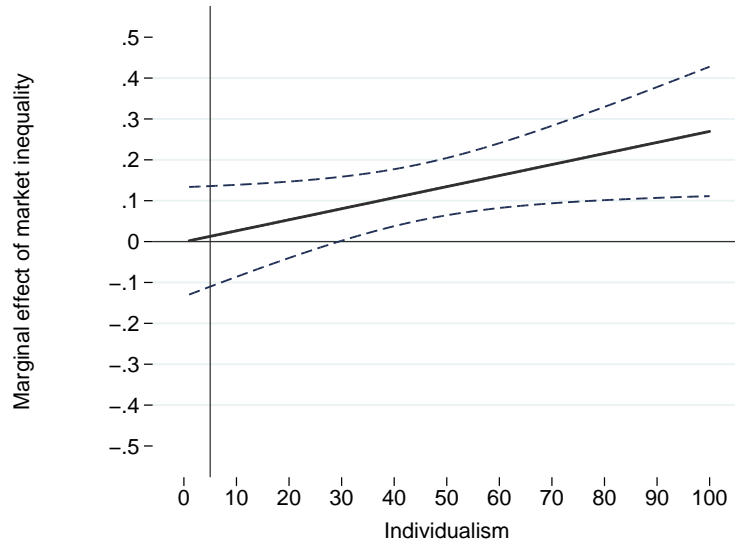


Figure 6 The effect of market inequality at different levels of individualism. Values are calculated using the results of Column (IND) of Table A3. The upwards sloping line plots the marginal effect of market inequality at different levels of individualism. Surrounding dashed lines represent the 90% confidence interval.

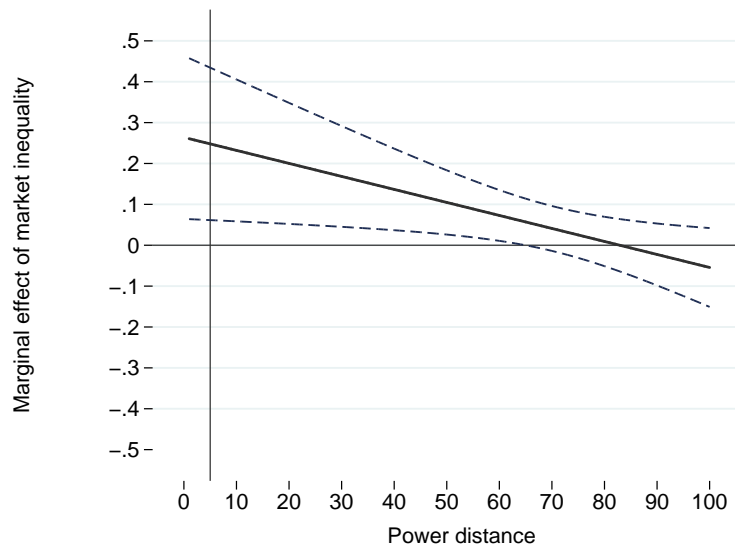


Figure 7 The effect of market inequality at different levels of power distance. Values are calculated using the results of Column (PDI) of Table A3. The downwards sloping line plots the marginal effect of market inequality at different levels of power distance. Surrounding dashed lines represent the 90% confidence interval.

4.5 Different development levels

The previous results are based on the whole sample of countries. However, the descriptive analysis in section 3.2 reveals substantial differences across countries depending on the development level of the economies. This section investigates differences in the determination of redistribution across different stages of development.

