

Köllner, Sebastian; Gründler, Klaus

**Conference Paper**

## Determinants of Governmental Redistribution: Income Distribution, Development Levels, and the Role of Perceptions

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2016: Demographischer Wandel - Session: Applied Microeconomics II, No. F01-V1

**Provided in Cooperation with:**

Verein für Socialpolitik / German Economic Association

*Suggested Citation:* Köllner, Sebastian; Gründler, Klaus (2016) : Determinants of Governmental Redistribution: Income Distribution, Development Levels, and the Role of Perceptions, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2016: Demographischer Wandel - Session: Applied Microeconomics II, No. F01-V1, ZBW - Deutsche Zentralbibliothek für Wirtschaftswissenschaften, Leibniz-Informationszentrum Wirtschaft, Kiel und Hamburg

This Version is available at:

<https://hdl.handle.net/10419/145619>

**Standard-Nutzungsbedingungen:**

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

**Terms of use:**

*Documents in EconStor may be saved and copied for your personal and scholarly purposes.*

*You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.*

*If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.*

# Determinants of Governmental Redistribution: Income Distribution, Development Levels, and the Role of Perceptions

---

## Abstract

We empirically investigate the relationship between income inequality and redistribution, accounting for the shape of the income distribution, different development levels, and subjective perceptions. Cross-national inequality datasets that have become available only recently allow for the assessment of the link for various sample compositions and several model specifications. Our results confirm the Meltzer-Richard hypothesis, but suggest that the relation between market inequality and redistribution is even stronger when using perceived inequality measures. The findings emphasize a decisive role of the middle class, though also approving a negative impact of top incomes. The Meltzer-Richard effect is less pronounced in developing economies with less sophisticated political rights, illustrating that it is the political channel through which higher inequality translates into more 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 applies the median voter theorem, originally developed by [Downs \(1957\)](#) and [Hotelling \(1929\)](#), to the field of inequality and redistribution. In a majority-voting framework, the Meltzer-Richard hypothesis predicts that a higher level of inequality leads to greater demand for redistribution that translates to an expansion of the welfare system. Although the theoretical basis of the Meltzer-Richard model is profound and broadly accepted, the empirical findings are far from consistent. A significant and positive relationship between inequality and redistribution is found by [Milanovic \(2000\)](#) and [Scervini \(2012\)](#), while other studies observe a negative link ([Georgiadis and Manning, 2007](#)), no significant relationship ([Kenworthy and McCall, 2008](#) and [Gouveia and Masia, 1998](#)), or multiple steady states ([Bénabou, 2000](#)).

So far, two main problems have impeded research on the inequality-redistribution nexus. 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 cross-national data on income inequality has long been rather scarce.

Although comparability and quality of the Luxembourg Income Study (LIS) are unparalleled among cross-national 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 research on inequality 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. Fortunately, some major progress has been made in cross-national inequality datasets in recent years, particularly with regard to the World Income Inequality Database (WIID) and the Standardized World Income Inequality Database (SWIID). The latest update of the SWIID to version 5.0 now includes 174 countries from 1960 to present, enabling acquisition of roughly 4,600 country-year observations that are comparable to those obtained by the LIS. The clear distinction between inequality before and after taxes and transfers allows for computation of a direct measure of redistribution via the “pre-post” approach. The large data coverage also permits inclusion of developing countries in the empirical analysis. However, as data quality in the SWIID varies across different country groups and periods, such analyses require careful treatment of the data. To account for the uncertainty in the SWIID data, we compare our baseline results with regressions based on multiple imputations and estimates that rely on the WIID data.

We make use of the recent advancement in data availability by examining the Meltzer-Richard hypothesis on a broad basis. In doing so, the contribution of the paper is threefold. First, we empirically investigate the redistribution-inequality nexus for a cross-nationally comparable dataset built entirely on national micro data. This analysis also includes the effect of different shapes of income distributions. The intuition of this strategy is that inequality may be driven by top or bottom income earners, yielding varying effects on redistribution due to different political influence of these groups. Second, we enlarge the sample and analyze the Meltzer-Richard effect in a broad panel of countries, thereby accounting for different development levels and varying sophistication of political rights. Finally, we elucidate the role of perceptions, illustrating that it is not the actual, but rather the subjective level of inequality that determines demand for redistribution.

In a majority voting model, groups other than the median voter should exert only negligible influence on redistribution. In practice, however, top incomes may be reluctant to support redistribution while the bottom decile of the income distribution typically benefits from a more expansive welfare system. To lower the financial burden through redistribution, top incomes might engage in rent-seeking behavior. Some studies (Scervini, 2012 and Bassett et al., 1999) state that de facto political power may be above the median, as higher income levels devote additional resources towards campaign contributions. Additionally, Rosenstone and Hansen (1993) show that political participation increases with income and education. This may also explain 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 (Scervini, 2012).

In democracies, the relationship between market income inequality and redistribution is stronger than in authoritarian regimes (Perotti, 1996). As gaining votes does not play a sig-

nificant role in policy making in non-democratic regimes, governments can ignore preferences of poorer voters (Milanovic, 2000). Empirical evidence regarding the impact of democracy on redistribution is, however, somewhat 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. (2015) refer to the fact that different institutional regimes have varying effects on redistribution depending, inter alia, on the stage of development.

Recent investigations further emphasize that individuals often hold erroneous beliefs about income inequality. Previous research focused on biased perceptions of inequality within a country or in the cross-section. Cruces et al. (2013) explore the perceptions of individuals in a micro study from Argentina and observe systematic biases in individuals' perceptions of their own relative position in the income distribution. Likewise, Norton and Ariely (2011) and Chambers et al. (2014) show that perceptions on the level of income and wealth inequality in the United States are heavily distorted. Fernández-Albertos and Kuo (2016) employ data from a web-based survey in Spain and find that only 14 percent of the participants correctly assigned themselves to the decile in the income distribution to which they actually belong. Further studies (Niehues, 2014, Engelhardt and Wagener, 2014, and Gimpelson and Treisman, 2015) use data from the International Social Survey Programme (ISSP) on self-assessment by individuals concerning their position on the income scale to compare actual and perceived inequality across countries. They provide some evidence that the Meltzer-Richard effect may be less pronounced when examining actual inequality, but may increase if perceived inequality measures are analyzed, implying that it may be the perception of the electorate rather than objective data that drives the demand for redistribution. In this paper, we follow earlier approaches, compiling subjective inequality measures based on the ISSP and the World Value Survey (WVS). Owing to recent advancements in data availability, our study provides a first attempt to explore the effect of perceptions on redistribution in a panel context.

Our findings point to a positive and significant link between market inequality and redistribution in the OECD countries. The results are robust to several model specifications and various sample compositions 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. 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. Moreover, our paper provides robust evidence that the shape of the income distribution is highly relevant for redistributive issues of the government. While the middle class exerts a significant influence on the amount of redistribution, we do not find any such impact for individuals at the bottom of the income distribution. Rather, 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.

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 yet 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.

The paper is structured as follows. Section 2 offers a description of the data and discusses the underlying empirical strategy. Section 3 outlines the main results for various sample compositions and extends the analysis for different development levels and perceptions. The final chapter concludes.

## 2. Empirical strategy

### 2.1. 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.

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

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” (see [Lupu and Pontusson, 2011](#) and [Van den Bosch and Cantillon, 2008](#) for a detailed discussion). A related measure that reflects assessment of the *relative* reduction in market inequality can be computed via

$$\text{REDIST}_{it}^{\text{rel}} = \frac{\text{GINI(M)}_{it} - \text{GINI(N)}_{it}}{\text{GINI(M)}_{it}}. \quad (2)$$

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).<sup>1</sup> While comparability and quality of the LIS data are unparalleled, the calculation of inequality measures based on harmonized micro data including a uniform set of assumptions and definitions restricts data availability. The LIS currently covers 232 country-year-combinations with data from 41 countries, seven of which are each represented by only one observation. This limitation makes cross-country analysis based on broad panels an impossible task and is also an impediment to implication of dynamic panel data techniques, which 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 data collections have been particularly successful in providing cross-national data with global coverage for relatively long time spans. These are the “World Income Inequality Database” (WIID) provided by [UNU-WIDER \(2014\)](#) and the “Standardized World Income Inequality Database” (SWIID) compiled by [Solt \(2009, 2016\)](#). An intense discussion has arisen on whether to use the WIID or the SWIID for cross-country analyses on inequality. As [Jenkins \(2015\)](#) 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 (see [Solt, 2015](#) and [Atkinson and Brandolini, 2009](#)). The provision of both gross and net Gini indices based on comparable welfare definitions enables calculation of redistribution according to Equation (1) that is consistent across countries. Second, while the revised version 3.0 A of the WIID from 2014 brings about a substantial expansion in the coverage of Gini indices—therefore enabling 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 only a few country-years include market *and* net Ginis.

As with any cross-national 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 an advantageous choice for redistribution studies based on broad panel estimation (see [Acemoglu et al., 2015](#)).

Our analysis relies on data on market and net inequality from the SWIID 5.0, made available in October 2014. 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 derived from source data. Whereas earlier versions of the SWIID are entirely based on the WIID, version 5.0 utilizes over ten thousand Gini coefficients

---

<sup>1</sup>Note, however, that even the LIS has recently been subject to some criticism (see the dispute between [Ravallion, 2015](#) and [Gornick et al., 2015](#)).

from national statistical offices, scholarly articles, Eurostat, the OECD, SEDLAC, [Deininger and Squire \(1996\)](#), as well as [Milanovic \(2014\)](#). Some concerns have been raised with regard to the multiple imputation procedure of version 4.0 of the SWIID ([Jenkins, 2015](#)). However, version 5.0 has addressed many of these issues.<sup>2</sup> Both the coverage and comparability of the SWIID exceed those of alternative inequality data collections.<sup>3</sup> 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 \(2016\)](#).

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.<sup>4</sup> To address this problem, the SWIID reports a subsample of redistribution data which only consists of country-years for which micro data on net and gross inequality is available. This sample further 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 2,030 country-years. Whenever feasible, we rely on the high-quality observations included in REDIST(S). As a consistency check of our results, we also run a sensitivity analysis based on the WIID data.

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.<sup>5</sup> The huge advantage of the method is that it yields a measurement 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 redis-

---

<sup>2</sup>This 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 \(2015\)](#) emphasizes, most of the remaining arguments are hardly tenable with respect to version 5.0 of the SWIID.

<sup>3</sup>“All the Ginis” from [Milanovic \(2014\)](#) and the WIID 3.0 A 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.

<sup>4</sup>Note, however, that the SWIID 5.0 avoids global fixed adjustments, as [Atkinson and Brandolini \(2001\)](#) highlight that differences between welfare definitions vary across countries and over time. Rather, the adjustments utilized in the SWIID vary over time and space as much as possible given the underlying data. A precise description of the multiple imputation procedure and a detailed documentation of the number of countries for which adjustments vary can be found in [Solt \(2016, 2015\)](#).

<sup>5</sup>[Van 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.

tribution, as it remains unclear to what extent such fiscal policy instruments are actually redistributive. Figure (A2) in the appendix shows the relationship between REDIST and social transfer payments. Both variables are positively correlated, indicating that a higher level of REDIST coincides with a more expansive social system. However, the R-squared of a bivariate regression of transfer payments on REDIST is only .33, which underscores our argument that social spending alone is insufficient to properly model redistribution.

Three methodological notes shall be made: first, as a measure of effective redistribution via taxes and transfers, REDIST does not include in-kind provision of public goods. Like most inequality databases, the SWIID is based on surveys covering household disposable income, which do not capture individual 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, 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 on transfers rather than relying on labor incomes. In line with Ostry et al. (2014), we suggest that the influence of redistribution on market inequality may be not essential, as both effects are—to some extent—offsetting. One way to mitigate the problems arising from potential second-order effects is application of relative redistribution measures. By division of REDIST by the pre-tax pre-transfer distribution of market income,  $REDIST^{rel}$  also captures feedback effects of redistributive policies. To assess stability of the results, we also report the outcomes based on  $REDIST^{rel}$  routinely for each estimation.

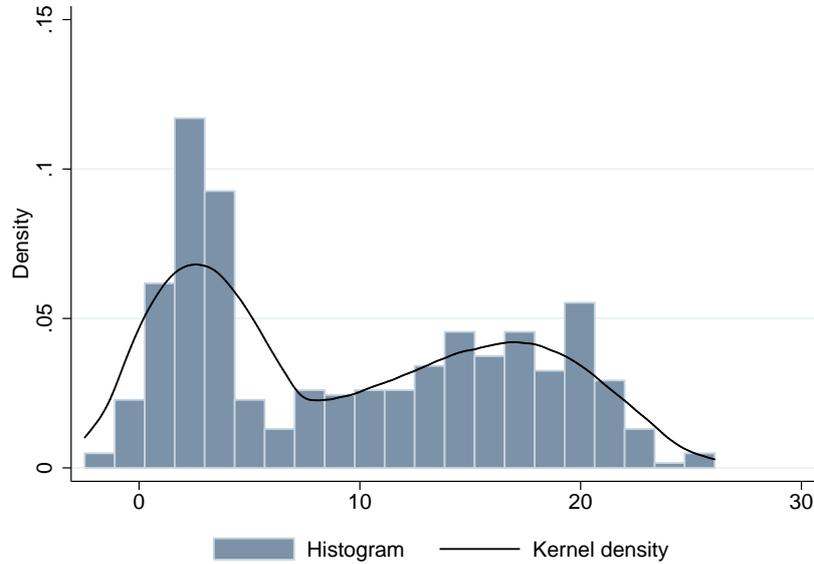
## 2.2. Redistribution and inequality across countries

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 9.65. However, the standard deviation of redistribution is high (7.35), pointing to substantial variations in the amount of redistribution across countries. Some nations with a generous social security system redistribute more than 20 Gini points, while redistributive efforts in other countries are considerably less pronounced. D’Agostino’s K-squared test rejects the assumption of a normal distribution.<sup>6</sup> In fact, the kernel density suggests a bimodal distribution, where the largest part of the data is located around a moderate redistribution level, and a second mode refers to a substantially higher level of REDIST(S).

