WP/21/252

IMF Working Paper

Measuring the Redistributive Capacity of Tax Policies

by Charles Vellutini and Juan Carlos Benítez

INTERNATIONAL MONETARY FUND

 WP/21/252

IMF Working Paper

Fiscal Affairs Department

Measuring the Redistributive Capacity of Tax Policies

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Authorized for distribution by Alexander Klemm

October 2021

Abstract

This paper presents a novel technique to measure and compare the redistributive capacity of observed tax (or transfer) policies. The technique is based on income distribution simulations and controls for differences in pre-tax income distributions. It assumes that the only information on the pre-tax distribution available in each country-year is the Gini coefficient and the mean (GDP per capita). We illustrate the technique with an application to the personal income tax, using a dataset of 108 countries over the 2007-2018 period.

JEL Classification Numbers: D31, C63, H23, H24

Keywords: Income distribution, redistribution, progressivity, personal income tax

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[1] We thank Alejandro Badel, Romain Duval, Stefania Fabrizio, Alexander Klemm, Roland Kpodar, Li Liu, Paulo Mauro, Miguel Pecho, Dmitriy Rozhkov, Alexandra Solovyeva, Jean-François Wen and other colleagues for very helpful comments.

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I. INTRODUCTION

Of the two *raisons d'être* of government, addressing externalities and redistribution, the latter has come to the fore of policy analysis over the past decades. In advanced economies, combating inequality, including through redistribution, has been the subject of intense research and a related effort to compile, standardize and publish microdata on income and wealth. In emerging markets and low-income countries, following a long-held concern for absolute poverty reduction, the need to confront rising inequality has also taken center stage, albeit often with a much lower availability of consistent microdata. In all economies, the COVID-19 pandemic, and its adverse consequences on global and within-country income inequality[2], has contributed to make the issue more pressing still.

Because what matters must be accurately measured, quantifying the redistributive capacity of economic policies has therefore never been more important. This, however, involves more complexity (and data) than is often realized. Particularly, assessing the contribution of taxation to redistribution is more than merely measuring how fast tax rates rise with taxable income (or wealth) in the tax code. This is because effective redistribution is the result of the interplay of tax rates with the distribution of the taxable base among households. For example, raising or reducing the tax rate on an income bracket with few or no taxpayers will have limited or no impact on the redistributive power of the tax system. An identical tax schedule will likewise have different redistributive effects in countries (or years) with differing pre-tax distributions.

The literature on progressivity and redistribution measurement has long recognized this fact, proposing indices that are functions of the features of both tax policy and the taxable base distribution. For instance, the widely used Reynolds and Smolensky (1977) redistribution index is the difference between the Gini coefficients of respectively the pre- and post-tax distributions of income (or wealth). But if valid measurements of the redistribution effects of tax policies need to account for pre-tax distributions, how, then, can the analyst isolate and compare the respective intrinsic redistributive intentions, or *capacities*, of these policies across countries and years? Observe for example that if, in the extreme, the Gini coefficient of the taxable base is zero (a situation of perfect equality, where there is nothing left to redistribute), the Reynolds-Smolensky index is zero for *any* tax configuration. How do we disentangle the influence of the pre-tax distribution from the genuine redistributive capacity of taxation?

The literature has introduced procedures that make redistribution indices comparable, controlling for differences in pre-tax distributions. A key contribution in that respect is Dardanoni and Lambert (2002), which proposes to "transplant" tax regimes into a common base with an identical pre-tax distribution, where they can be safely compared. A critical point, however, is that this procedure relies on consistent and comparable household-level microdata of income – a challenge in many emerging economies and low-income countries.

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[2] See International Monetary Fund (2021).

With a focus on applicability in environments with limited data availability, this paper introduces a simplified implementation of the transplant-and-compare method. It is assumed that the only information on the pre-tax income distribution available in each country-year is the Gini coefficient and the mean. which are then used to generate simulated microdata. This implementation makes it possible to derive meaningful comparisons of redistributive capacities across more countries and years, and with lower computational complexity. Just like the original transplant-and-compare procedure, it equally applies to transfer policies[3].

We illustrate the technique with an application to the personal income tax (PIT), using a dataset of PIT characteristics covering 108 countries over the 2007-2018 period. Our main results are as follows. First, contrasting redistribution indices based on our simplified approach with the same indices based on household-level microdata for the sub-set of countries-years where it is available, we report that the two sets of indices are strongly correlated. This lends some degree of confidence that a simulated-data approach provides valid redistribution measurements when microdata is missing or cannot be used. Second, we use our large sample of countries-years to revisit the issue of whether the redistributive capacity of the PIT is correlated to pre-tax inequality, searching for a possible "Robin-Hood" paradox[4] – a common theme in the income redistribution literature. An application of transplant-and-compare indices to this question is especially relevant since not adjusting for differences in pre-tax distributions leads to overestimating the correlation between pre-tax Gini coefficients and redistribution capacities. We report no evidence of a Robin-Hood paradox, even with our adjusted indices. Finally, we examine the redistribution capacity of the PIT across country groups (low-income developing countries (LIDCs), emerging market economies (EMEs), advanced economies (AEs)) and time, and its decomposition into its progressivity and policy size components.

The next section reviews the literature on the measurement of the redistributive capacity of tax policy. Section III presents the proposed simulation-based technique. Section IV reports on an application to the PIT. Section V concludes.