Table 5 uses exactly the same specifications as the baseline estimations reported in Table 1, but includes an interaction term $\text{GINI} \times \text{GDP}_{pc}$, which is the product of the market GINI and the logarithmic value of real per capita GDP. The advantage of this interaction is that it allows us to explore the effect for different levels of development without using fixed income levels to distinguish between different stages of development. As there are virtually no changes in the effect of the covariates, the table only reports the variables of interest, for reasons of lucidity. The first column shows the effect of the variables in a very reduced model, which only incorporates inequality, the development level, past redistributive efforts, and the interaction term. The effect of market inequality at a development level of zero is essentially negative. At the same time, the interaction term has a positive sign, suggesting that the influence of gross inequality becomes positive with an increasing development level. This result provides evidence that the Meltzer-Richard effect cannot be observed in poorer economies, but becomes prevalent in richer economies. Apparently, market inequality plays a less pronounced role for redistribution in developing economies, where democratic structures are often less firmly established. Yet with an increase in wealth—which is typically accompanied by the implementation of free elections, active participation in the political process, as well as enhanced human rights and the rule of law—the Meltzer-Richard effect gains in importance. This basic result remains stable across the different specifications of the baseline regressions, where the effect of market inequality at a development level of zero is either negative or strongly insignificant, and the effect of the interaction term is positive in each of the regressions.

Figure 8 illustrates the effect of market inequality at different development levels using the reduced model of Table 5. At early stages of development, the marginal effect of $\text{GINI}(M)$ is zero, but it increases as the economy develops. The effect becomes significant if the economies exceed a critical income level of roughly 2,500 USD. In the post-2010 period, 38 countries were still below that critical level. At the median level (gray vertical line), the effect of market inequality on redistribution is positive and strongly significant.

One peculiar result detected in section 4.3 concerns the effect of fraud in the election. The results of the whole sample estimation provide a clear indication of a positive relationship between the variables, suggesting that politics and parties that enter into government via fraud tend to redistribute more. A possible explanation of this phenomenon is that the effect mainly stems from developing economies. In these countries political institutions and electoral rights are often less established and the elite control political

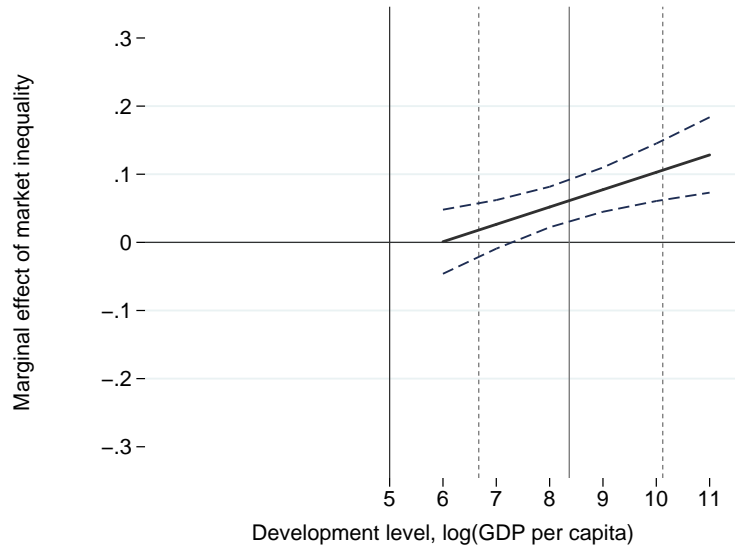


Figure 8 The effect of market inequality at different development levels. Values are calculated using the results of Column (1) of Table 5, where the interaction term $\text{GINI} \times \text{GDP}_{pc}$ is included. The upwards sloping line plots the marginal effect of market inequality at different levels of development. Surrounding dashed lines represent the 90% confidence interval. Vertical lines indicate the distribution of the development level in the sample: dashed gray lines mark the 10th and 90th percentiles, the solid gray line marks the median value.