---

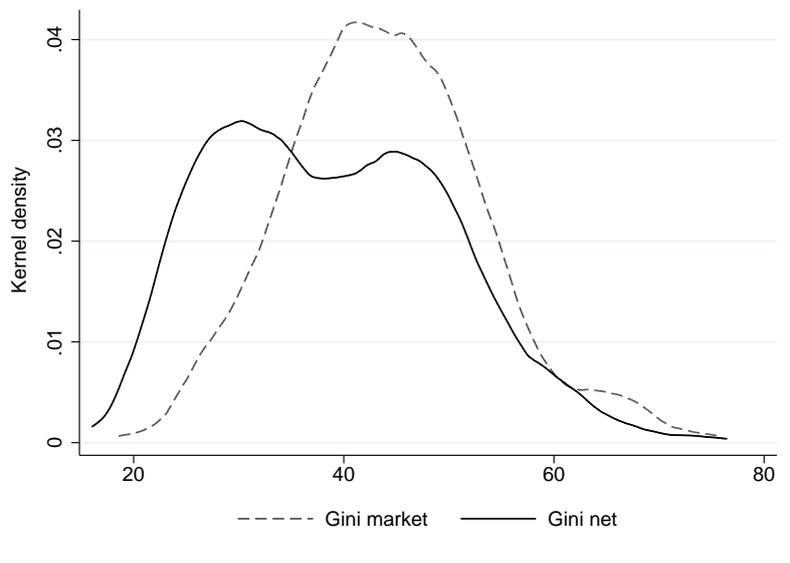
<sup>6</sup>We apply the version of D’Agostino’s K-squared test published in D’Agostino et al. (1990) which corrects standard errors by the sample size.



**Figure 1** The distribution of the amount of redistribution across countries, REDIST(S) ( $N = 453$ , skewness= 0.2683, kurtosis= 1.6277). Kernel is Epanechnikov.

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 14.53 Gini points, which substantially exceeds the mean redistribution level of developing countries (4.28 with regard to REDIST(S) and 3.62 in the broader sample REDIST). In addition, we observe a significantly higher amount of redistribution in democracies (11.30) compared to countries with a non-democratic form of government (2.52).

Figure (2) illustrates the kernel density of the Gini coefficients before and after taxes and transfers, when all data from the broad sample of the SWIID is used. 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 with regard to market inequality. In fact, the Gini coefficients of democracies (43.92) and non-democracies (43.22) are nearly equal. While caution is advised in interpreting this result, the potential implication is that governmental activities yield differences in inequality across countries, whereas market forces tend to lead to comparable amounts of inequality across different forms of government. However, there are substantial deviations in market inequality across different levels of development, where low-income countries (46.03) are faced with



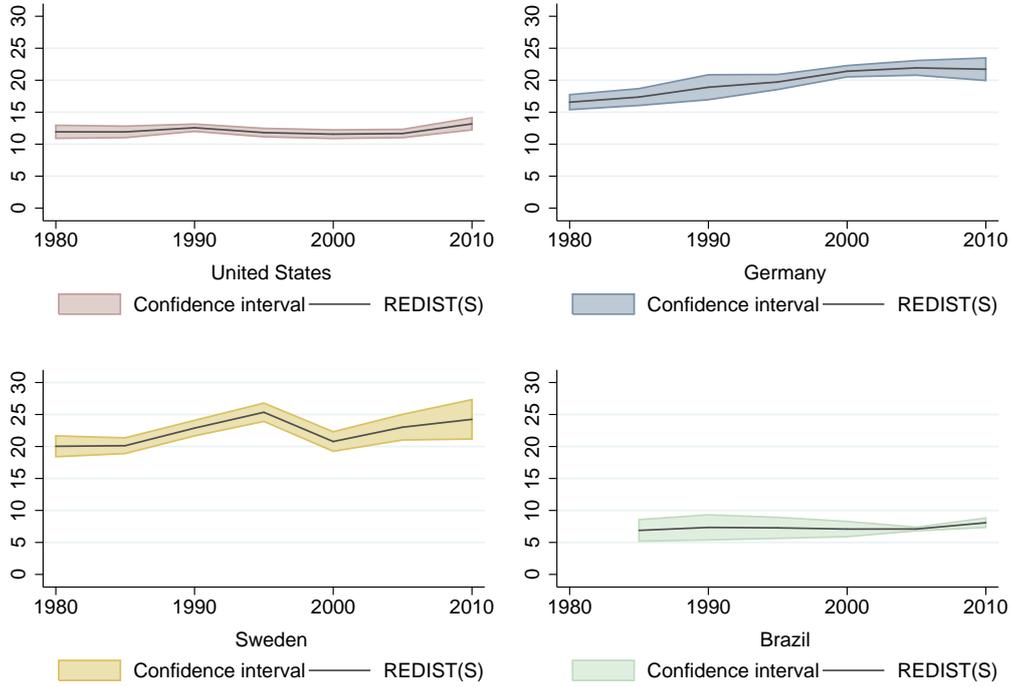
**Figure 2** Kernel density of Gini coefficients before and after taxes and transfers, whole sample period. Kernels are Epanechnikov.

a much higher level of inequality than advanced economies (39.97).

Figure (3) exemplary graphs the extent of redistribution for the United States, Germany, Sweden, and Brazil, using data from REDIST(S). The graphs suggest that redistribution is particularly strong in Sweden (24.25 Gini points in the post-2010 period) and Germany (21.72), where a substantial increase is to be observed during the last decades. Both countries possess expansive social security systems, which is why we would expect REDIST(S) to assume relatively high values. However, while GDP per capita in both countries resembles the income level of the United States, their redistributive efforts are considerably higher by reason of more expansive public unemployment and health insurance systems. On average, the advanced OECD member states redistributed 16.77 Gini points in the post-2010 period.

Redistribution in Brazil has remained remarkably stable since the early 1980s and falls short of the level observed in the other countries illustrated in Figure (3). The low level of redistribution (8.08) is typical for Latin American nations, where social security systems are less advanced compared to most of the OECD member states. Rather, it resembles the values of its neighboring states Argentina (4.11), Chile (2.58), Colombia (1.75), and Uruguay (8.74). Whereas we may expect a significantly higher degree of redistribution in Venezuela due to the substantial expansion of public social security systems by Hugo Chávez since the late 1990s, market inequality is reduced by only 2.80 Gini points. The reason is that funding of the social security programs is mainly achieved by taking advantage of the nation's rich oil reserves rather than by a progressive tax system (Buxton, 2014).

At first glance, a bivariate analysis of the link between the market Gini and the amount of redistribution reveals no robust relationship (see Figure 4). When taking the level of economic development into account, however, the analysis points to a positive relationship between market inequality and redistribution in both the sample of low-income countries



**Figure 3** The development of the level of redistribution in the United States, Germany, Sweden, and Brazil. The graph uses REDIST(S), for which micro data on net and market inequality is available. The colored areas around the point estimates of redistribution mark the 95 percent confidence intervals.

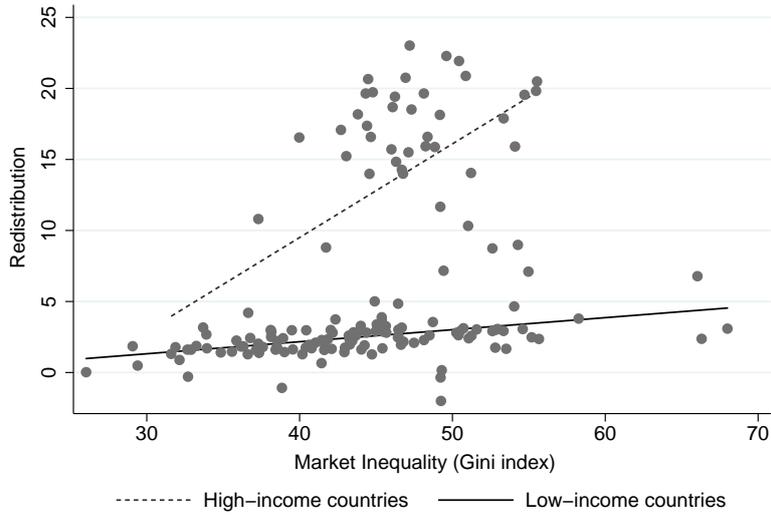
(correlation: 55.22 percent) and the sample of advanced economies (39.87). What distinguishes these groups from one another is that high levels of market inequality in developing economies are accompanied by a much lower degree of redistribution compared to advanced countries. This underlines that the relationship between inequality and redistribution has to be examined while holding constant some crucial variables that distinguish the countries.

### 2.3. 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

$$\text{REDIST}_{it} = F(\text{REDIST}_{it-1}, \text{GINI}(M)_{it}, \mathbf{X}_{it}, \eta_i, \xi_t), \quad (3)$$

where  $i = 1, \dots, N$  denotes countries,  $t = 1, \dots, T$  is the time index with  $t$  and  $t - 1$  five years apart,  $\xi_t$  is a specific effect of period  $\xi_t$ , and  $\eta_i$  is a country specific-effect which accounts for unobserved heterogeneity. Equation (3) specifies that redistribution in  $t$  depends on its level in  $t - 1$ , incorporating path dependencies in the model. The idea is that institutions, once established, are typically difficult to reform in the short to medium term (Acemoglu



**Figure 4** 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 advanced and developing economies, respectively. Country classification refers to the World Bank.

et al., 2015). A similar pattern is observable in Figure (3).  $\mathbf{X}_{it}$  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 between 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 subsequent step, we analyze the impact of different socio-economic groups on the extent of redistribution, dependent upon their income level. This includes the income shares of the richest 1 percent (TOP-1), the lowest decile of the income distribution (BOTTOM-10), 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 QUINT<sub>3</sub> only incorporates the middle quintile. The role of the public pension system in the redistribution process is analyzed by inclusion of AGE, the age dependency ratio of the population older than 64 to the working age population. Additionally, we enlarge the basic system in later sections by utilizing measures of perceived inequality.

Data concerning the development level, fertility, unemployment, age dependency, 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 4.0, which is the latest version covering data on the income share of the top 1 percent. Due to potential concerns about the data quality of version 4.0 of the SWIID, we analyze robustness of our results using data on top incomes from the World Wealth and Income Database (WID), compiled by [Alvaredo et al. \(2015\)](#). In addition, as data regarding the shape of the income distribution is partly from World Bank and partly stems from the SWIID, Figure (A1) in the appendix conducts a consistency check between inequality measures of both sources. This test highlights a high degree of comparability between the data.

We consider the variables to be linked additively and transform Equation (3) into a 5-year panel data model to capture the long-term determinants of redistribution, which yields

$$\text{REDIST}_{it} = \vartheta \text{REDIST}_{it-1} + \alpha \text{GINI(M)}_{it} + \boldsymbol{\delta}' \Delta \mathbf{X}_{it} + (\eta_i + \xi_t + v_{it}), \quad (4)$$

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 (4) would yield a bias in the estimates, as RE requires by construction that  $\text{Cov}[\eta_i, \text{REDIST}_{it-1}] = 0$  and  $\text{Cov}[\eta_i, \mathbf{X}_{it-1}] = 0$ , while the application of WG would lead to a correlation of the transformed error term and the time-demeaning transformation of  $\text{REDIST}_{it-1}$  ([Nickell, 1981](#)). 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 (4) to

$$\Delta \text{REDIST} = \vartheta \Delta_2 \text{REDIST} + \alpha \Delta \text{GINI(M)} + \boldsymbol{\delta}' \Delta \mathbf{X} + \Delta \xi + \Delta v \quad (5)$$

and to use sufficiently lagged values of REDIST, GINI(M), and  $\mathbf{X}$  as instruments for  $\Delta k$  and  $\Delta_2 \text{REDIST}$ . These instruments are valid provided that the error term is serially uncorrelated. However, first differencing Equation (4) 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  $\eta_i$  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.<sup>7</sup> In this case, additional

---

<sup>7</sup>The assumption regarding the initial condition is  $E(\eta_i \Delta \text{REDIST}_{i2}) = 0$ , which holds when the process is mean stationary, i.e.  $\text{REDIST}_{i1} = \eta_i / (1 - \vartheta) + v_i$  with  $E(v_i) = E(v_i \eta_i) = 0$ .

orthogonality conditions for the level equation in (4) can be exploited, using lagged values of  $\Delta k$  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.<sup>8</sup>

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

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

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 equation in levels, which in our case are

$$\text{E}\{(v_{it} + \eta_i)(\mathbf{A}_{i,t-1} - \mathbf{A}_{i,t-2})\} = 0 \text{ for } t \geq 3. \quad (7)$$

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 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.