II. MEASURING THE REDISTRIBUTIVE EFFECT OF TAX POLICY

A. Progressivity and Redistribution Indices

The standard indices of progressivity and redistribution found in the literature, which will be used throughout the paper, are defined below.[5] For an arbitrary country-year *i*, denote X_i the

[3] In the rest of the paper, we refer to income taxation for simplicity of exposition but unless otherwise indicated all results apply to transfers as well as wealth taxation (and the related wealth inequality).

[4] The so-called Robin Hood paradox refers to the proclivity of countries (especially advanced democracies) with low levels of inequality to redistribute more, while countries with high levels of inequality tend to redistribute less (Keen and Broadway 2000).

[5] See Lambert, Nesbakken, and Thoresen (2010) for a review of progressivity and redistribution indices, and for how other common indices are similarly not robust to variations in pre-tax distributions.

pre-tax income[6] distribution. $N(.)$ is a tax schedule mapping x, a value of X_i, into final income $N_i(x) = x - t_i(x)$, where $t_i(x)$ is the tax liability. Following Dardanoni and Lamber (2002), the tax regime in *i* is noted $\langle N_i(.), X_i \rangle$, emphasizing that it is composed of a tax schedule (a mapping) and a pre-tax distribution.

Noting $N_i(X_i)$ the post-tax distribution, the Reynolds-Smolensky[7] index of redistributive power is formally defined as:

$$R_i \equiv G_{X_i} - G_{N_i(X_i)}, \tag{1}$$

where the Gini coefficient of any distribution *Z* is noted G_Z. R_i is a global measure in that it synthetizes the redistributive power of a tax policy over the entire income distribution. Other indicators, such as the residual progression, are local, measuring redistribution for a given level of income[8]. Because this paper is concerned with comparing and ranking policies across countries-years, we use global measures.

Next, the Kakwani progressivity index (Kakwani 1977) is defined as, again, the difference of two Gini coefficients, this time of respectively pre-tax income and tax liabilities:

$$P_i \equiv G_{T_i(X_i)} - G_{X_i}, \tag{2}$$

where $T_i(X_i) = X_i - N_i(X_i)$. Here, the intuition is that any distribution of taxes which is more unequal than the distribution of the taxable base will contribute to redistribution and is therefore deemed progressive.

A nice property of R_i is that it can be decomposed into its progressivity and size components as $R_i = \frac{\tau_i}{1-\tau_i} P_i$, where τ_i is the aggregate average tax rate (the ratio of the mean tax over the mean pre-tax income, also measured as tax revenue over GDP) and where the term $\frac{\tau_i}{1-\tau_i}$ can be interpreted as the *policy size* component[9].

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[6] We use the term "pre-tax income" interchangeably with the term "market income" as defined in Solt (2021). This is income before income tax and transfers but including private transfers and private pensions. This definition follows the LIS standard (LIS 2016).

[7] Also referred to as the Musgrave-Thin index (Musgrave and Thin 1948).

[8] The residual progression is the elasticity of post-tax income with respect to pre-tax income (Dardanoni and Lambert 2002).

[9] See Appendix I.

For our purposes, the important point is that these indices depend on the pre-tax income distribution X_i, as made clear in expressions (1) and (2). Specifically, a more spread pre-tax distribution mechanically strengthens the equalizing effect of an unchanged policy configuration, and vice-versa (Immervoll and Richardson 2011). Note that this also applies to indices normalized by G_{X_i}, such as the Pechman and Okner (1974) index of relative redistributive power, $\frac{G_{X_i} - G_{N_i(X_i)}}{G_{X_i}}$[10].

B. Correcting for Differences in Pre-Tax Distributions

Standard measurements of progressivity and redistribution thus reflect both tax policy and the pre-tax income distribution. This is perfectly appropriate, and no further adjustment is needed if the analyst's objective is to measure or simulate the actual Gini coefficient change caused by tax policy in a specific country and period (as captured by R_i). However, if the objective is to compare intrinsic redistributive capacities, correcting for the pre-tax distribution in each economy is warranted. Observe that this is especially important if these indices are to be used as (exogenous) explanatory variables in cross-section or panel studies.

The literature has proposed several corrections. A first approach is the so-called "fixed-income" method, where an identical pre-tax distribution is assumed across time and countries. Norregaard (1990) applies the German income distribution to all other OECD countries to compare the progressivity of their respective tax systems. In the same spirit, Kasten, Sammartino, and Toder (1994) uses the US pre-tax income distribution for a specific year to evaluate federal income tax reforms (comparing progressivity before and after the reforms). Gerber et al. (2020) belongs to this strand of the literature. These authors use an identical parametric distribution of income (the uniform distribution, calibrated on each country-year's GDP per capita) to estimate the progressive capacity of the PIT in OECD countries. A well understood limitation of the fixed-income method is, however, that the resulting progressivity and redistribution rankings are not robust to the choice of the specific fixed distribution (Dardanoni and Lambert 2002; Lambert, Nesbakken, and Thoresen 2020). Because, again, redistribution measurements reflect the interplay of the tax schedule and the distribution the taxable base, it follows that an arbitrary fixed pre-tax distribution may, or may not, produce more, or less, progressive indices in any given country-year.