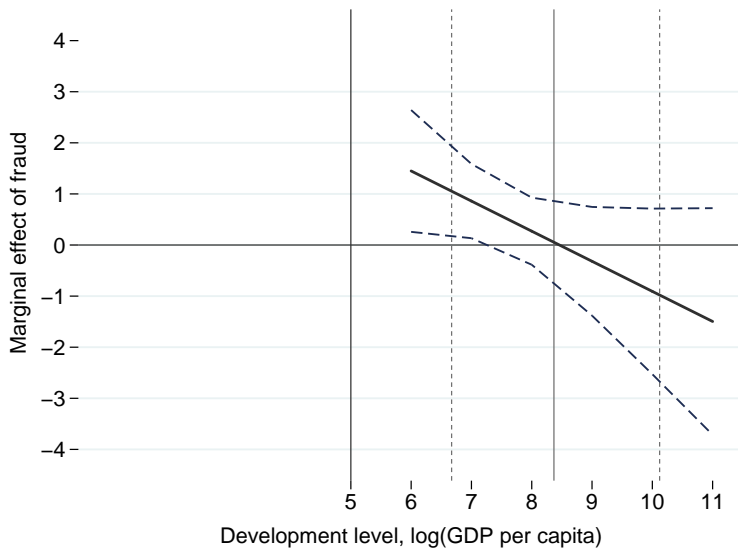


Figure 9 The effect of fraud at different development levels. Values are calculated using the results of Column (5) of Table A4, where the interaction term $\text{GINI} \times \text{GDP}_{pc}$ is included. The downwards sloping line plots the marginal effect of fraud at different levels of development. Surrounding dashed lines represent the 90% confidence interval. Vertical lines indicate the distribution of the development level in the sample: dashed gray lines mark the 10th and 90th percentiles, the solid gray line marks the median value.

Table 5 The determinants of redistribution for different development levels. Dependent variable is redistribution (REDIST).

	(1)	(2)	(3)	(4)	(5)	(6)
GINI(M)	-0.152* (0.0850)	-0.140 (0.0945)	0.0641 (0.132)	0.0411 (0.108)	0.0717 (0.130)	0.0206 (0.152)
Log(GDP _{pc})	-0.407 (0.412)	-0.818 (0.595)	-0.440 (0.567)	-0.415 (0.537)	-0.420 (0.629)	-0.361 (0.633)
GINI×GDP _{pc}	0.0255** (0.0101)	0.0224* (0.0119)	0.0195 (0.0123)	0.0188* (0.0111)	0.0203 (0.0131)	0.0192 (0.0164)
REDIST(<i>t</i> − 1)	0.896*** (0.0343)	0.957*** (0.0290)	0.774*** (0.0630)	0.803*** (0.0777)	0.763*** (0.0816)	0.813*** (0.0693)
Observations	849	572	430	433	430	152
Countries	145	140	126	126	126	59
Hansen p-val	0.643	0.455	0.981	0.988	0.998	1.000
Diff-Hansen	0.886	0.566	1.000	1.000	1.000	1.000
AR(1) p-val	0.0000148	0.000666	0.0284	0.0276	0.0317	0.313
AR(2) p-val	0.149	0.373	0.881	0.774	0.896	0.264
Instruments	147	134	161	161	174	152

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-in-Hansen reports the p-value of the C statistic of the difference in the p-values of the restricted and the unrestricted model. The unrestricted model ignores the [Arellano and Bover \(1995\)](#) conditions. 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 specifications of the equations equal the specifications in the baseline table. Covariates are excluded for reasons of lucidity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

power including the electoral process. However, those excluded may pose a threat to the elite and exert *de facto* political power as they form the majority and may attempt to overthrow the existing regime. Thus, a revolution constraint is placed on the elite as proposed by [Acemoglu and Robinson \(2006b\)](#). Fearing Coup d’Etats, the elite make concessions and redistribute more toward the underprivileged.

Figure 9 displays the effect of fraud at different stages of development. The underlying model is equivalent to the method in Table 5, introducing an interaction term between per capita incomes and fraud (FRAUD×GDP_{pc}) in the baseline model. The results are reported in Table A4 in the appendix. The examination of fraud at different stages of development reveals major deviations over the course of the development process: in poor economies, the marginal effect of fraud is positive and strongly significant. However, as economies become wealthier, this effect declines and becomes insignificant. In advanced economies, fraud tends to decrease redistribution, but the effect is far from being significant.