### 3. Results

#### 3.1. Baseline results: Redistribution in the OECD countries

Table (1) reports the results of our baseline estimates. The specifications use REDIST(S), the subsample of observations available in the SWIID that is entirely built on national micro data. In addition, we start our analysis by examining only the OECD countries, where social security systems have reached a comparable level of sophistication. To avoid overfitting problems which might potentially arise due to the small number of cross-sections included in the panel, we collapse the instrument matrix as suggested by [Roodman \(2009\)](#). Column (1) presents a reduced model which only incorporates the effect of market inequality, the development level, and the lagged dependent variable. The estimation is built on 33 OECD member states for which inequality data is available. In the subsequent columns, limited availability of data concerning the top income share necessitates exclusion of South Korea, Luxembourg, New Zealand, and Portugal, resulting in a total of 29 OECD countries included

---

<sup>8</sup>A more detailed description of the estimator in the context of the empirical application can be found in [Bond et al. \(2001\)](#) and [Roodman \(2009\)](#).

in the estimation. As hypothesized by [Meltzer and Richard \(1981\)](#), Column (1) highlights 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 that richer economies on average tend to redistribute more. Meanwhile, the lagged endogenous variable points to persistency of redistribution over time, implying that there are few changes in the composition of social security systems in the medium term.

Column (2) introduces several variables that distinguish the countries and that may affect the level of governmental redistribution. These predictors include unemployment, the degree of democratization, and the fertility rate in the model. We may expect that governments that attend to the support of the indigent redistribute more if unemployment is prevalent. Likewise, there may be a close entanglement between fertility and redistribution, as higher fertility rates may generate higher demand for social transfers, e.g. via child allowance or maternity leave programs. Finally, a higher degree of democratization theoretically assures that demand for redistribution translates into actual policy actions. The results of Column (2), however, imply that neither of these variables is decisive in the OECD countries. With the exception of a positive contribution of the level of democratization in the last column, the additional variables are insignificant irrespective of the alternate model specifications depicted in the subsequent columns. Yet this result does not necessarily mean that redistribution is entirely unaffected by fertility, unemployment, or democracy, as the OECD countries are highly comparable with respect to these additional variables. Intuitively, if each country in the sample possesses a similarly high level of democratization, then it is impossible to detect a potential impact of less sophisticated political rights. We will come back to this issue in [Section 3.2](#).

Columns (2)–(4) further account for the shape of the income distribution by incorporation of the income share held by the middle class, the top 1 percent, and the bottom 10 percent. The reason for the inclusion of these variables is that different shapes of income distributions can result in similar Gini indices. However, inequality can be driven by numerous factors, e.g. by a large share of top income earners or by a large fraction of the population with low incomes. Whereas these different shapes yield comparable Gini indices, their influence on the level of redistribution may differ substantially, as different income groups deviate in their ability to exert political power. The estimated parameter of MIDDLECLASS is positive and highly significant, suggesting that the middle class plays a decisive role in redistributive issues. Column (3) features the same regression as Column (2) but replaces MIDDLECLASS with  $QUINT_3$ , the income share held by the third quintile, more distinctively capturing the influence of the median income. As in the case of MIDDLECLASS, we can observe a significantly positive impact on redistribution. Since 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](#)).

Unlike the effect of the middle class, the estimated coefficient of TOP-1 is negative and significant in most specifications, fostering notions of their engagement in rent-seeking behaviour and cronyism. As high-income earners are typically net-payers of redistributive policies, they tend to reject expansions of the welfare system. In contrast, the political power

**Table 1** Baseline regressions, determinants of redistribution in the OECD countries. Dependent variables are absolute redistribution, REDIST(S), in Panel A and relative redistribution, REDIST(S)<sup>rel</sup>, in Panel B.

	(1)	(2)	(3)	(4)	(5)
Panel A: Absolute redistribution, REDIST(S)					
GINI(M)	0.430*** (0.118)	0.567*** (0.175)	0.570*** (0.159)	0.598*** (0.140)	0.573*** (0.208)
Log(GDP <sub>pc</sub> )	1.482 (2.052)	-0.744 (1.683)	1.328 (0.903)	0.963 (1.403)	-0.671 (1.535)
REDIST ( $t - 1$ )	0.577*** (0.114)	0.219* (0.119)	0.262* (0.147)	0.199** (0.0915)	0.184 (0.130)
UNEMP		-0.0630 (0.144)	-0.0282 (0.102)	-0.0473 (0.102)	-0.0391 (0.130)
POLRIGHT		1.008 (1.635)	-0.224 (1.551)	-0.238 (1.401)	1.850* (1.113)
Log(FERT)		1.260 (2.014)	-3.053 (3.042)	-0.634 (2.716)	-0.856 (3.163)
MIDDLECLASS		0.861*** (0.192)		0.741*** (0.183)	0.840*** (0.195)
TOP-1		-0.305 (0.206)	-0.503*** (0.167)	-0.287** (0.138)	-0.333 (0.215)
QUINT <sub>3</sub>			1.705*** (0.412)		
BOTTOM-10				0.901 (0.591)	
AGE					0.133 (0.0959)
Panel B: Relative redistribution, REDIST(S) <sup>rel</sup>					
GINI(M)	0.00888** (0.00366)	0.00680* (0.00385)	0.00178 (0.00261)	0.00577 (0.00450)	0.00886** (0.00391)
Observations	202	111	111	111	111
Countries	33	29	29	29	29
Hansen p-val	0.932	0.941	0.981	0.977	0.973
Diff-Hansen	0.613	1.000	1.000	1.000	1.000
AR(1) p-val	0.0992	0.830	0.433	0.840	0.461
AR(2) p-val	0.214	0.234	0.544	0.172	0.482
Instruments	48	39	39	42	42
Collapsed	Yes	Yes	Yes	Yes	Yes

*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 and collapsed to prevent instrument proliferation. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

of the poor seems to be considerably weaker. Column (4) captures the effect of the income share held by the lowest decile of the distribution, denoted by BOTTOM-10. The estimated parameter is positive, but far from being significant. This result strongly resembles the effect of the unemployment rate, implying that the poor exert little influence on the level of redistribution. This points to two possible explanations: Governmental redistribution is either not affected by the interests of the bottom incomes, or redistributive activities are weakly targeted.

Finally, the last column of Table (1) incorporates the age dependency ratio (AGE), i.e. the ratio of people older than 64 to the working-age population. Inclusion of AGE allows us to investigate the extent to which redistribution is composed of pension payments. The results suggest that a higher age dependency ratio is generally associated with more redistribution. Yet this effect is not significant at the commonly used levels ( $p = 0.29$ ).

Panel B documents the effect of market inequality on governmental redistribution when redistribution is measured in relative terms ( $\text{REDIST}(S)^{\text{rel}}$ ). Similar as in the results reported in Panel A, a higher level of market inequality is positively related to redistribution. However, in the case of relative redistribution, the effect is slightly less pronounced, which indicates that second-order effects to some extent may play a role. The model specifications are identical to Panel A, where little change in the effects of the remaining variables can be observed.

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.

### 3.2. Redistribution in a broad sample of countries

While the restriction of the sample to advanced economies for which micro data on gross and net Ginis are available ensures the highest possible degree of comparability, it is accompanied by two distinct disadvantages. First and most obvious, the number of observations included in the sample is low, which is why the results should be interpreted with caution. Second, reliance on the sample of highly developed countries may not be sufficient to reveal the deeper institutional determinants of redistribution. As political rights have reached sophisticated levels in each OECD member state, the estimations provide no information on the Meltzer-Richard channel in countries with less democratization or authoritarian governments. For these reasons, it is not guaranteed that it is the *political* channel through which market inequality translates to more redistribution. One way to cope with both disadvantages is to compare the results of Table (1) to identical specifications on the basis of a broader sample that also includes developing economies with less developed political rights.

Such estimations, however, present the challenge of accounting for specific effects arising from different countries and development levels. To account for specific institutional

frameworks, the analysis includes unobserved heterogeneity, as described in Section 2.3. In addition, there may be effects emanating from different development levels that are common to countries in the same income group, but differ from those found in richer or poorer nations. Such effects stem mainly from underdeveloped institutions, corruption, or fraud. As in the previous estimations, we consider these effects by the inclusion of real per capita GDP.

Table (2) enlarges the baseline regressions of Table (1) by applying two different variants of the redistribution measure. The first group of regressions uses all available observations for which gross and net Gini's are available in the SWIID 5.0 (REDIST), yielding a significant increase in the number of countries included in the estimation. However, it bears emphasizing that for some of the 126 countries included in the regressions, data on either net or gross Ginis relies on estimates (see Section 2.1). The second concept used in Table (2) is based entirely on country-years for which micro data of market and net inequality is available (REDIST(S)). In both cases, Table (2) reports Columns (3), (5), and (6) of the baseline regressions to capture the effect of all covariates included in the baseline estimates.<sup>9</sup> Panel A reports the results based on absolute redistribution, whereas Panel B examines the effect of market inequality when a relative measure of redistribution is used as dependent variable.

The results of Table (2) highlight that the change in the sample composition does not yield a considerable deviation in the main drivers of governmental redistribution. As in the baseline regressions, the effect of market inequality on redistribution is positive and strongly significant. However, when analyzing the effect in a broad sample that includes a number of less-developed countries, the marginal effect of market inequality is smaller than in the sample of OECD countries. This shrinking impact implies that the Meltzer-Richard effect is less pronounced in the additional countries included in the broader samples. Meanwhile, the results suggest that redistribution is higher in countries with more sophisticated political rights and higher income levels. As argued previously, both effects are undetectable in the baseline regressions, as the sample of OECD countries is composed entirely of highly advanced countries with established democratic institutions. Taken together, these findings provide a more robust indication that it is the political channel through which market inequality is transmitted to redistribution. In developing economies, market inequality may raise demand for redistribution in the same way that it does in OECD countries. However, less developed democratic structures may impede the transmission of redistributive preferences in the political process. As in the baseline estimations, redistribution is negatively related to the top income share, which again underscores the political power of the rich. In contrast, a broad middle class is positively associated with redistributive activity of the government. The findings also imply that social benefits are weakly targeted to the poor, as neither the unemployment rate, nor the income level of the bottom 10 percent assume a significant impact on redistribution. Finally, the age dependency rate of the population older than 64 is positively related to redistribution, but this effect is not significant.

---

<sup>9</sup>The Table neglects the second concept of the middle class (QUINT<sub>3</sub>), as the effects of this variable are strongly comparable to those of the broader concept MIDDLECLASS. For this reason, Column (4) of Table (1) is excluded in Table (2).

**Table 2** Baseline regressions, determinants of redistribution in a broad sample. Dependent variables are absolute redistribution, REDIST and REDIST(S), in Panel A and relative redistribution, REDIST<sup>rel</sup> and REDIST(S)<sup>rel</sup>, in Panel B.

	REDIST (All available country-years)			REDIST(S) (All available country-years)		
	(3)	(5)	(6)	(3)	(5)	(6)
Panel A: Absolute redistribution, REDIST and REDIST(S)						
GINI(M)	0.232*** (0.0720)	0.208*** (0.0576)	0.221*** (0.0636)	0.334*** (0.107)	0.314** (0.135)	0.355*** (0.128)
Log(GDP <sub>pc</sub> )	0.423 (0.258)	0.388 (0.256)	0.629** (0.281)	2.005*** (0.631)	1.756** (0.772)	2.484*** (0.932)
REDIST ( $t - 1$ )	0.792*** (0.0793)	0.813*** (0.0712)	0.770*** (0.0831)	0.336*** (0.121)	0.372** (0.152)	0.274** (0.120)
UNEMP	-0.00741 (0.0256)	-0.00188 (0.0240)	-0.0129 (0.0256)	0.108 (0.105)	0.0993 (0.0968)	0.0882 (0.0943)
POLRIGHT	0.152* (0.0861)	0.157* (0.0872)	0.153* (0.0885)	0.582* (0.346)	0.579* (0.336)	0.535* (0.319)
Log(FERT)	-0.381 (0.393)	-0.353 (0.355)	-1.240 (0.851)	-0.453 (1.506)	-0.536 (1.507)	-2.247 (2.353)
MIDDLECLASS	0.182** (0.0785)	0.150** (0.0667)	0.159** (0.0746)	0.408*** (0.132)	0.386*** (0.143)	0.371** (0.165)
TOP-1	-0.146** (0.0640)	-0.111** (0.0550)	-0.166*** (0.0646)	-0.207 (0.166)	-0.210 (0.156)	-0.271* (0.143)
BOTTOM-10		0.170 (0.204)			-0.0308 (0.948)	
AGE			0.0292 (0.0231)			0.0797 (0.0606)
Panel B: Relative redistribution, REDIST <sup>rel</sup> and REDIST(S) <sup>rel</sup>						
GINI(M)	0.00305*** (0.000885)	0.00316*** (0.000862)	0.00287*** (0.000933)	0.00418*** (0.00153)	0.00414** (0.00161)	0.00411** (0.00170)
Observations	443	443	443	253	253	253
Countries	126	126	126	66	66	66
Hansen p-val	0.937	0.970	0.985	0.137	0.152	0.133
Diff-Hansen	0.998	1.000	1.000	0.249	0.215	0.257
AR(1) p-val	0.105	0.103	0.106	0.270	0.265	0.315
AR(2) p-val	0.440	0.438	0.393	0.973	0.866	0.840
Instruments	148	161	161	39	42	42
Collapsed	No	No	No	Yes	Yes	Yes

*Notes:* Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. Labeling of columns refers to the model specification of the baseline results reported in Table (1). All regressions include period fixed effects. Test statistics refer to Panel A. 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. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

The test statistics given in the lower part of Table (2) again attest the validity of our results. To prevent instrument proliferation, the regressions based on REDIST(S) again use a collapsed version of the instrument matrix. However, this procedure is not possible with regard to REDIST, as Hansen’s J test in this case implies that the choice of instruments is invalid.