The second approach found in the literature, the so-called "transplant-and-compare" method, follows the seminal contribution of Dardanoni and Lambert (2002). Under this procedure, pre-

[10] Deviating from these standard indices, some assessments of progressivity are based on the features of tax policy alone. For instance, Peter, Buttrick, and Duncan (2010) regresses the average (or marginal) PIT rate on taxable income (as given in the tax code alone) and treats the resulting coefficient as an index of progressivity. While possible, this notion of progressivity ignores the fact that ultimately the redistributive effect of taxation depends on the distribution of the taxable base. Tax policies with an identical value of this index have differing values of the standard progressivity and redistribution indices when applied to different pre-tax distributions.

tax distributions and the associated tax schedules are *transplanted* into a "common base" where valid comparisons of the standard progressivity and redistribution indices can be made. Dardanoni and Lambert (2002) shows that this method produces robust, unbiased rankings of these indices, independently from respective pre-tax distributions. This approach has been implemented in a number of comparative studies of tax regimes and reforms (Förster and Tóth 2015; Thoresen, Jia, and Lambert 2016; Lambert, Nesbakken, and Thoresen 2020; Lambert and Thoresen 2009). Yet, it entails a complex and data-intensive process as we detail in the next section.

Finally, it is important to note that there is a second source of bias in the measurement of redistributive effects of tax policies: the reverse influence of taxation on pre-tax income distributions, most notably through its (partial or general equilibrium) influence on labor supply (Keen and Broadway 2000; Piketty and Saez 2013; Thoresen, Jia, and Lambert 2016; Badel, Huggett, and Luo 2020). This endogenous response of the pre-tax distribution is not addressed here; we therefore assume an inelastic tax base. This assumption is of course consistent with our emphasis on ease of applicability, but it is also used in many international studies of progressivity ((Causa and Hermansen 2019; Gerber et al. 2020), as well as in past implementations of the transplant-and-compare method (Dardanoni and Lambert 2002; Thoresen, Jia, and Lambert 2016). This caveat should nevertheless be borne in mind.

III. A SIMPLIFIED IMPLEMENTATION OF THE TRANSPLANT-AND-COMPARE METHOD

A. The Transplant-and-Compare Mechanics[11]

Let us start by defining what "transplantation" means in this context. Consider a real function $g(.)$ of $\mathbb{R}^+$ into $\mathbb{R}^+$ and think of it as the transplantation function. A tax regime $\langle N_i(.), X_i \rangle$ is said to be transplanted through $g(.)$ into $\langle N_i^g(.), X_i^g \rangle$ if $X_i^g = g(X_i)$ and if $N_i^g(.)$ maps every $g(x_i)$ into $g(N_i(x_i))$. In other words, if the original tax schedule $N_i(.)$ maps pre-tax income x_i into post-tax income $N_i(x_i) = y_i$, the transplanted tax schedule $N_i^g(.)$ is defined as a mapping of the transplanted pre-tax income $g(x_i)$ into $g(y_i)$.

Equipped with this definition and given two arbitrary tax regimes $\langle N_1(.), X_1 \rangle$ and $\langle N_2(.), X_2 \rangle$, the key result from Dardanoni and Lambert (2002) is that if an iso-elastic transplantation $g(x) = Ax^B$, $A, B > 0$, such that $g(X_1) = X_2$ can be found, then rankings of Lorenz curve-based progressivity and redistribution indexes (such as (1) and (2) above) of the transplanted tax schedule $N_1^g(.)$ and $N_2(.)$ hold for any arbitrary pre-tax distribution X. In practice, this means that if one can identify iso-elastic transformations of pre-tax distributions into one

[11] This section draws on Dardanoni and Lambert (2002).

another, tax regimes can be transplanted into a "common base" where robust, unbiased progressivity and redistribution indices can be compared.

A particularly simple situation is when all pre-tax distributions are (or can be approximated as) lognormal.[12] In this case, a convenient procedure is to transplant all regimes into a common base where the pre-tax distribution is the standard lognormal distribution. Specifically, if X_i is lognormally distributed for any regime *i*, $\ln x_i$ can be transformed into $a_i + b_i \ln x_i$ where a_i and b_i satisfy $a_i + b_i \lambda_i = 0$ and $b_i \sigma_i = 1$, with λ_i and σ_i respectively the scale and shape parameters of X_i. With these steps, $a_i + b_i \ln x_i$ follows the standard normal distribution. Exponentializing, the transformation of the pre-tax income distribution X_i is $g_i(x_i) = e^{a_i} x_i^{b_i}$. The tax schedule $N_i(.)$ is then transplanted by applying the same transformation $g_i(.)$ to $y_i = N_i(x_i)$. After this procedure, each regime $\langle N_i(.), X_i \rangle$ has been transplanted into a (standardized) common base, where progressivity and redistribution indices can be reliably computed and compared.

In the original Dardanoni and Lambert (2002) study as well as in subsequent implementations (Lambert and Thoresen 2009; Lambert, Nesbakken, and Thoresen 2010; 2020), the transplant-and-compare procedure uses microdata. Normality of every $\ln x_i$ is tested and, if verified, the corresponding regime is transplanted as shown above. In the more general case where lognormality of each individual pre-tax income distribution is not necessarily ascertained, each $\ln x_i$ is regressed (using simple OLS) on a reference regime's pre-tax or -transfer distribution[13] to assess the existence of an iso-elastic transformation. This is a regression in the form $\ln x_j = a_i + b_i \ln x_i$ where *j* is the reference regime.[14] If the goodness-of-fit of regressions is deemed adequate, each regime $\langle N_i(.), X_i \rangle$ is transplanted into the reference regime using the estimated iso-elastic transformation $g_i(x) = e^{a_i} x^{b_i}$.

B. Using Parametric Distributions of Pre-Tax Income

To reduce the data requirements and complexity of the standard transplant-and-compare procedure, we borrow the idea of using parametric distributions of pre-tax income from Gerber et al. (2020). While these authors employ a uniform distribution, the lognormal is the natural

[12] Recall that all lognormal distributions are iso-elastic transformations of one another.