4.6 Perceived inequality

Our baseline results clearly support the Meltzer-Richard effect. However, evidence stems from actual market inequality, whereas perceived inequality may be of even greater importance in the creation of demand for redistribution, as discussed in recent studies (e.g. [Niehues, 2014](#) and [Engelhardt and Wagener, 2014](#)). These studies emphasize that perceptions of inequality are often biased, since individuals hold erroneous beliefs about income inequality, where the true extent of inequality is often underestimated. When comparing official inequality statistics with subjective perceptions, it can be observed that misperceptions vary across countries, with the result that inequality rankings of countries change. In this section, we investigate whether the baseline results are altered if we consider perceptions rather than officially reported statistics.

To achieve suitable measures of perceived inequality, we follow the approach of [Engelhardt and Wagener \(2014\)](#), which is based on data from the International Social Survey Programme (ISSP). The ISSP is a continuing annual program of cross-national collaboration on surveys covering topics relevant to social science research, including comparable data for 48 countries. Our measures refer to the question

”In our society there are groups which tend to be towards the top and groups which tend to be towards the bottom. Below is a scale that runs from top to bottom (10 top — 1 bottom). Where would you put yourself now on this scale?”

Data on this question is available for 44 countries—26 among them OECD members—for the years 1987, 1992, 1999, and 2006-2009. As a result, the data allows us to calculate perceived inequality measures for the five-year periods 1985-1989, 1990-1994, 1995-1999, and 2005-2009 of our empirical specification. We assume that self-assessments are mainly made in terms of income, so that the answers can be interpreted as the perceived position of the individual in the income distribution. In order to obtain an inequality measure, we calculate the mean-to-median ratio (MMR) of the given answers for all OECD countries. This method is identical to the approach of [Engelhardt and Wagener \(2014\)](#). In addition, we calculate a Gini index of the subjective assessments for all of the countries in the ISSP, which enhances comparability to the previous investigations. We refer to this variable as $\text{GINI}_{per} \text{ ISSP}$.

Whereas the ISSP is often considered the best available database covering public opinion on inequality, one major drawback is the limited number of included countries. This limitation not only results in a severe reduction in the number of observations, it may also be the source of a sample selection bias in empirical studies, as the member states of the ISSP are mainly highly developed economies. To obtain a measure which can be calculated for a larger set of countries, we use data from the World Value Survey (WVS). The WVS is a global research project which aims to explore values and beliefs of individuals. It covers a question quite similar to the subjective assessment of the ISSP:

"On this card is an income scale on which 1 indicates the lowest income group and 10 the highest income group in your country. We would like to know in what group your household is. Please, specify the appropriate number, counting all wages, salaries, pensions and other incomes that come in."

Data on this question is available for 84 countries in six waves, which allows us to calculate inequality measures for the 5-year periods 1980-1984, 1990-1994, 1995-1999, 2000-2004, 2005-2009, and 2010-2014. Yet, as in the case of ISSP data, the composition of countries changes between the waves. We denote the Gini coefficient built on the WVS as $GINI_{per}$ WVS.

We follow [Engelhardt and Wagener \(2014\)](#) in weighting the perceived measures by the actual inequality. The reason for this is that perceptions of inequality are larger the more unequal a country actually is. Indeed, actual inequality can be expected to exert feedback effects on perceived inequality: if reported official statistics discussed in the media or in political debates indicate a large level of inequality, individuals are likely to adjust their subjective assessment.