### 3.3. Sensitivity analysis

To investigate the robustness of our results, this section provides a sensitivity analysis of the baseline findings. This analysis is concerned with two questions. First, we want to examine whether different econometric specifications yield different outcomes. This analysis also includes a direct assessment of the uncertainty in the SWIID by using multiple imputation regressions. Second, in light of the problems that arise when using cross-country data collections on inequality (see Section 2.1), we aim to analyze changes in the results when using other data sources than the SWIID.

Table (3) reports the results of the baseline model specifications when Within-Group (WG) and First-Difference GMM (Arellano-Bond) estimators are used as empirical technique. Labeling of the columns refers to the model specification used in the baseline Table, where we again report the results of models (3), (5), and (6) for the purpose of capturing each variable of interest and to save space.<sup>10</sup> Due to the high probability of a dynamic panel bias, the WG estimates exclude the lagged dependent variable (see Nickell, 1981). The table reports results of three different Panels to illustrate the effect of market inequality and our covariates for a broad sample of countries (REDIST in Panel A), the sample that only includes observations for which pre and post micro data on inequality are available (REDIST(S) in Panel B), and for relative redistribution (REDIST(S)<sup>rel</sup> in Panel C).

The results of Table (3) strongly support the findings of our baseline outcomes, suggesting that a higher level of market inequality significantly enhances the scope of redistribution. This effect is visible regardless of the redistribution measure used as dependent variable. Similar to the baseline results, the effect of market inequality is larger in the sample of REDIST(S), which is composed of a substantially higher fraction of advanced economies. Meanwhile, the results in Panel C highlight that market inequality is a significant predictor not only of absolute redistribution, but also assumes a similar influence on redistribution in relative terms.

In addition, the models in Table (3) again highlight that the shape of the income distribution matters. While a broader middle class is associated with a higher level of redistribution, a higher share of top incomes is negatively related to redistributive efforts of the government. As in the previous regressions, redistribution seems to be weakly targeted to the poor, as the bottom income share is again insignificant in each of the regressions. The table, however, illuminates a notable exception: When estimating the effect of the unemployment rate using WG regressions, the table reveals a positive relationship to redistribution.

While the results point to a high degree of robustness of our baseline estimates, it must be emphasized that both WG and First-Difference GMM are not considered ideal for identifying

---

<sup>10</sup>Note, however, that the results of columns (1) and (4) provide highly comparable outputs.

**Table 3** Sensitivity analysis of the baseline results, different estimation techniques. Dependent variables are absolute redistribution, REDIST and REDIST(S), in Panels A and B, respectively, and relative redistribution, REDIST(S)<sup>rel</sup>, in Panel C.

	Within-Group estimation			First-Difference GMM		
	(3)	(5)	(6)	(3)	(5)	(6)
Panel A: Absolute redistribution, REDIST						
GINI(M)	0.274*** (0.0504)	0.290*** (0.0517)	0.287*** (0.0530)	0.225** (0.0878)	0.225*** (0.0860)	0.166* (0.0852)
REDIST ( $t - 1$ )				-0.00390 (0.181)	-0.0433 (0.192)	0.0621 (0.193)
Log(GDP <sub>pc</sub> )	-0.0439 (0.750)	0.0643 (0.739)	0.177 (0.728)	0.482 (0.778)	0.597 (0.803)	0.909 (1.179)
UNEMP	0.0801* (0.0408)	0.0836** (0.0398)	0.0834** (0.0395)	0.0164 (0.0743)	0.00180 (0.0788)	-0.0196 (0.0743)
POLRIGHT	-0.0313 (0.0892)	-0.0179 (0.0873)	-0.0189 (0.0871)	-0.0880 (0.201)	-0.107 (0.217)	-0.163 (0.210)
Log(FERT)	1.580** (0.735)	1.580** (0.736)	1.168 (0.987)	2.885* (1.536)	2.818* (1.620)	1.640 (1.784)
TOP-1	-0.132** (0.0666)	-0.128* (0.0672)	-0.128* (0.0666)	-0.384* (0.205)	-0.436** (0.222)	-0.401** (0.198)
MIDDLECLASS	0.160*** (0.0551)	0.135** (0.0558)	0.133** (0.0558)	0.145 (0.0928)	0.175* (0.0947)	0.134 (0.0958)
BOTTOM-10		0.344 (0.223)	0.356 (0.222)		-0.619 (0.731)	-0.477 (0.650)
AGE			0.0139 (0.0167)			0.0417 (0.0391)
Panel B: Absolute redistribution, REDIST(S)						
GINI(M)	0.363*** (0.0709)	0.399*** (0.0728)	0.393*** (0.0772)	0.392** (0.169)	0.382** (0.162)	0.326** (0.141)
Panel C: Relative redistribution, REDIST(S) <sup>rel</sup>						
GINI(M)	0.00388*** (0.00138)	0.00475*** (0.00139)	0.00484*** (0.00146)	0.00587* (0.00300)	0.00592** (0.00287)	0.00497** (0.00214)
Observations	474	474	474	294	294	294
Countries	134	134	134	110	110	110
R squared	0.32	0.32	0.32			
F p-val	0.000	0.000	0.000			
Hansen p-val				0.682	0.727	0.659
AR(1) p-val				0.487	0.616	0.361
AR(2) p-val				0.303	0.226	0.745
Instruments				49	49	57

*Notes:* Table reports Within-Group (WG) estimations with cluster-robust standard errors and first-difference system GMM (Arellano-Bond) estimations. Labeling of the columns refers to the model specification of the baseline results in Table (1). All regressions include period fixed effects. The test statistics refer to Panel A, with little change to be observed in Panels B and C. F p-val gives the p-value of the F test, Hansen p-val reports the J-test for overidentifying restrictions. AR(1) p-val and AR(2) p-val report the  $p$ -values of the AR(n) test. Instruments illustrates the number of instruments. The instrument matrix is restricted to lag 2. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

the determinants of redistribution. The Within-Group estimator is insufficient to capture the persistency inherent in social security systems and neglects potential problems of endogeneity. In addition, the technique neglects the information in the equation in levels. The latter also holds true for First-Difference GMM, which would be particularly advantageous if the restrictions on the initial conditions necessary for validity of the additional orthogonality conditions of system GMM were violated. Yet the Difference-in-Hansen statistics reported in Tables (1) and (2) show quite clearly that the extra moment conditions are valid, which implies substantial efficiency losses when using First-Difference GMM. Moreover, the application of Arellano-Bond results in a decline in the number of observations, as the estimator requires having at least three consecutive observations for each of the regressors, thereby magnifying gaps in our sample.

Up to this point, our analysis uses point estimates of inequality to assess its effect on redistribution, as is common in the recent literature (see, e.g., [Ostry et al., 2014](#); [Acemoglu et al., 2015](#)). The SWIID 5.0 also contains 100 multiply-imputed values for each of the inequality measures, allowing for multiple imputation (MI) estimation of the empirical models. Using MI yields larger standard errors on coefficients, as it takes into account the imputation variability (for a detailed discussion with a focus on the SWIID, see [Jenkins, 2015](#)). To estimate the impact of the uncertainty introduced by the MI procedure on estimation precision, Table (A1) in the appendix reports the results when estimating the models of Table (1) based on multiply-imputed market inequality and redistribution. As the main concern of data quality is raised with regard to the broad sample, we use multiple imputations of REDIST as dependent variable ( $REDIST_{MI}$ ).<sup>11</sup> The results of the MI estimations underscore a high degree of robustness of the baseline findings. While market inequality exerts a significant effect on redistribution in each of the estimations, the parameters reflecting the shape of the income distribution remain their direction of influence and—with the exception of the narrow definition of the middle class—their significance. These results are encouraging, as they emphasize that neglect of the imputation variability does not produce notable changes in the standard errors, which is why we can safely proceed with the standard system GMM estimator.

The second branch of sensitivity analyses engages in examining the robustness of our results when using data sources other than the SWIID. Although we try to base most of our analysis on observations for which micro data on the pre and post level of incomes is available, some of the regressions include country-years that rest upon estimations conducted by [Solt \(2016\)](#). Table (4) illustrates the exact replication of the baseline table when using the WIID 3.0 A instead of the SWIID 5.0. As the robustness across different data sources is a highly important issue, the table reports all model specifications analyzed in Table (1). As is the case with each cross-country dataset on inequality, both the SWIID and the WIID are characterized by missing country-years, which is inevitable due to missing underlying micro data on the country level. However, this drawback is particularly severe when calculating redistribution measures based on WIID data. Whereas the WIID provides an extensive

---

<sup>11</sup>Note, however, that there are little changes if the system instead utilizes REDIST(S) in the OECD countries.

**Table 4** Sensitivity analysis of the baseline regressions. Dependent variables are absolute redistribution,  $\text{REDIST}_{\text{WIID}}$ , in Panel A and relative redistribution,  $\text{REDIST}_{\text{WIID}}^{\text{rel}}$ , in Panel B. Redistribution data is from WIID 3.0 A.

	(1)	(2)	(3)	(4)	(5)
Panel A: Absolute redistribution $\text{REDIST}_{\text{WIID}}$					
$\text{GINI(M)}_{\text{WIID}}$	0.957*** (0.155)	0.718*** (0.0940)	0.712*** (0.0862)	0.737*** (0.0669)	0.798*** (0.122)
$\text{Log(GDP)}_{pc}$	-1.075 (2.974)	2.367 (1.739)	2.164 (1.615)	3.379* (1.763)	2.515** (1.200)
$\text{REDIST}_{\text{WIID}}(t-1)$	0.188 (0.117)	0.147** (0.0712)	0.163** (0.0672)	0.169*** (0.0623)	0.133 (0.103)
UNEMP		-0.393 (0.283)	-0.355 (0.306)	-0.147 (0.188)	-0.371 (0.359)
POLRIGHT		-0.0393 (0.888)	0.00721 (0.935)	-0.495 (0.625)	-0.0621 (0.797)
$\text{Log(FERT)}$		-5.115 (4.030)	-4.863 (4.557)	-4.078 (3.161)	0.954 (4.113)
MIDDLECLASS		0.592** (0.264)		0.694*** (0.227)	0.613* (0.324)
TOP-1		-0.575* (0.330)	-0.525* (0.303)	-0.291 (0.223)	-0.703 (0.550)
QUINT <sub>3</sub>			1.707*** (0.573)		
BOTTOM-10				1.467 (0.903)	
AGE					-0.243 (0.149)
Panel B: Relative redistribution $\text{REDIST}_{\text{WIID}}^{\text{rel}}$					
$\text{GINI(M)}_{\text{WIID}}$	0.0233*** (0.00353)	0.0164*** (0.00223)	0.0165*** (0.00224)	0.0142*** (0.00194)	0.0168*** (0.00263)
Observations	181	116	116	116	116
Countries	48	41	41	41	41
Hansen	0.523	0.378	0.465	0.595	0.343
AR(1) p-val	0.798	0.0320	0.0280	0.0736	0.110
AR(2) p-val	0.678	0.919	0.847	0.458	0.783
Instruments	23	37	37	46	45
Collapsed	Yes	Yes	Yes	Yes	Yes

*Notes:* Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses based on inequality data in the WIID 3.0 A. 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 and collapsed to prevent instrument proliferation. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

collection of a variety of inequality data based on different income concepts, the distinction between gross and net incomes is less explicit, which hinders comparability of the computed levels of redistribution (see Section 2.1 for a detailed description). When utilizing data of the WIID, the number of observations reduces to a total of 264 country-years and declines further when a lagged value (181 country-years) or the sub-sample of OECD members (149 country-years) is to be considered. Thus, Table (4) reports the results based on all available observations in the WIID, denoted by  $\text{REDIST}_{\text{WIID}}$ .