[13] Chosen among the tax regimes be compared. For example, Lambert, Nesbakken, and Thoresen (2020) use Denmark, 2010.

[14] In practice, quantiles $x_i(p)$ and $x_j(p)$ are formed at rank $p \in [0,1[$ and OLS is used on the equation $\ln x_j(p) = a_i + b_i \ln x_i(p)$, where an observation is a quantile. There should be an equal number of quantiles in each distribution (see Dardanoni and Lambert (2002), footnote 23).

choice here as it is embedded in the simplest implementation of the transplant-and-compare method. Again, a lognormal distribution is an iso-elastic transformation of any other lognormal distribution. The lognormal specification has other benefits too. It is a long-standing workhorse of income distribution modeling and has proven reasonably effective in approximating empirical data in many contexts (Duangkamon Chotikapanich 2008; Pinkovskiy and Sala-i-Martin 2009). In contrast with the uniform distribution, it is not bounded from above, making it easier to capture features of the tax policy for high incomes. Finally, and conveniently for our purposes, it is a two-parameter distribution. For a given country-year i, its shape (λ_i) and scale (σ_i) parameters can be calibrated on observed Gini coefficients and means of pre-tax income[15]. Transplanting a tax regime $\langle N_i(.), X_i \rangle$ into a (standardized) common based is then straightforward, as shown above. These lower data requirements make it possible to implement the (simplified) transplant-and-compare procedure in many more situations. Gini coefficients of pre-tax market income are now available for many countries and years; mean pre-tax income can be approximated as GDP per capita (see below, Data).

This simplicity clearly rests on the assumption that a lognormal specification is an acceptable approximation for our purposes. A well-known limitation is that the lognormal distribution is often not the best fit for the highest incomes (Badel, Huggett, and Luo 2020; Duangkamon Chotikapanich 2008); if the interest of the analyst is focused on progressivity and redistribution in the highest income tranches, the parametric lognormal approach could therefore be suboptimal. However, if microdata availability and computational costs are a constraint, we submit that using a parametric transplant-and-compare approach is a better option than redistribution indices unadjusted for differences in pre-tax income distributions (or no pre-tax distribution assumptions at all[16]), if the objective is to draw valid cross-section or panel comparisons. In addition, the relevance of lognormal-based indices can be tested on the sub-set of countries-years where microdata on pre-tax income is available, which we do below in our application to the PIT.

Lastly, other specifications could be considered. The Weibull, for example, is another two-parameter distribution that can be calibrated on a Gini coefficient and a mean. It has been used in income modeling (Duangkamon Chotikapanich 2008). Hybrid parametric distributions using the lognormal for the low- and middle-income segments and the Pareto for high incomes have been proposed, and more generally mixtures of distributions (Duangkamon Chotikapanich

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[15] The Gini coefficient of a lognormal distribution with shape parameter σ_i and scale parameter λ_i is $G_i = 2\Phi(\sigma_i / \sqrt{2}) - 1$, where $\Phi(.)$ is the cumulative of the standard normal distribution. Its mean is $\mu_i = \exp(\lambda_i + \sigma_i^2 / 2)$. Solving for σ_i and λ_i, the lognormal distribution can be calibrated on any Gini coefficient and mean.

[16] See footnote 10.

2008, chap. 5). Further research could shed light on the benefits on these alternatives. Observe, however, that the immediate simplicity of iso-elastic transformations across distributions, which is at the center of transplant-and-compare method, is a strong advantage of the lognormal specification.

C. A Simplified Step-by-Step Recapitulation

The steps of the proposed simplified implementation of the transplant-and-compare method are as follows, for each country-year i to be compared.

1. *Calibration*. Calibrate a lognormal parametric distribution based on the Gini coefficient and mean of pre-tax income (proxied by GDP per capita), solving for the shape parameter σ_i and scale parameter λ_i (footnote 15).
2. *Simulation*. (a) Generate 10,000 (or more) simulated taxpayers each with pre-tax income randomly drawn from the calibrated lognormal distribution and obtain a simulated X_i. (b) For each simulated taxpayer, compute post-tax income based on known tax rules and obtain a simulated $N_i(X_i)$. The simulated tax regime $\langle N_i(.), X_i \rangle$ is available.
3. *Transplantation*. (a)Transplant $\langle N_i(.), X_i \rangle$ into the (standardized) common base by applying the iso-elastic transformation $g_i(x_i) = e^{a_i} x_i^{b_i}$ to X_i and $N_i(X_i)$, where a_i and b_i satisfy $a_i + b_i \lambda_i = 0$ and $b_i \sigma_i = 1$. (b) Compute transplanted taxes as $T_i^g = N_i^g(X_i^g) - X_i^g$.
4. *Comparison*. Using the 3 transplanted distributions X_i^g, $N_i^g(X_i^g)$ and T_i^g, compute the comparable indices P_i^g, τ_i^g, and R_i^g.

Note that nothing precludes a forward-looking analysis (typically, of tax reform scenarios). In that case, keeping with our assumption of an inelastic tax base, the latest Gini information in Step 1 is assumed to hold, unless additional information is available. In Step 2, policy changes are simulated.

IV. An Application: Redistributive Capacity of the PIT Around the World

A. Objective and Caveats

We apply this simplified transplant-and-compare strategy to the analysis of the redistributive and progressive capacity of the PIT worldwide.

Such a broad and systematic application of the procedure comes with several additional caveats and assumptions. First, as noted, this strategy rests on the assumption that a lognormal approximation is acceptable for the purpose of comparing the progressive and redistributive capacities of the PIT. As we report below, compare-and-transplant rankings based on full microdata are in fact strongly consistent with our simplified lognormal-based approach, suggesting that the exercise is meaningful in countries-years where the only option is to use a parametric approximation.