Table 6 reports the effect of the perceived inequality measures on the level of redistribution. For each inequality measure, we conduct two different estimations. The first estimation uses pooled OLS with cluster robust standard errors. Due to the limited number of observations, this may be the most reliable approach when working with perceived inequality measures. To compare the marginal effects with the results of the baseline estimations, we also conduct a system GMM estimation that is identical to the specification used in the baseline model. The results strongly support the Meltzer-Richard hypothesis. In each of the specifications, perceived inequality contributes significantly to redistribution, regardless of the measure used to capture perceptions of individual incomes.

As both perceived and actual inequality significantly enhance redistributive efforts by the government, perceived inequality tends to have an even higher impact than officially reported inequality. Figure 10 shows the marginal effect of a one standard deviation change in the inequality measures on redistribution. This effect is 0.61 in the reduced model in the baseline estimation reported in Table 1. Whereas WVS data implies that this effect is smaller (0.34), the regressions based on ISSP reveal substantially larger marginal effects of both the MMR (0.81) and the Gini (1.03). As MMR only includes data of OECD countries, the results indicate that the effect is stronger in developed economies where political institutions and electoral rights are typically well established. Indeed, if we calculate the marginal effect of the WVS inequality measure including only OECD countries, the impact significantly increases to 1.24, which resembles the impact of the ISSP Gini. Overall, the data suggests that perceived inequality has a larger impact on redistribution than actual inequality.

Table 6 Perceived inequality and redistribution. Dependent variable is redistribution REDIST.

	Perceived Gini (WVS)		Perceived Gini (ISSP)		Perceived MMR (ISSP)	
	OLS	SGMM	OLS	SGMM	OLS	OLS
GINI_{per} WVS	0.997** (0.426)	1.493** (0.744)				
GINI_{per} ISSP			3.036** (1.230)	5.772* (3.031)		
MMR					30.54*** (8.251)	8.663** (3.559)
$\text{REDIST}(t-1)$	0.987*** (0.0190)	0.956*** (0.0403)	0.945*** (0.0598)	1.009*** (0.310)		0.832*** (0.0830)
$\text{Log}(\text{GDP}_{pc})$	0.235* (0.131)	0.776** (0.339)	0.518 (0.470)	1.303 (2.659)	2.532 (2.106)	0.237 (0.711)
Observations	207	207	88	88	68	68
Countries	84	84	41	41	26	26
Hansen p-val		0.723		0.756		
Instruments		51		25		
R squared	0.95		0.85		0.36	0.82

Notes: Table reports two-step system GMM and OLS estimations using the baseline specification of Column (1) of Table 1. Windmeijer-corrected (system GMM) and cluster robust (OLS) standard errors in parentheses. Hansen p-val gives the J-test for overidentifying restrictions. Instruments illustrates the number of instruments. The instrument matrix is restricted to lag 2. The specifications of the equations equals the specification of Column (1) of the baseline table. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

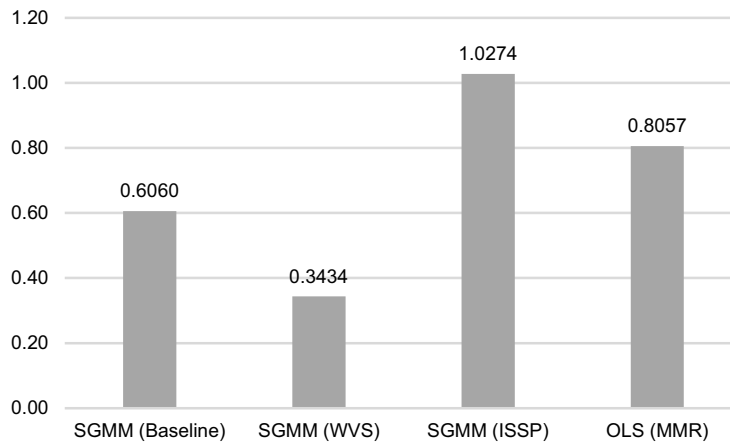


Figure 10 Marginal effect of a one standard-deviation change. Values are calculated using the results of Column (1) of Table 1 and the system GMM estimations (SGMM) using perceived Ginis of WVS and ISSP, as well as the OLS using the perceived mean-to-median ratio of Table 6.