The results reveal a remarkable degree of robustness of our baseline findings. The redistribution-enhancing effect of market inequality is strongly pronounced in each of the regressions. Moreover, the marginal effect of  $\text{GINI}(M)$  on redistribution based on the WIID data is slightly stronger than implied by the SWIID. The results again highlight that the level of redistribution is persistent over time, and that richer economies tend to redistribute more. In addition, a broader middle class is positively associated with redistribution, whereas top incomes tend to impede redistributive policies. Supporting the findings of the baseline estimates, we find that redistributive measures are not significantly affected by the income share held by the poor or by the unemployment rate. The age dependency ratio is positively related to the amount of redistribution, but this influence is again not significant.

Finally, Table (A2) in the appendix provides a detailed robustness check concerning the influence of top income earners, as there has been some concern regarding the data quality of the top income shares in the SWIID 4.0 (Jenkins, 2015). The table reports the effect of the top-1%, top-0.5%, top-0.1%, top-0.05%, and the top-0.01% on redistribution based on the WID, the source data upon which the top income series of the SWIID 4.0 relies. Whereas the WID perhaps provides the most reliable data series of top-incomes, it does so with reduced scope compared to the SWIID 4.0. The obvious drawback is a strong decline in data availability, which is why the table focuses on the reduced effect of top incomes on  $\text{REDIST}(S)$ , holding constant only market inequality, redistribution in  $(t - 1)$ , and the development level. It turns out that the marginal effect of the Top 1% when using the WID (-0.561\*\*\*) is nearly identical to the effect identified by the SWIID (-0.553\*); however, statistical significance rises substantially. When narrowing the scope of the analyses to more explicitly capture the effect of the (super) rich—i.e. examining the effect of the Top-0.5% to Top-0.001%—the marginal effect increases considerably. This result highlights that is primarily the extraordinary wealthy that exercise political power.

### 3.4. Different development levels

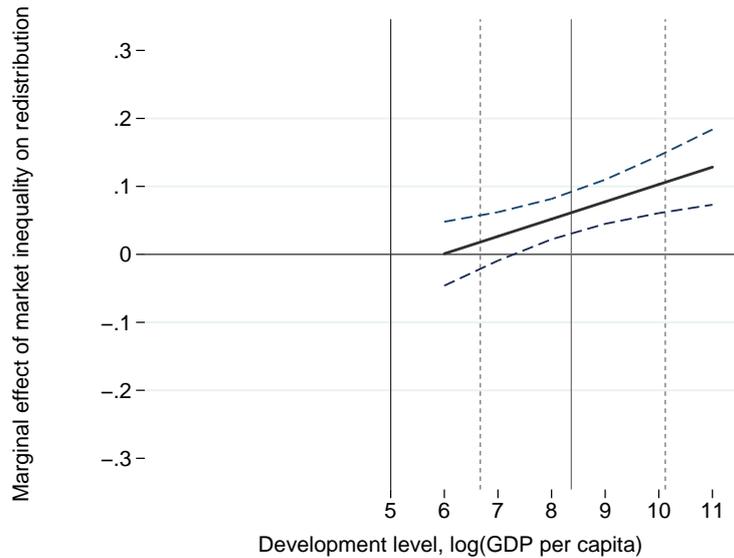
The previous estimations revealed differences in the determination of redistribution between the sample of highly advanced OECD members and the broader sample of countries. As argued in Section 3.2, the shrinking influence of market inequality on redistribution is a strong indication that the Meltzer-Richard effect is less prevalent in developing countries. The positive effect of political rights in the enlarged sample of countries further documents that the political mechanism crucially affects the degree to which policy measures are redistributive. This section is concerned with a more in-depth analysis of the development process in the explanation of redistribution.

**Table 5** The determinants of redistribution for different development levels. Dependent variable is absolute redistribution, REDIST.

	(1)	(2)	(3)	(4)	(5)
GINI(M)	-0.152* (0.0850)	0.0560 (0.126)	0.0381 (0.112)	0.0431 (0.0996)	0.0892 (0.118)
Log(GDP <sub>pc</sub> )	-0.407 (0.412)	-0.425 (0.559)	-0.300 (0.583)	-0.519 (0.490)	-0.385 (0.545)
GINI(M) × Log(GDP <sub>pc</sub> )	0.0255** (0.0101)	0.0213* (0.0121)	0.0174 (0.0111)	0.0259** (0.0111)	0.0170 (0.0110)
REDIST ( $t - 1$ )	0.896*** (0.0343)	0.760*** (0.0719)	0.806*** (0.0695)	0.725*** (0.0841)	0.735*** (0.0672)
Observations	849	430	433	430	430
Countries	145	126	126	126	126
Hansen p-val	0.643	0.984	0.963	0.999	0.996
Diff-Hansen	0.886	1.000	1.000	1.000	1.000
AR(1) p-val	0.0000148	0.0303	0.0262	0.0335	0.0280
AR(2) p-val	0.149	0.913	0.714	0.996	0.714
Instruments	147	161	161	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. The specifications of the equations equal the specifications in the baseline table. Covariates are excluded for reasons of lucidity. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table (5) uses identical model specifications as the baseline estimates of 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 for examination of the effect of 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 concentrates on the variables of interest, for reasons of lucidity. In the first (reduced) model, the effect of market inequality is essentially negative when considering less developed economies. 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 emphasizes 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 and 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 low development levels is either negative or strongly insignificant,



**Figure 5** The effect of market inequality on redistribution 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.

and the effect of the interaction term is positive in each of the regressions.

Figure (5) illustrates this effect graphically, 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 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.

Even more distinct than in the previous estimations, the results of this section imply that the market inequality exerts its influence on redistribution via the political process, which is why the Meltzer-Richard effect is considerably less pronounced in countries with less sophisticated democratic structures. With regard to the democracy indicator of Freedom House used in our empirical specification (which runs on a scale from 1 to 7), the average level of democratization in the group of advanced economies is 6.20, whereas political institutions and electoral rights are substantially less established in non-OECD economies (3,59). In some of these countries, the elite control political power including the electoral process, preventing a higher demand for redistribution from translating into real policy action.

### 3.5. Perceived inequality

The results so far imply that greater income disparities enhance redistribution. However, evidence stems from actual market inequality, whereas individual perceptions may be of

greater importance in the creation of demand for redistribution, as discussed in recent studies (Niehues, 2014, Engelhardt and Wagener, 2014, and Gimpelson and Treisman, 2015). These examinations 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. Forming judgments about subjective inequality is essentially a statistical inference problem which agents build on limited information that may be difficult and costly to access. In a seminal paper, Cruces et al. (2013) show that preferences for redistribution increase when respondents who overestimate their individual position are informed of their true ranking. Therefore, it is to be expected that demand for redistribution is higher if the degree of misperception is low. When comparing official inequality statistics with subjective perceptions across countries, 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. Founded in 1984 by research institutions from Australia, the United States, the United Kingdom, and Germany, it currently includes comparable data for 48 countries. Our measure refers to the question (V44 in the 2009 ISSP wave)<sup>12</sup>

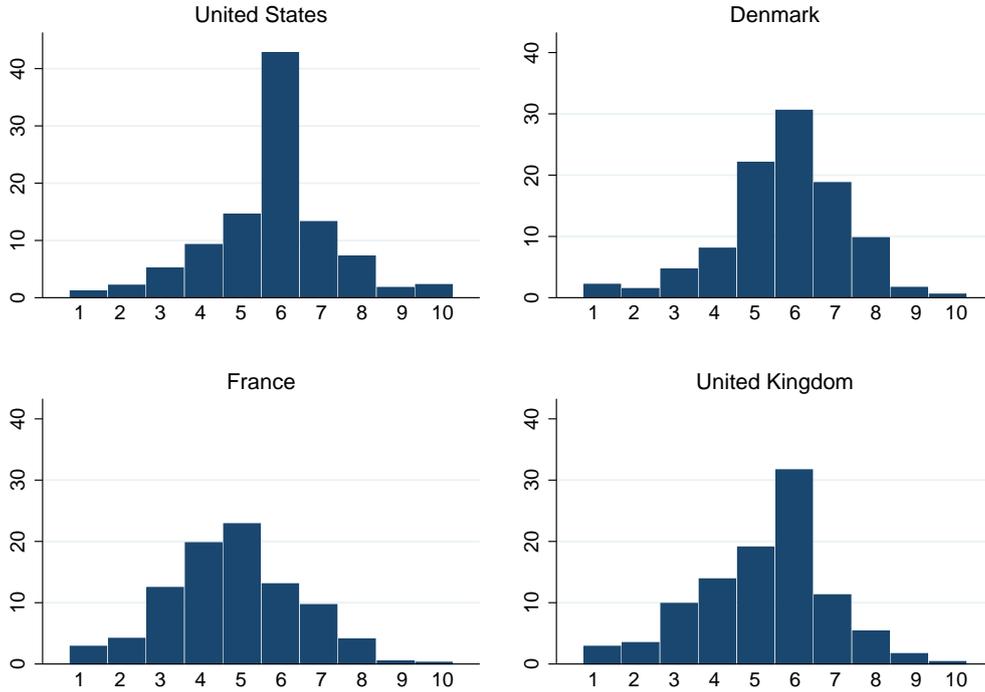
*"In our society there are groups which tend to be towards the top and groups which tend to be towards the bottom. Below is a scale that runs from top to bottom (10 top — 1 bottom). Where would you put yourself now on this scale?"*

Data on this question is available for 44 countries—26 of which are OECD members—for the years 1987, 1992, 1999, and 2006-2009. As a result, the data allows for calculation of 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. Figure (6) illustrates the distribution of the self-assessment in the United States, Denmark, France, and the United Kingdom as documented in the ISSP 2009. Whereas income distributions are typically right-skewed, the figure highlights that the respondents tend to classify their subjective income level following a normal distribution. In the United States and the United Kingdom, an extraordinarily large fraction of the population classifies themselves as earning above-average incomes equivalent to the 6th category on the scale.

Using the empirical discrete probability density function  $\Phi(y_i)$  implied by the ISSP, we compute a Gini index  $G_{\text{per}}$  on income perception  $y_i$  as

---

<sup>12</sup>Note that the exact wording of the question deviates slightly between different countries. The exact formulation for each country can be reviewed in the official ISSP documentation.

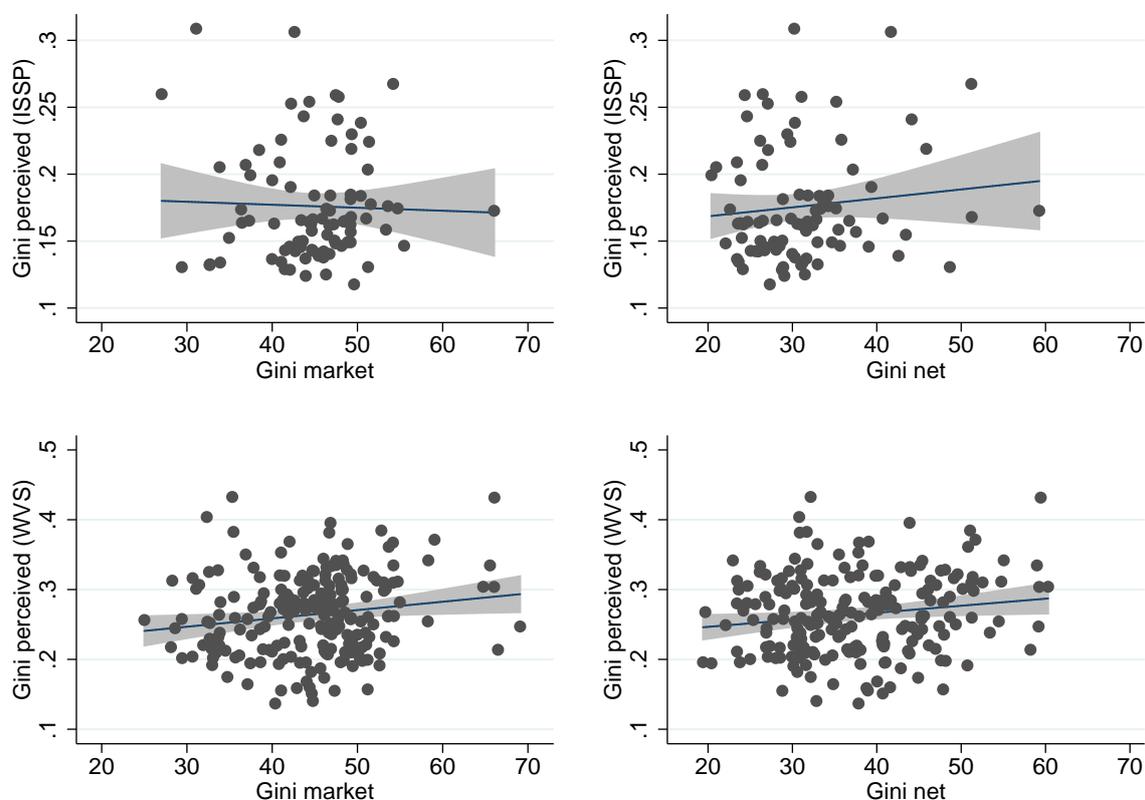


**Figure 6** The subjective distribution of incomes in the United States, Denmark, France, and the United Kingdom. Data on perceived inequality is from ISSP 2009 (GESIS Study No. 5400 v3.0.0).

$$G_{\text{per}} = 1 - \frac{\sum_{i=1}^{10} \Phi(y_i)(B_{i-1} + B_i)}{B_{10}}, \quad (8)$$

where  $B_i = \sum_{k=0}^i \Phi(y_k)y_k$ ,  $B_0 = 0$ , and  $i = 1, \dots, 10$  are the empirical realizations of the particular groups. One methodological drawback is that subjects are asked to classify their income on a scale ranging from 1 to 10, where the implicit assumption is that incomes in each class are identical. Particularly with respect to the 10th class, this is a rather bold assumption, as measures of income distribution are often driven by top income earners. As a result,  $G_{\text{per}}$  neglects the high degree of inequality usually detected in the top income groups.