Second, a systematic compilation of PIT characteristics implies a simplification of actual tax rules in each country-year. Particularly, the concept of taxable income varies across countries (and sometimes years). Interest, dividends, capital gains and other types of capital income are often but not always taxed at flat, lower rates (see Figure 1 for capital gains and Figure 2 for business income). The Gini coefficients of pre-tax income and GDP per capita that we use include elements of capita income – whereas our database of PIT characteristics is on the taxation of "ordinary" income, in practice primarily employment (labor) income. Since capital income is typically more concentrated than labor income (Davies and Shorrocks 2000), our progressivity and redistribution indices will consequently be biased upwardly in those countries-years where it is taxed at lower rates than ordinary income.

Figure 1. Taxation of Capital Gains

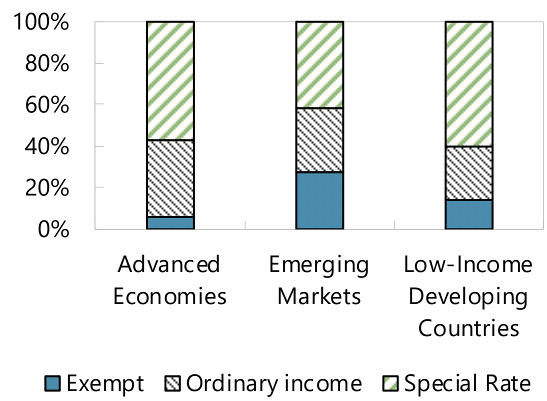
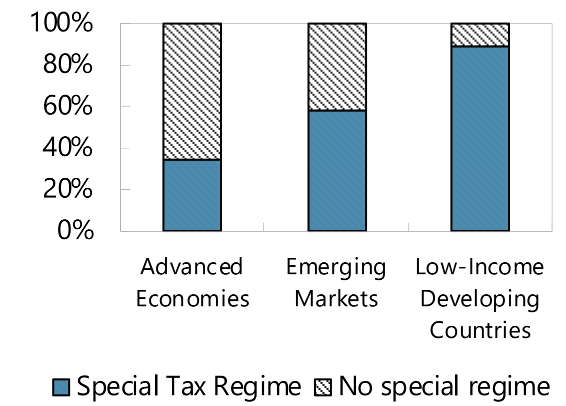


Figure 2. Special Tax Regimes for Unincorporated Business Income



Source: Benedek, Benítez and Vellutini (2021)
Note: for year 2019.

Third, the notion of a PIT tax unit (i.e., household or individual) varies across countries and here again, some simplification is unavoidable. The Gini coefficients that we use follow the standard practice of using equivalized individual income on a square root scale, along with other studies using the LIS microdata for progressivity analysis.[17] This assumption is embedded in our estimates and although it is not specific to this work, it does imply some approximation of

[17] See Lambert, Nesbakken, and Thoresen (2020). Dardanoni and Lambert (2002) uses a double-parametric formula that includes the number of children, following Katz and Cutler (1992).

situations where, for instance, the number of children plays a role in PIT determination (such as France).

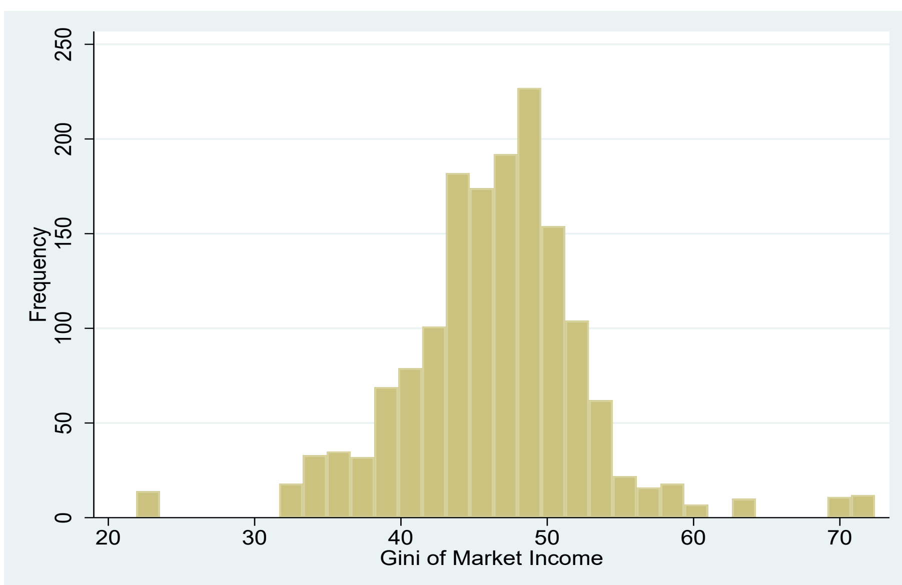
Finally, the analysis does not account for taxpayers' effective compliance or lack thereof (including informality, which is widespread in LIDCs), It only captures the redistributive power of the PIT as intended in tax codes. In that, it follows the standard methodology of separating policy analysis from policy implementation. However, the proposed approach could perfectly be applied to compliance-adjusted post-tax income distributions if the corresponding data is available[18].

B. Data

Gini Coefficients

The data on Gini coefficients of pre-tax income comes from the Standardized World Income Inequality Database version 9.1 (Solt 2021). The SWIID provides comparable Gini coefficients of pre-tax income distribution for 198 countries over the 1960-2020 period. Figure 3 shows the relatively spread distribution of the Gini coefficients of pre-tax (market) income, illustrating the benefits of adjusting progressivity and redistribution indices for differences in income distributions.