5 Concluding remarks

The present paper investigates the determinants of governmental redistribution and closes the existing gap in the literature. Retesting the Meltzer-Richard hypothesis, we present affirmative empirical evidence which is robust to different variables of income inequality. Furthermore, we account for the role of different socio-economic groups in the income distribution and partly confirm the median voter model. The middle class exerts a significant influence on the extent of redistribution in all specifications. However, top incomes also have a significant impact on redistributive issues in a majority of our regressions. These findings support notions of cronyism since top incomes may reduce the financial burden from redistribution. Whereas low incomes are often suspected of wielding influence on the level of redistribution, our results indicate that governments do not incorporate the objectives of the poorest in determining the amount of redistribution.

Our analysis provides further evidence of the significant influence of political institutions on redistribution. Religious dedication of a government as well as higher stability of the administration reduce the extent of redistribution. On the other hand, governments which come into office by fraud redistribute more than others. This could be due to the fact that those governments fear political uprisings of the population and intend to moderate respective sentiments through higher redistribution ([Acemoglu and Robinson, 2006b](#)). Owing to the vastly expanded data availability, we have been able to examine the determinants of redistribution for different subsamples. Our findings indicate that top incomes exert a significant influence on governmental redistribution when voter turnout is low. In other words, only a high voter turnout reassures the exclusively decisive role of the middle class and prevents crony capitalism. Splitting the sample according to the religious background of a government provides valuable insights. In countries where governments are dedicated to a certain religion, the role of the poorest is of utmost importance in redistributive issues. This is in stark contrast to countries with a secular government where top incomes have a significant impact and bottom incomes do not play a significant role in determining the amount of redistribution. In addition, we illustrate that the Meltzer-Richard effect is mainly driven by highly-developed nations where democratic structures have already been established. In earlier stages of development we cannot confirm a significant connection between income inequality and redistribution.

Further, we reveal that the Meltzer-Richard effect depends to some extent on cultural forces, particularly the acceptance of inequality in a country. The Meltzer-Richard effect is less pronounced in collectivist societies, where the social group acts as a social safety net. Finally, we provide evidence that perceived inequality is more important than actual inequality in terms of redistribution, as individuals hold erroneous beliefs about their position in the income distribution. If citizen-voters consider the income distribution to be strongly unequal, we observe a strong demand for redistribution, even if “real” market inequality is moderate

or low. Conversely, if voters are not aware of the “true” extent of inequality, demand for redistribution is considerably lower than that induced by the actual distribution of incomes.

Our paper offers a cross-nationally comparable analysis of the relationship between income inequality and redistribution, including a large number of countries for which data has become available only recently. However, future research should focus on the improvement of data availability of perceived inequality measures. In this paper, we provide perceived Gini indices for 84 countries, yielding a maximum number of 207 country-years that can be used in empirical analyses. Increasing this number would enable more precise estimates of the effect of perceived inequality. Improvements, however, are particularly necessary concerning the time-dimension, achievement of which is unrealistic in the near future, since we cannot expect harmonized micro data of earlier periods to become available. As we utilize data on *effective* redistribution, further research may also evaluate the redistributive effect of specific fiscal policy instruments, since they have varying redistributive consequences. This may shed light on how governments best perform the balancing act of effective redistribution while avoiding disturbing side effects.