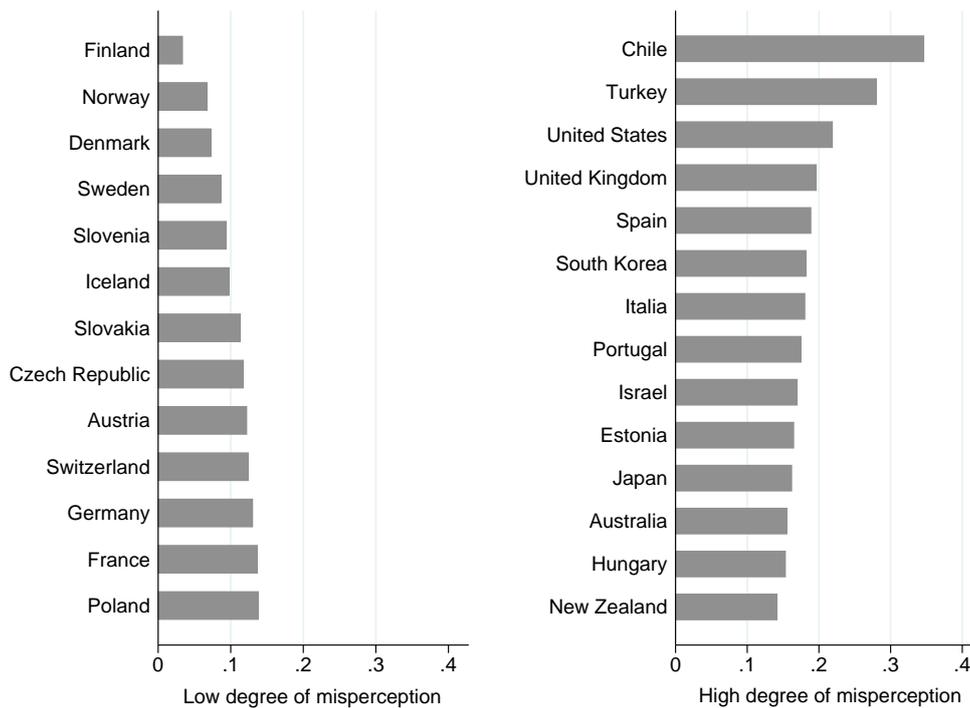
Whereas the ISSP is often considered the most reliable database covering public opinion on inequality, one major drawback is the limited number of included countries. This limitation not only results in a severe reduction in the number of observations, it may also be the source of a sample selection 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) to compile a measure in a way similar to the procedure described in Equation (8). The WVS is a global research project which aims to explore values and beliefs of individuals. It employs a question quite similar to the subjective assessment of the ISSP:



**Figure 7** The relationship between actual inequality and perceived inequality, measured with data based on the ISSP and the WVS. The gray-shaded area around the regression line marks the 95% confidence interval.

*"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."*

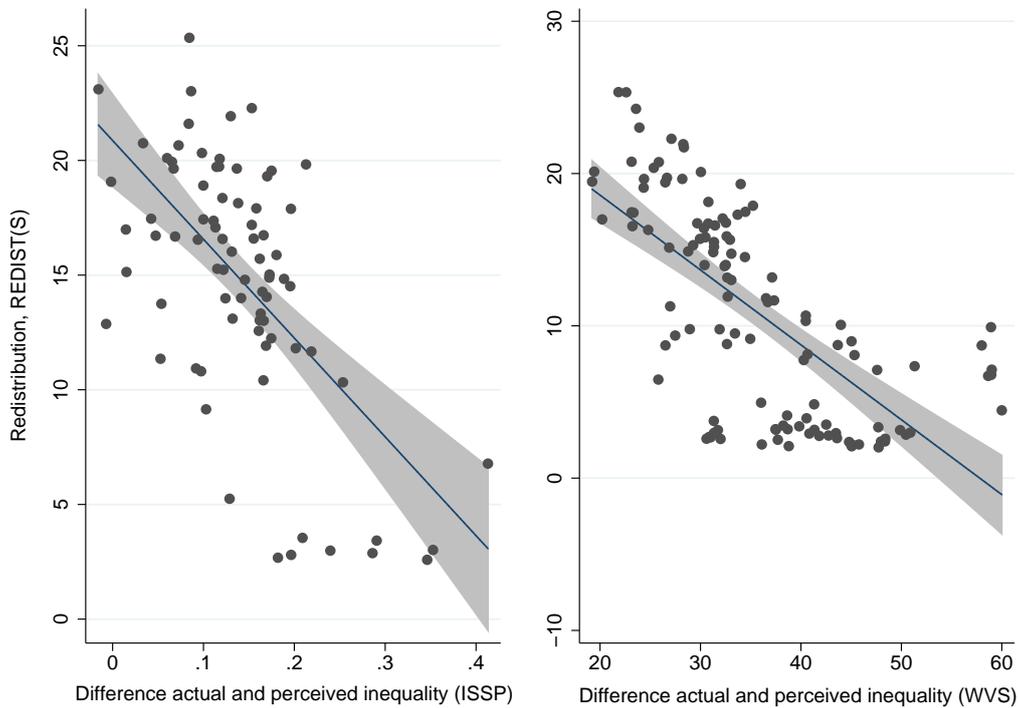
Data on this question is available for 84 countries in six waves, which allows us to calculate inequality measures for the 5-year periods 1980-1984, 1990-1994, 1995-1999, 2000-2004, 2005-2009, and 2010-2014. Yet, as in the case of ISSP data, the composition of countries changes between the waves. We denote the Gini coefficients built on the ISSP and the WVS as  $\text{GINI}_{\text{WVS}}$  and  $\text{GINI}_{\text{ISSP}}$ , respectively. In computing the perceived measures, we follow [Engelhardt and Wagener \(2014\)](#) in weighting the Gini's 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.



**Figure 8** The difference between perceived and actual inequality in the period 2005-2009. Data on perceived inequality is from ISSP 2009 (GESIS Study No. 5400 v3.0.0).

Figure (7) illustrates the relationship between perceived and both actual market and actual net inequality. With regard to the ISSP measures, the correlation between actual and perceived inequality is weak and insignificant. Whereas the bivariate correlation between the variables remains relatively weak when considering perceived measures obtained by the WVS, the relationship is significant on the 5% level. This implies that there is a slight tendency for unequal societies to classify their level of inequality higher than societies with a more equal distribution of incomes.

Figure (8) lists the countries with the highest and the lowest misjudgment of national inequality in the group of OECD countries. Employing data from the ISSP 2009, it can be seen that inequality is perceived to be much lower than actual inequality in each OECD member state. Whereas citizens in some of the non-OECD countries tend to overrate income disparities, they are systematically underestimated in the group of advanced economies. Actual net inequality in the OECD countries averages 30.73 Gini points, while the mean of perceived Ginis is 15.6 ( $GINI_{ISSP}$ ) and 27.41 ( $GINI_{WVS}$ ), respectively. Differences between the ISSP and the WVS have their origin in deviating survey designs and sample sizes. There are, however, only minor differences in the ranking of inequality misjudgments between the ISSP and the WVS. Particularly in the Scandinavian countries of Finland, Norway, Denmark, and Sweden, perceived inequality is close to officially reported Gini coefficients. This also holds for some of the eastern European countries, such as the Slovak Republic, Slovenia, and the



**Figure 9** The relationship between the extent of misjudgment and governmental redistribution in the period 2005-2009. Redistribution variable is REDIST(S). The gray-shaded area around the regression line marks the 95% confidence interval.

Czech Republic. The highest misperceptions of inequality can be found in Chile and Turkey, followed by the Anglo-Saxon nations the United States and the United Kingdom, and the Mediterranean economies of Spain, Italy, and Portugal. Figure (A3) in the appendix provides a direct comparison between the perceived and the actual income distribution based on a scale running from 1 to 10. To compile actual distributions of income, we use data of Round 7 of the [European Social Survey \(2014\)](#) (ESS), which is available for 14 European countries. Illustrated are subjective assessments and actual distributions for Finland, Austria, France, and Switzerland. The figure underscores that citizen's self-positioning in each of the graphed countries is strongly biased to the center of the distribution, resulting in a considerable misjudgment of the individual rank. While very few of the probands classify themselves as having incomes coinciding with the borders of the (1, 10) interval, the actual distribution of incomes implies that a much higher fraction of individuals ranks in the classes 1-3 and 8-10 than implied by subjective assessments. This bias is less pronounced in Finland, which is in accordance with the (relatively) low degree of misperception depicted in Figure (8). Note, however, that the limited number of included countries in the ESS impedes the illustration of countries with a high degree of misperception, as data concerning countries located on the right side of Figure (8) is unavailable.

While the extent of misjudgement differs substantially among OECD countries, there is a

distinct relationship between errors in perception and the level of redistribution. Figure (9) depicts the relationship between redistribution and the degree of misperception, highlighting a strong negative correlation of -61.39 (ISSP) and -67.38 (WVS), respectively, that emerges regardless of the data source used to compile perceived inequality measures. This emphasizes that the preference for redistribution is lower if individuals underestimate the “true” degree of inequality. However, if the individuals are aware of national income disparities—i.e. the degree of misperception is low—demand for redistribution is higher, resulting in greater redistributive activity in the political process.

While Figure (9) provides a first intuitive sign for a redistribution-enhancing effect of subjective inequality, Table (6) is concerned with a more in-depth examination of this link. The table analyzes the effect of perceived inequality measures in a reduced model specification similar to Column (1) of Table (1), as the limited availability of subjective Gini’s yields a significant reduction in the included country-years when incorporating a wide range of covariates. To ensure comparability of the results with the previous findings, we report the outcomes of three different sample compositions with respect to each of the perceived measures. The first sample takes into account data from OECD countries, the second only incorporates observations that are included in the baseline regressions of Table (1), and the third specification is built on all country-years for which data is available. Due to unavailability of data for some of the OECD countries in the REDIST(S) sample, the first and second samples differ to some extent. The table investigates the effect on both absolute (Panel A) and relative (Panel B) redistribution.

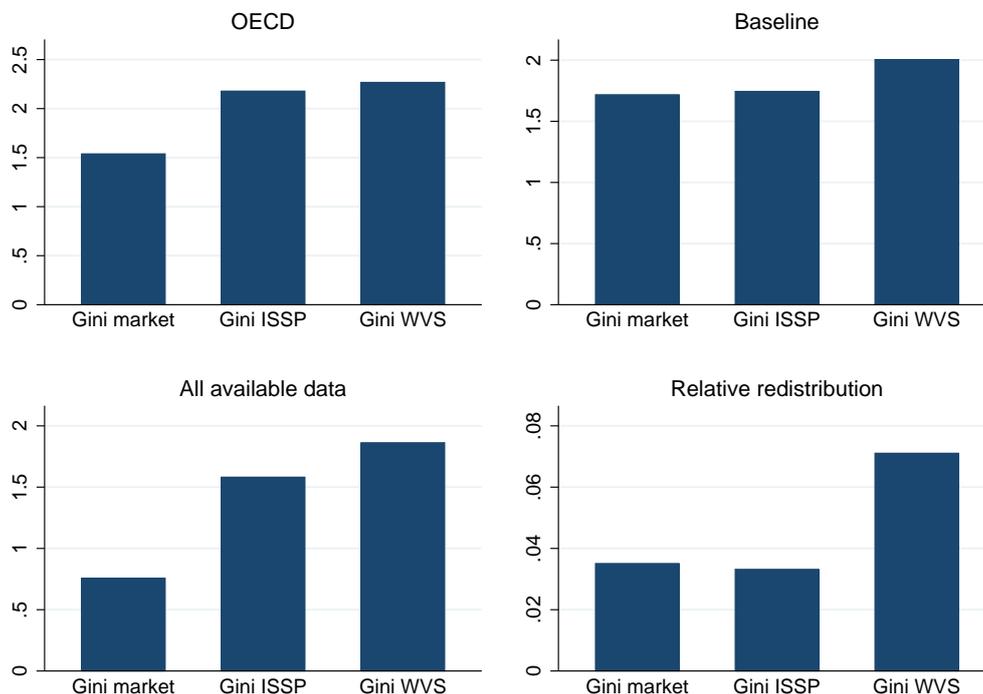
The results suggest that redistributive efforts of the government are considerably influenced by subjective redistribution. With respect to the ISSP data, we find a positive and strongly significant effect of perceived inequality on both absolute and relative redistribution. As in the previous estimations based on market inequality, this effect is particularly strong in OECD countries with established democratic structures. When using information from the whole sample for which data is available, the marginal effect shrinks slightly. This reduction is weaker than in the case of market inequality; however, data on self-assessment in the ISSP is available only for relatively advanced economies. This results in both a less pronounced reduction in the marginal effect across the different sample compositions and insignificance of the development level. The subjective inequality measure based on WVS data confirms the positive relationship between perceptions of inequality and redistribution. This effect is more prevalent in absolute rather than in relative terms. Note, however, that drawing on all available data on subjective measures yields a substantial increase in the number of observations, particularly with respect to  $GINI_{WVS}$ .