Figure 3. Distribution of Market Income Gini Coefficients



Source: SWIID 9.1

Notes: 157 countries, 2000-2019.

[18] This would imply the computation of compliance-adjusted post-tax incomes in Step 2 (Section III.C).

While widely used, the SWIID database is not without limitations (Atkinson and Bourguignon 2015). Many of the reported Gini coefficients are imputed, as data is missing for some years in many countries. The author, however, carefully reports standard errors for each country-year, enabling one to make informed decisions on whether and when to use the data. For example, the reported two standard error range for the Gini coefficient in Suriname for 2016 is 40–52 Gini points, arguably a wide range. In this study, we have excluded countries-years where the two standard error range is above 10 Gini points.

Mean Income: GDP per Capita

GDP per capita is used as an approximation of the mean of pre-tax income. In the specific case of our implementation on the PIT, we have reconstructed GDPs per capita denominated in original local currency units from the archives of the IMF's World Economic Outlook. This step was necessary as several countries have changed the denomination of their currency over the period, typically by dropping 3 or more zeros from their currency unit (e.g., Zimbabwe, Argentina). In such a situation, statisticians (correctly) adjust the GDP series backward, with the problematic consequence for our purposes that the adjusted data is inconsistent with the historical currency denominations of PIT characteristics (thresholds, allowances, and credits) in the years before the change.

PIT Characteristics

A dataset of PIT design characteristics (rates, thresholds, deductions, standard allowances and credits) has been tabulated from EY's historical Worldwide Personal Tax Guides and the IBFD database.[19] Combined with the availability of Gini coefficients and GDP per capita data, the countries and periods included in the dataset are reported in Table 1.

[19] This is the dataset used in Benedek, Benítez, and Vellutini (2021).

Table 1. Structure of the Dataset by Country Group

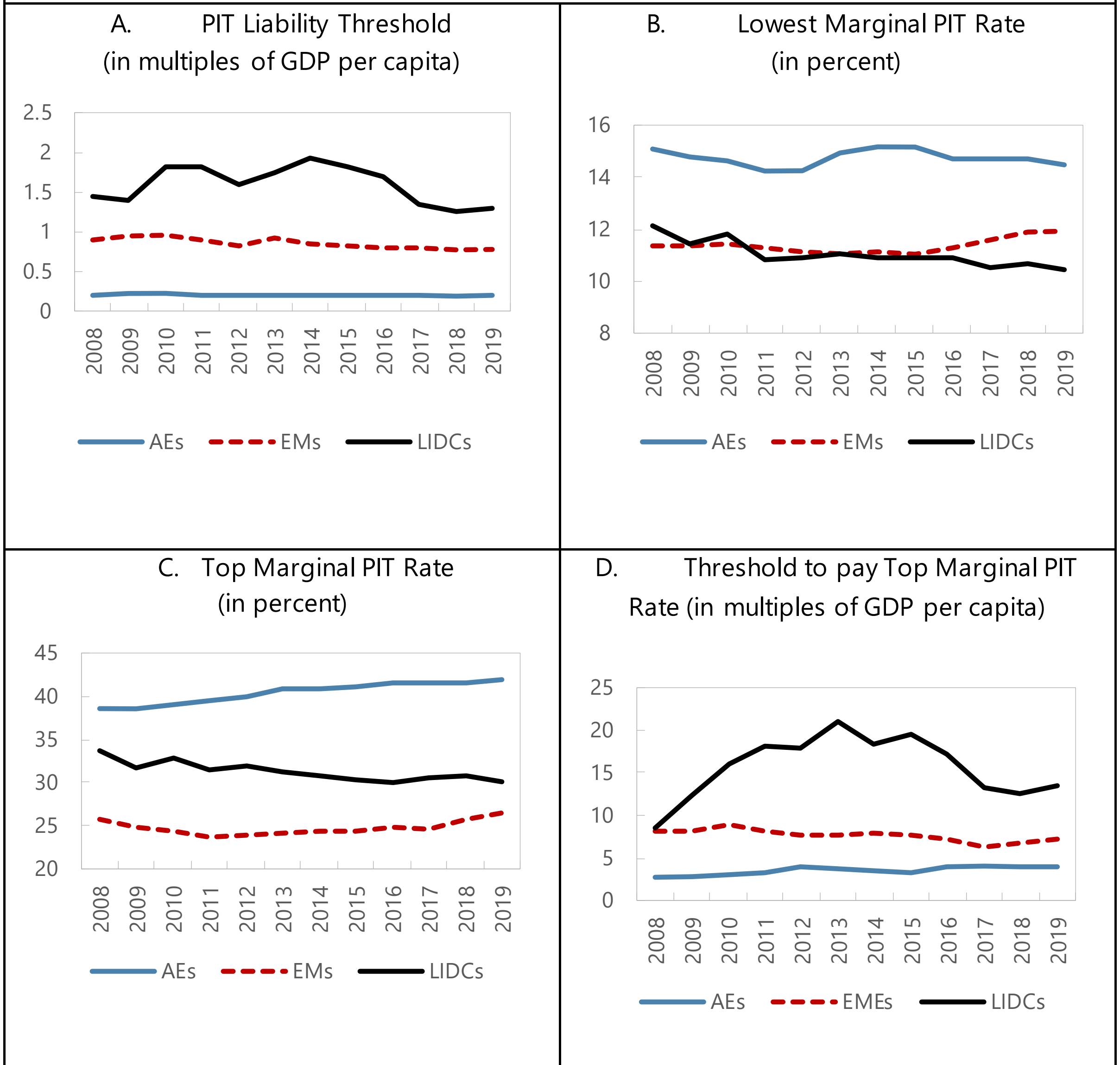
Year	Country Group			
	LIDCs	EMEs	AEs	Total
2007	23	50	35	108
2008	23	54	35	112
2009	23	55	35	113
2010	25	61	35	121
2011	27	60	35	122
2012	26	57	35	118
2013	28	61	35	124
2014	32	66	35	133
2015	33	66	35	134
2016	34	67	35	136
2017	43	74	35	152
2018	43	75	35	153