Appendix

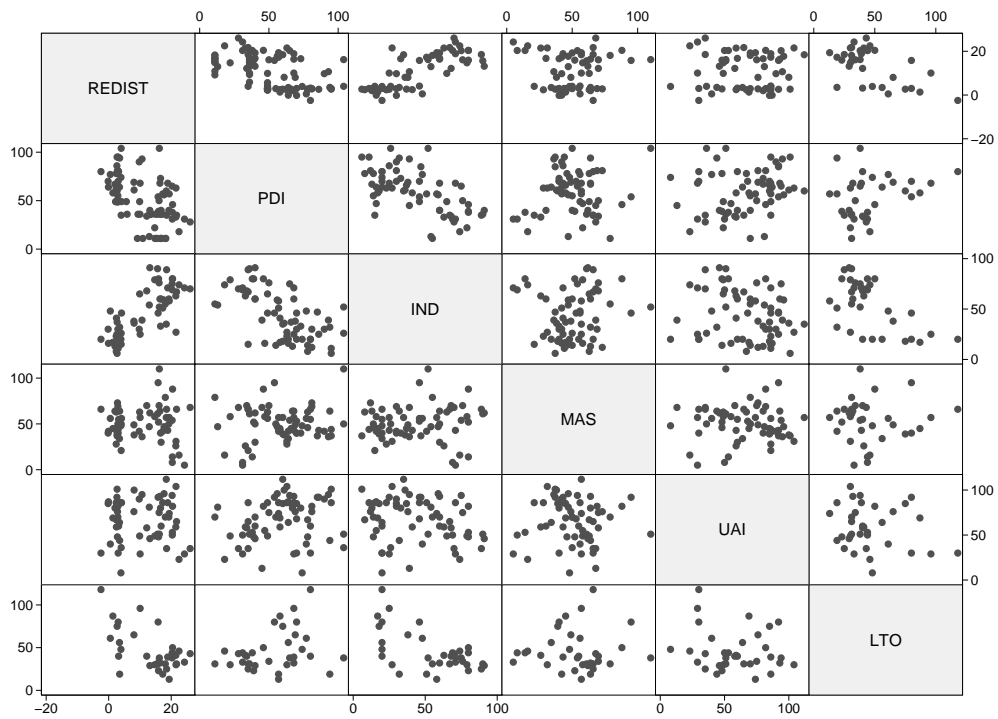


Figure A1 The relationship between the extent of redistribution (REDIST) and the cultural dimensions of Hofstede (2001).

Table A2 Baseline regressions, sample REDIST(S). Dependent variable is redistribution REDIST(S).

	(1)	(2)	(3)	(4)	(5)	(6)
GINI(M)	0.393*** (0.148)	0.0759 (0.0959)	0.334*** (0.107)	0.276*** (0.0996)	0.314** (0.135)	0.493*** (0.143)
Log(GDP _{pc})	1.702 (1.062)	2.188*** (0.833)	2.005*** (0.631)	2.158*** (0.550)	1.756** (0.772)	-0.203 (1.132)
REDIST($t - 1$)	0.599*** (0.197)	0.539*** (0.136)	0.336*** (0.121)	0.405*** (0.129)	0.372** (0.152)	0.625*** (0.124)
UNEMP		0.261** (0.119)	0.108 (0.105)	0.126 (0.113)	0.0993 (0.0968)	0.0724 (0.109)
POLRIGHT		0.409 (0.338)	0.582* (0.346)	0.457 (0.359)	0.579* (0.336)	0.306 (0.427)
Log(FERT)		-2.065 (1.669)	-0.453 (1.506)	-0.478 (1.567)	-0.536 (1.507)	-0.986 (2.741)
MIDDLECLASS			0.408*** (0.132)		0.386*** (0.143)	0.526*** (0.192)
TOP-1			-0.207 (0.166)	-0.239 (0.168)	-0.210 (0.156)	-0.0166 (0.184)
QUINT ₃				0.759* (0.426)		
DECI ₁₀					-0.0308 (0.948)	
POVERTY						0.00173 (0.0206)
Observations	379	318	253	253	253	97
Countries	73	71	66	66	66	33
Hansen p-val	0.00166	0.124	0.137	0.242	0.152	0.967
Diff-Hansen	0.000	0.019	0.249	0.371	0.215	0.999
AR(1) p-val	0.122	0.0874	0.270	0.220	0.265	0.317
AR(2) p-val	0.436	0.619	0.973	0.821	0.866	0.381
Instruments	20	33	39	39	42	45