The results thus far imply that both officially reported market inequality and perceived Gini’s exert strong influences on redistribution. However, the estimated parameters cannot be compared directly, as the mean and standard deviation of the measures are different, particularly in light of deviating sample compositions. To enable a more direct comparison, Figure (10) depicts the marginal effect of a one standard-deviation-change in the inequality measures on redistribution. With respect to OECD countries, the figure highlights a substantially stronger impact of subjective inequality compared to officially reported Gini indices. While a change in  $GINI(M)$  of one standard deviation results in an increase in re-

**Table 6** The effect of perceived inequality on redistribution. Dependent variables are absolute redistribution, REDIST and REDIST(S), in Panel A and relative redistribution, REDIST<sup>rel</sup> and REDIST(S)<sup>rel</sup>, in Panel B.

	Perceived inequality (ISSP)			Perceived inequality (WVS)		
	OECD	Baseline	All data	OECD	Baseline	All data
Panel A: Absolute redistribution, REDIST and REDIST(S)						
GINI <sub>ISSP</sub>	0.105** (0.0456)	0.0956* (0.0532)	0.0710*** (0.0188)			
GINI <sub>WVS</sub>				0.105* (0.0635)	0.101 (0.108)	0.0939** (0.0453)
Log(GDP <sub>pc</sub> )	2.217 (4.984)	4.398 (2.993)	6.152 (5.625)	3.894* (2.164)	9.033 (10.92)	8.005** (3.263)
REDIST( $t - 1$ )	-0.165 (0.532)	0.0886 (0.444)	0.210 (0.506)	0.684** (0.331)	-0.0181 (0.530)	-0.0204 (0.346)
Panel B: Relative redistribution, REDIST <sup>rel</sup> and REDIST(S) <sup>rel</sup>						
GINI <sub>ISSP</sub>	0.00149** (0.000751)	0.000808*** (0.000290)	0.00120*** (0.000444)			
GINI <sub>WVS</sub>				0.00329* (0.00186)	0.00140 (0.00610)	0.00109 (0.00178)
Observations	61	38	77	72	46	207
Countries	28	23	38	25	23	84
Hansen p-val	0.474	0.232	0.154	0.296	0.601	0.588
AR(1) p-val	0.850	0.909	0.580	0.307	0.274	0.931
Instruments	13	13	18	15	13	15
Collapsed	Yes	Yes	Yes	Yes	Yes	Yes

*Notes:* Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. Regressions are based on perceived inequality measures based on the ISSP and the WVS. 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 and collapsed to prevent instrument proliferation. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .



**Figure 10** The marginal effect of actual and perceived inequality on redistribution at a one standard-deviation-change of the underlying variable. The graph illustrates the marginal effects estimated in the sample of OECD countries, the sample used in the baseline regressions in Table (1), the sample that includes all available redistribution data, and the sample of relative redistribution based on OECD countries. Each effect is computed based on the reduced model in Column (1).

distribution of 1.54 Gini points, perceived inequality measures imply a considerably higher marginal effect of 2.18 ( $GINI_{ISSP}$ ) and 2.268 ( $GINI_{WVS}$ ), respectively. Although less distinct, similar differences can be detected when analyzing only the observations included in the baseline regression of Table (1). The deviation between actual and subjective inequality is strongest when examining the effect of inequality in the broadest possible sample of countries, where the strong effect of perceived measures of 1.58 ( $GINI_{ISSP}$ ) and 1.86 ( $GINI_{WVS}$ ) stands in sharp contrast to a substantially weaker effect implied by actual market inequality (0.76). However, comparability of the marginal effects in this case is limited, as the sample is composed of different country-years for the different inequality measures.

Overall, Figure (10) highlights that the marginal effect on redistribution is higher when considering perceived measures rather than officially reported market inequality. This result emphasizes that a higher level of income inequality translates to greater redistributive efforts by the government if citizens are aware of national income disparities. In the presence of misperceptions, however, demand for redistribution may be low, even if market incomes may be distributed highly unequally.

#### 4. Concluding remarks

This article investigates the empirical relationship between income inequality and redistribution on a broad basis. Retesting the Meltzer-Richard hypothesis, we present affirmative evidence which is robust to different sample compositions and several model specifications. Our study incorporates a variety of actual and perceived inequality measures from multiple recently collected cross-national inequality datasets, allowing to assess the entanglement between income disparities and redistributive policies in a panel context.

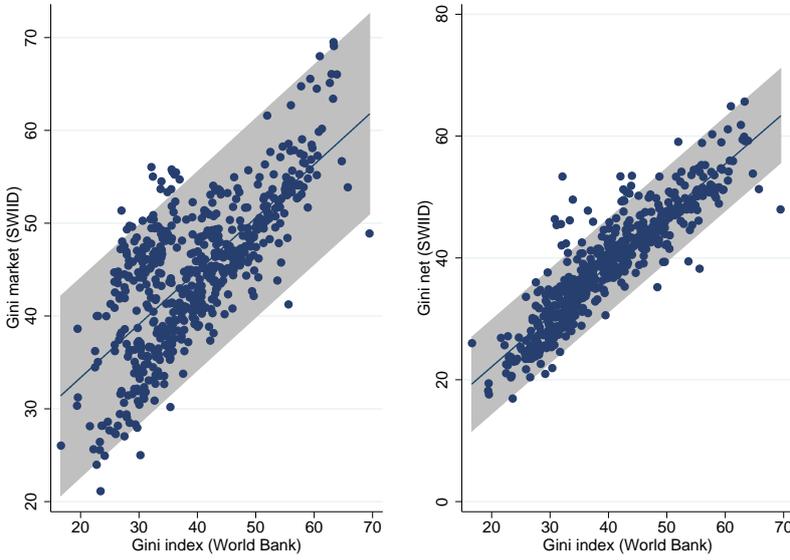
Additionally, we account for the shape of the income distribution and determine the impact of different income groups on redistribution. The results imply that the middle class exerts a significant influence on the extent of redistribution in all specifications. However, top incomes also appear to play a crucial role in redistributive issues, supporting notions of cronyism which might arise to reduce the financial burden from redistribution. Meanwhile, our findings indicate that governments do not incorporate the objectives of the poorest in determining the amount of redistribution.

Accounting for different development levels and varying sophistication of political rights, our analysis provides evidence for the importance of the political channel which translates market inequality into more redistribution. We observe that the Meltzer-Richard effect is less pronounced when democratic structures are less developed, impeding the transmission of redistributive preferences of the population in the political process.

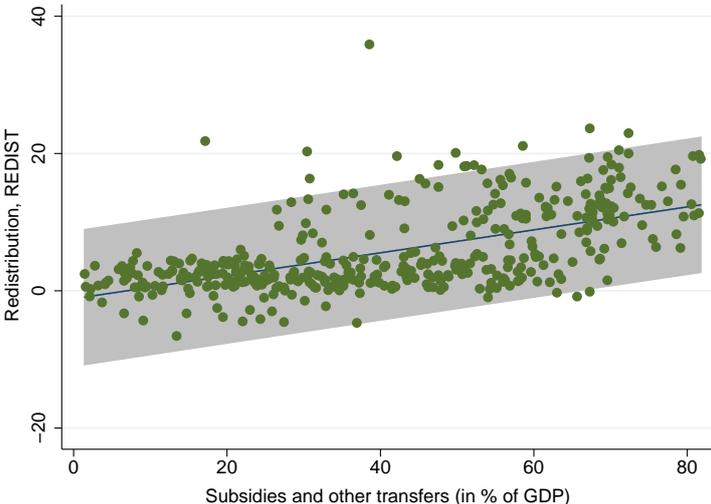
Finally, we demonstrate that individual perceptions of inequality are often biased. Based on different data sources, we show that perceived inequality is often lower than actual disparity of incomes, albeit to varying degrees. In countries where citizens are conscious of the “true” extent of inequality, demand for redistribution is higher. The regression estimates imply that the Meltzer-Richard effect is even stronger when using perceived inequality measures, indicating that governmental redistribution is influenced by subjective perceptions rather than actual inequality.

Our paper offers a cross-nationally comparable analysis of the Meltzer-Richard hypothesis, including countries for which data has long been rather scarce. However, future research should focus on the improvement of data availability of perceived inequality measures. In this article, 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 reliable micro data of earlier periods to become available. Further research may also evaluate the redistributive effect of specific fiscal policy instruments, as they may 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 inequality levels implied by the data of the World Bank and the SWIID. The gray-shaded area around the regression line marks the 95% confidence interval. The bivariate regression of GINI(N) on GINI<sub>World Bank</sub> yields a marginal effect of 0.9996\*\*\* (0.021) and R-squared of 0.80, which suggests consistency across both data sources.



**Figure A2** The relationship between REDIST and social transfer payments. The gray-shaded area around the regression line marks the 95% confidence interval. Data source is [World Bank \(2014\)](#).

**Table A1** Baseline regressions, determinants of redistribution in a broad sample, multiple imputations estimations. Dependent variable is redistribution,  $\text{REDIST}_{\text{MI}}$ .

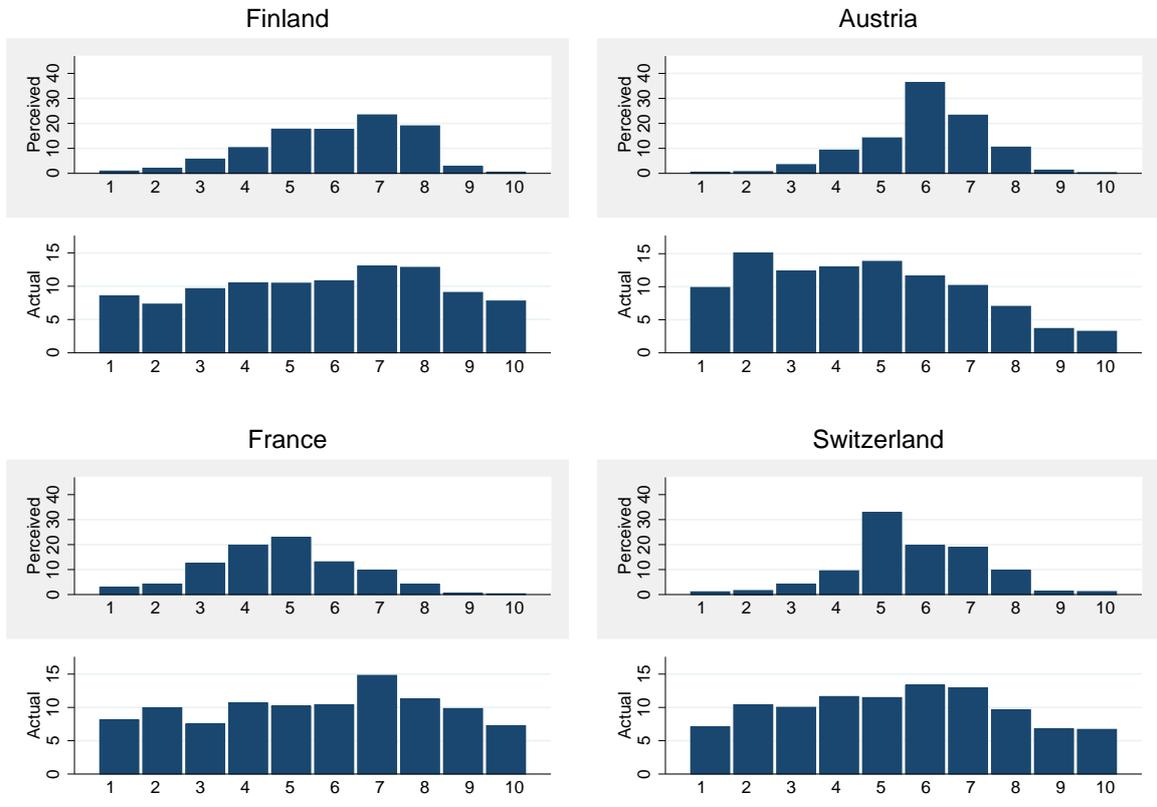
	(1)	(2)	(3)	(4)	(5)
$\text{GINI(M)}_{\text{MI}}$	0.294*** (0.0805)	0.537*** (0.118)	0.506*** (0.119)	0.518*** (0.141)	0.482*** (0.118)
$\text{Log(GDP}_{pc})$	2.307*** (0.634)	2.665** (1.106)	2.831** (1.174)	2.377** (1.143)	3.328*** (1.282)
$\text{REDIST}_{\text{MI}}(t-1)$	0.465*** (0.125)	0.183 (0.155)	0.212 (0.166)	0.203 (0.159)	0.143 (0.157)
UNEMP		0.0373 (0.117)	0.0358 (0.131)	0.0386 (0.116)	-0.00866 (0.120)
POLRIGHT		0.604* (0.336)	0.615* (0.360)	0.627* (0.345)	0.567* (0.318)
$\text{Log(FERT)}$		0.688 (1.543)	0.430 (1.576)	0.620 (1.674)	-2.971 (2.789)
MIDDLECLASS		0.418* (0.232)		0.470* (0.280)	0.327 (0.253)
TOP-1		-0.431** (0.217)	-0.499** (0.220)	-0.432* (0.239)	-0.477** (0.209)
QUINT <sub>3</sub>			0.801 (0.597)		
BOTTOM-10				-0.369 (1.575)	
AGE					0.117 (0.0751)
Observations	873	443	443	443	443
Countries	146	126	126	126	126
MI F Stat	12.32	27.09	23.41	21.95	22.26
MI F p-val	2.27e-25	1.07e-61	1.26e-52	7.14e-53	9.74e-54
Average RVI	0.460	0.458	0.415	0.429	0.376
Largest FMI	0.428	0.373	0.364	0.356	0.357
Imputations	100	100	100	100	100
Instruments	69	39	39	42	42