Source: Authors' computations

Figure 4 presents a summary of key PIT rates and thresholds over the period. These characteristics can be discussed in terms of their expected impact on redistributive capacity – and these expectations are in fact remarkably ambivalent. The influence of the bottom threshold, or the liability threshold[20] (Panel A), on redistribution is generally ambiguous: while lowering that threshold has a negative effect on progressivity as defined above, it has a positive effect on the aggregate tax rate τ – making the overall effect on redistribution theoretically undetermined (depending on how that threshold interacts with the pre-tax distribution). In LIDCs specifically the liability threshold has been historically high, as shown in Panel A, often excluding middle-high incomes from taxation and concentrating on a relatively small group of high-income earners in the formal sector (Benedek, Benítez, and Vellutini Forthcoming). This has not only affected the revenue potential of the PIT, but has also undermined, if not its progressivity, its redistributive power (Clements et al. 2015). It is therefore plausible that the downward trend of the liability threshold in LIDCs be associated with more redistributive capacity (and, theoretically, with an increase in revenue). The lowest statutory rate (Panel B) has decreased as well in LIDCs, which also has an ambiguous effect on progressivity (as it depends on the liability threshold) but always reduces τ; again, we have an ambiguous total effect on redistribution. A diminishing the top statutory rate (Panel C) in LIDCs also contributes to a lower τ but has an ambiguous effect on progressivity – similarly depending on how the top threshold (Panel D) interacts with pre-tax distributions. These observations confirm the importance of empirical computations of progressivity and redistribution indices that account for distributions of the taxable base.

[20] This is the minimum income below which no PIT is due.

Figure 4. Features of the PIT



Source: Benedek, Benítez and Vellutini (2021)

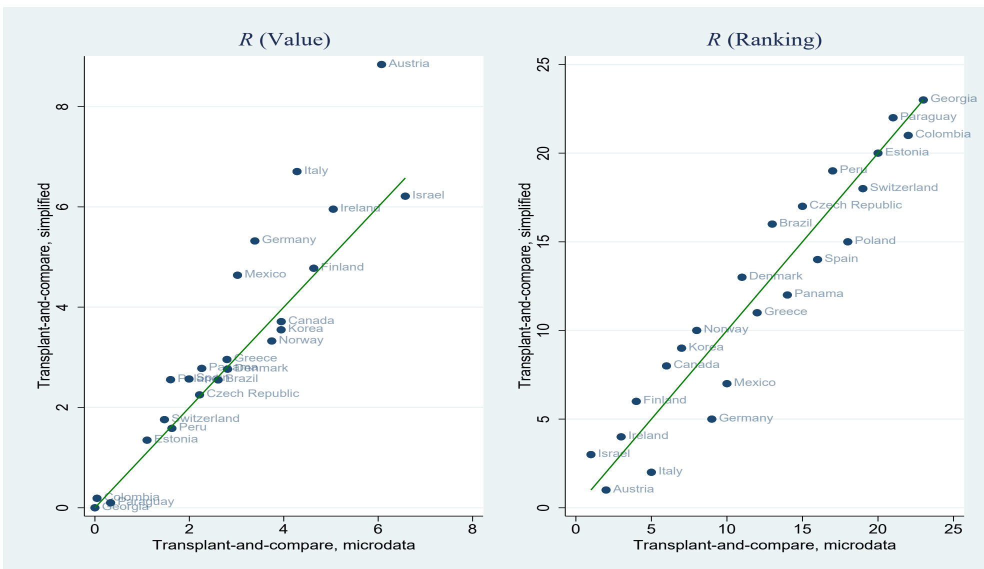
Note: Unweighted averages.

C. Results

Contrasting Simulation-Based and Microdata-Based Indices

Figure 5 reports results from a comparison of our simplified approach to transplant-and-compare[21] with the microdata-based implementation of the procedure, for the 23 countries where LIS income data is available for the year 2016 (LIS 2016). The left panel shows that the simplified Reynolds-Smolensky *R* index is close to its microdata counterpart in most cases, with a correlation coefficient of 0.922. The implied rankings are similarly close (with a 0.925 correlation coefficient), but they are not identical. These results suggest that a simplified approach is useful where and when it is the only option – but that using actual microdata if available does make a difference. Tests on the logarithm of pre-tax income in the microdata reject normality in all 23 countries at standard levels of significance[22], suggesting that errors between the two sets of indices are at least partly related to the lognormal approximation.

Figure 5. PIT Transplant-and-Compare Indices, Simplified vs Microdata



Sources: authors' calculations, LIS (Wave X), IMF, EY, SWIID 9.1.

Notes: For year 2016. In the microdata-based computation, Italy is the reference country. Green lines are the 45-degree diagonals.

Is There a PIT "Robin Hood" Paradox?

But just how quantitatively important is correcting for differences in pre-tax distributions? An example of a policy question where not correcting would seem particularly problematic is the analysis of the so-called "Robin Hood" effect – do countries with more initial inequality

[21] Using data on Gini coefficients and GDP as described above – not Gini coefficients and means from the LIS microdata.