Notes: Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. Specification of the models refers to the baseline estimation reported in Table 1. All regressions include period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. Diff-in-Hansen reports the p-value of the C statistic of the difference in the p-values of the restricted and the unrestricted model. The unrestricted model ignores the [Arellano and Bover \(1995\)](#) conditions. 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 collapsed and restricted to lag 2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3 The effect of culture on redistribution (REDIST).

	(PDI)	(IND)	(UAI)	(MAS)	(LTO)
GINI(M)	0.264** (0.121)	-0.000666 (0.0814)	0.0975 (0.0968)	0.160* (0.0821)	0.0483 (0.0507)
REDIST($t - 1$)	0.922*** (0.0468)	0.759*** (0.0583)	0.996*** (0.0306)	0.975*** (0.0326)	0.967*** (0.0372)
CULTURE	0.117* (0.0690)	-0.0442 (0.0615)	0.0317 (0.0577)	0.0750 (0.0634)	-0.00573 (0.0357)
GINI(M) \times CULTURE	-0.00318* (0.00165)	0.00270* (0.00157)	0.0317 -0.000635	0.0750 (0.00152)	-0.00573 (0.000928)
Observations	560	560	560	560	560
Countries	66	66	66	66	66
Hansen p-val	1.000	1.000	1.000	1.000	1.000
Diff-Hansen	1.000	1.000	1.000	1.000	1.000
AR(1) p-val	0.00695	0.00771	0.00439	0.00372	0.00404
AR(2) p-val	0.318	0.232	0.222	0.208	0.216
Instruments	125	125	125	125	122

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 over-identifying restrictions. Diff-in-Hansen reports the p-value of the C statistic of the difference in the p-values of the restricted and the unrestricted model. The unrestricted model ignores the [Arellano and Bover \(1995\)](#) conditions. 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 A4 The effect of fraud in the election at different development levels. Dependent variable is redistribution (REDIST).

	(1)	(2)	(3)	(4)	(5)	(6)
FRAUD	5.006 (3.183)	7.432** (3.127)	4.817 (3.221)	6.128* (3.136)	4.984* (2.947)	5.455 (5.280)
Log(GDP _{pc})	0.820*** (0.244)	0.257 (0.219)	0.456* (0.260)	0.467* (0.269)	0.408 (0.274)	0.553 (0.411)
FRAUD×GDP _{pc}	-0.641 (0.406)	-0.939** (0.402)	-0.551 (0.419)	-0.720* (0.405)	-0.589 (0.384)	-0.643 (0.662)
GINI(M)	0.0702*** (0.0194)	0.0574** (0.0264)	0.228*** (0.0660)	0.185*** (0.0585)	0.222*** (0.0733)	0.222** (0.0996)
REDIST($t - 1$)	0.894*** (0.0389)	0.952*** (0.0356)	0.768*** (0.0795)	0.814*** (0.0756)	0.784*** (0.0836)	0.752*** (0.111)
Observations	849	572	430	433	430	152
Countries	145	140	126	126	126	59
Hansen p-val	0.833	0.469	0.996	0.999	1.000	1.000
Diff-Hansen	0.890	0.458	1.000	1.000	1.000	1.000
AR(1) p-val	0.0000165	0.000706	0.0333	0.0293	0.0331	0.538
AR(2) p-val	0.137	0.383	0.741	0.513	0.687	0.106
Instruments	160	147	174	174	187	152

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-in-Hansen reports the p-value of the C statistic of the difference in the p-values of the restricted and the unrestricted model. The unrestricted model ignores the [Arellano and Bover \(1995\)](#) conditions. 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. Covariates are excluded for reasons of lucidity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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