*Notes:* Table reports multiple imputations two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. All regressions include period fixed effects.  $\text{REDIST}_{\text{MI}}$  and  $\text{GINI(M)}_{\text{MI}}$  denote the multiple-imputed variants of REDIST and GINI(M) as they originally appear in the SWIID 5.0. MI F Stat gives the F statistic of the multiple imputation estimations, MI F p-val reports the referring  $p$ -values. Average RVI documents the average relative variance increase due to nonresponse, largest FMI reports the largest fraction of missing information. Instruments illustrates the number of instruments. The instrument matrix is restricted to lag 2. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Table A2** The effect of top income shares on redistribution. Dependent variable is redistribution, REDIST(S).

	SWIID	World Wealth and Income Database (WID)				
	(1)	(2)	(3)	(4)	(5)	(6)
GINI(M)	0.543*** (0.144)	0.476*** (0.157)	0.517*** (0.183)	0.389*** (0.133)	0.911** (0.398)	0.494*** (0.151)
Log(GDP <sub>pc</sub> )	3.255*** (0.786)	2.917 (2.645)	5.245*** (1.698)	3.213** (1.634)	14.25** (6.575)	3.654** (1.843)
REDIST( $t - 1$ )	0.255** (0.112)	0.407*** (0.101)	0.120 (0.173)	0.372* (0.195)	0.642* (0.331)	0.500*** (0.185)
TOP-1%	-0.553* (0.320)					
TOP-1%		-0.561*** (0.198)				
TOP-0.5%			-0.951*** (0.338)			
TOP-0.1%				-0.894* (0.480)		
TOP-0.05%					-11.46** (5.418)	
TOP-0.01%						-1.892*** (0.682)
Observations	375	87	84	81	34	60
Countries	73	17	16	17	7	13
Hansen p-val	0.000947	0.691	0.895	0.561	1.000	0.960
AR(1) p-val	0.571	0.409	0.618	0.374	0.267	0.229
AR(2) p-val	0.913	0.928	0.667	0.882	0.174	0.876
Instruments	19	19	19	19	19	19
Collapsed	Yes	Yes	Yes	Yes	Yes	Yes

*Notes:* Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. The Table uses top income shares of the World Wealth and Income database (WID) of [Alvaredo et al. \(2015\)](#). Due to the small number of observations, the regressions exclude period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. AR(1) p-val and AR(2) p-val report the  $p$ -values of the AR(n) test. Instruments illustrates the number of instruments. The instrument matrix is restricted to lag 2. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .



**Figure A3** Perceived and actual distribution of incomes among classes on a scale from 1 to 10. Data on actual distribution of incomes is from [European Social Survey \(2014\)](#), perceived measurements are calculated as described in Section 3.5. Grey-shaded areas mark the distribution of perceptions.

## References

- Acemoglu, D., Naidu, S., Restrepo, P., and Robinson, J. A. (2015). Democracy, redistribution, and inequality. In Atkinson, A. B. and Bourguignon, F., editors, *Handbook of Income Distribution*, volume 2, pages 1885–1966. North-Holland, Amsterdam (NL). [3](#), [5](#), [10](#), [21](#)
- Alesina, A. and Rodrik, D. (1994). Distributive politics and economic growth. *Quarterly Journal of Economics*, 109(2):465–490. [3](#)
- Alvaredo, F., Atkinson, A. B., Piketty, T., Saez, E., and Zucman, G. (2015). *The World Wealth and Income Database*. <http://www.wid.world>. [12](#), [37](#)
- Arellano, M. and Bond, S. (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58(2):277–297. [12](#)
- Arellano, M. and Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68(1):29–51. [12](#), [13](#), [15](#), [18](#), [22](#), [24](#), [32](#)
- Atkinson, A. B. and Brandolini, A. (2001). Promise and pitfalls in the use of secondary data-sets: Income inequality in OECD countries as a case study. *Journal of Economic Literature*, 39(3):771–799. [4](#), [5](#), [6](#)
- Atkinson, A. B. and Brandolini, A. (2009). On data: a case study of the evolution of income inequality across time and across countries. *Cambridge Journal of Economics*, 33(3):381–404. [5](#)
- Atkinson, A. B. and Brandolini, A. (2011). On the identification of the middle class. ECINEQ Working Paper No. 217, Society for the Study of Economic Inequality. [14](#)
- Bassett, W. F., Burkett, J. P., and Putterman, L. (1999). Income distribution, government transfers, and the problem of unequal influence. *European Journal of Political Economy*, 15(2):207–228. [2](#)
- Bénabou, R. (2000). Unequal societies: Income distribution and the social contract. *American Economic Review*, 90(1):96–129. [1](#)
- Bergh, A. (2005). On the counterfactual problem of welfare state research: How can we measure redistribution? *European Sociological Review*, 21(4):345–357. [7](#)
- Blais, A. (2000). *To Vote or Not to Vote*. University of Pittsburgh Press, Pittsburgh. [2](#)
- Blundell, R. and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1):115–143. [12](#)
- Blundell, R., Bond, S., and Windmeijer, F. (2000). Estimation in dynamic panel data models: improving on the performance of the standard GMM estimator. IFS Working Paper No. 00/12, Institute for Fiscal Studies. [13](#)
- Bond, S., Hoeffler, A., and Temple, J. (2001). GMM estimation of empirical growth models. CEPR Discussion Paper No. 3048, Centre for Economic Policy Research. [12](#), [13](#)
- Buxton, J. (2014). Social policy in Venezuela: Bucking neoliberalism or unsustainable clientelism. UNRISD Working Paper 2014-16, United Nations Research Institute for Social Policy. [9](#)
- Chambers, J. R., Swan, L. K., and Heesacker, M. (2014). Better off than we know: Distorted perceptions of incomes and income inequality in America. *Psychological Science*, 25(2):613–618. [3](#)
- Cruces, G., Perez-Truglia, R., and Tetaz, M. (2013). Biased perceptions of income distribution and preferences for redistribution: Evidence from a survey experiment. *Journal of Public Economics*, 98:100–112. [3](#), [26](#)
- D’Agostino, R., Belanger, A., and D’Agostino, R. J. (1990). A suggestion for using powerful and informative tests of normality. *The American Statistician*, 44(4):316–321. [7](#)
- Deininger, K. and Squire, L. (1996). A new data set measuring income inequality. *The World Bank Economic Review*, 10(3):565–591. [6](#)
- Downs, A. (1957). An economic theory of political action in a democracy. *Journal of Political Economy*, 65(2):135–150. [1](#)
- Engelhardt, C. and Wagener, A. (2014). Biased perceptions of income inequality and redistribution. Hannover Economic Papers No. 526, University of Hannover. [3](#), [26](#), [28](#)
- European Social Survey (2014). *ESS Round 7: European Social Survey Round 7 Data*. Norwegian Social Science Data Services, Norway. Data Archive and distributor of ESS data for ESS ERIC. [30](#), [38](#)
- Fernández-Albertos, J. and Kuo, A. (2016). Income perception, information, and progressive taxation: Evidence from a survey experiment. *Political Science Research and Methods*, forthcoming. [3](#)

- Freedom House (2014). *Freedom in the World Database*. Freedom House, Washington D.C. [12](#)
- Georgiadis, A. and Manning, A. (2007). Spend it like Beckham? Inequality and redistribution in the UK, 1983-2004. CEP Discussion Paper No. 816, Centre for Economic Performance. [1](#)
- Gimpelson, V. and Treisman, D. (2015). Misperceiving inequality. NBER Working Paper No. 21174, National Bureau of Economic Research. [3](#), [26](#)
- Gornick, J., Jäntti, M., Munzi, T., and Kruten, T. (2015). Luxembourg Income Study - response. *The Journal of Economic Inequality*, 13(4):549–556. [5](#)
- Gouveia, M. and Masia, N. A. (1998). Does the median voter model explain the size of government?: Evidence from the states. *Public Choice*, 97(1/2):159–177. [1](#)
- Grabka, M. M. and Frick, J. R. (2008). The shrinking german middle class: Signs of long-term polarization in disposable income? *DIW Weekly Report*, 4(4):21–27. [14](#)
- Hotelling, H. (1929). Stability in competition. *The Economic Journal*, 39(153):41–57. [1](#)
- Jenkins, S. P. (2015). World income inequality databases: an assessment of WIID and SWIID. *The Journal of Economic Inequality*, 13(4):629–671. [5](#), [6](#), [21](#), [23](#)
- Kenworthy, L. and McCall, L. (2008). Inequality, public opinion and redistribution. *Socio-Economic Review*, 6(1):35–68. [1](#)
- Lupu, N. and Pontusson, J. (2011). The structure of inequality and the politics of redistribution. *American Political Science Review*, 105(2):316–336. [4](#)
- Meltzer, A. H. and Richard, S. F. (1981). A rational theory of the size of government. *Journal of Political Economy*, 89(5):914–27. [1](#), [14](#)
- Milanovic, B. (2000). The median-voter hypothesis, income inequality, and income redistribution: an empirical test with the required data. *European Journal of Political Economy*, 16(3):367–410. [1](#), [3](#)
- Milanovic, B. (2014). Description of *All the Ginis* dataset. Working Paper, World Bank Research Department. [6](#)
- Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica*, 49(6):1417–1426. [12](#), [19](#)
- Niehues, J. (2014). Subjective perceptions of inequality and redistributive preferences: An international comparison. Discussion paper, Cologne Institute for Economic Research. [3](#), [26](#)
- Norris, P. (2002). *Democratic Phoenix*. Cambridge University Press, Cambridge. [2](#)
- Norton, M. I. and Ariely, D. (2011). Building a better America – One wealth quintile at a time. *Perspectives on Psychological Science*, 6(1):9–12. [3](#)
- Ostry, J. D., Berg, A., and Tsangarides, C. G. (2014). Redistribution, inequality, and growth. IMF Staff Discussion Notes 14/02, International Monetary Fund. [7](#), [21](#)
- Perotti, R. (1996). Growth, income distribution, and democracy: What the data say. *Journal of Economic Growth*, 1(2):149–187. [2](#), [3](#)
- Persson, T. and Tabellini, G. (1994). Is inequality harmful for growth? *American Economic Review*, 84(3):600–621. [3](#)
- Ravallion, M. (2015). The Luxembourg Income Study. *The Journal of Economic Inequality*, 13(4):527–547. [5](#)
- Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics*, 71(1):135–158. [13](#)
- Rosenstone, S. J. and Hansen, J. M. (1993). *Mobilization, Participation, and Democracy in America*. Longman, London. [2](#)
- Scervini, F. (2012). Empirics of the median voter: democracy, redistribution and the role of the middle class. *The Journal of Economic Inequality*, 10(4):529–550. [1](#), [2](#), [3](#)
- Solt, F. (2009). Standardizing the World Income Inequality Database. *Social Science Quarterly*, 90(2):231–242. [5](#)
- Solt, F. (2015). On the assessment and use of cross-national income inequality datasets. *The Journal of Economic Inequality*, 13(4):683–691. [5](#), [6](#)
- Solt, F. (2016). The Standardized World Income Inequality Database. *Social Science Quarterly*, forthcoming. [5](#), [6](#), [21](#)
- UNU-WIDER (2014). *World Income Inequality Database (WIID 3.0 A)*. The United Nations University

- World Institute for Development Economics Research. [5](#)
- Van den Bosch, K. and Cantillon, B. (2008). Policy impact. In Goodin, R., Moran, M., and Rein, M., editors, *The Oxford Handbook of Public Policy*, pages 296–318. Oxford University Press, Oxford. [4](#), [6](#)
- Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics*, 126(1):25–51. [13](#)
- World Bank (2014). *World Development Indicators (WDI)*. The World Bank, Washington D.C. [11](#), [35](#)