[22] The full OLS method was therefore implemented.

implement more redistributive policies?[23] As noted, we have reasons to think that unadjusted measurements overestimate the association between pre-tax income Gini coefficients and redistribution indices. Column (1) in Table 2 reports results from a pooled regression of the unadjusted redistribution index *R*[24] explained by the pre-tax Gini coefficient, on the full sample. This regression suggests no Robin Hood paradox: the coefficient on the pre-tax Gini coefficient is positive and significant at the 1 percent level; the more unequal pre-tax income, the more redistributive PIT. Column (2) shows results using our transplant-and-compare redistribution indices, now controlling for the bias in the measurement of *R*. The absence of a Robin Hood paradox is again verified, but with a much smaller coefficient and at lower level of statistical significance. Columns (3) and (4) show the same regressions controlling for GDP per capita, with essentially the same differences. Estimations not reported here similarly show that this holds in each of the three country groups (LIDCs, EMEs and AEs) taken separately. The

takeaway from these results is that correcting from differences in pre-tax dispersions does matter, but even when doing so there is no evidence of a Robin Hood paradox.

Table 2. PIT Redistribution and Pre-tax income Inequality

VARIABLES	(1) *R* Unadjusted Pooled	(2) *R* Transplant-and-compare Pooled	(3) *R* Unadjusted Pooled	(4) *R* Transplant-and-compare Pooled
Gini pre-tax income	0.0914***	0.0555**	0.0774***	0.0404**
	(0.0184)	(0.0228)	(0.0139)	(0.0167)
GDP per capita			5.33e-05***	5.67e-05***
			(1.05e-05)	(1.13e-05)
Constant	-1.617**	0.290	-1.900***	-0.00817
	(0.811)	(1.042)	(0.610)	(0.773)
Observations	1,364	1,364	1,356	1,356
R-squared	0.091	0.030	0.388	0.332

Standard errors in parentheses

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

Sources: authors' calculations, IMF, EY, SWIID 9.1

Notes: Regressions over 108 countries, 2007-2018, with cluster-robust standard errors. GDP per capita in constant 2010 USD.

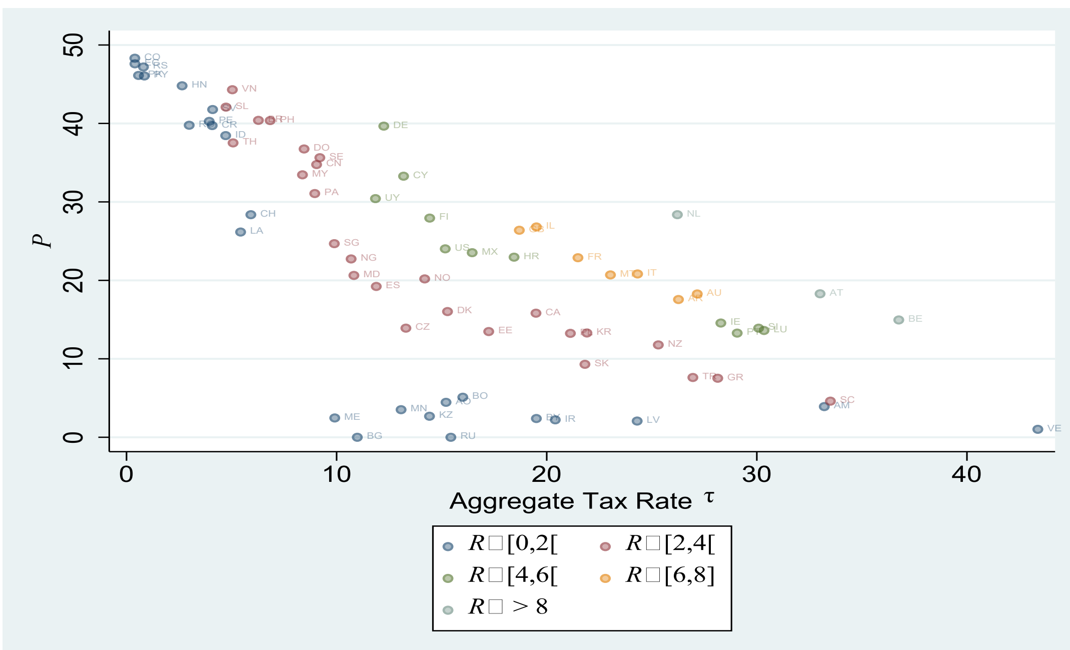
[23] The literature on redistribution has long debated the empirical validity of a Robin Hood effect or, on the contrary, paradox (Persson 1995; Bénabou 1996; Lindert 2004). Lambert, Nesbakken, and Thoresen (2010) examine the issue on a subset on OECD countries with the aid of a transplant-and-compare procedure to measure redistributive capacity independently from initial income dispersions. They find a weak positive relationship of redistribution with pre-tax income inequality, neither supporting a Robin Hood effect nor a Robin Hood paradox.

[24] The unadjusted *R* is computed ommitting the transplantation step of the proposed procedure (Section III.C).

Lessons from the Kakwani Decomposition

Our adjusted indices computed over a large number of countries are also useful to analyze general charateristics of the redistributive capacity of the PIT wordwide. For each country in our sample, Figure 6 displays the Kakwani decomposition for 2018 (the last year of our sample), illustrating the interplay of the PIT's progressive capacity with its size (driven by τ, the aggregate tax rate) and showing that there are multiple ways to achieve a given redistributive capacity[25]. This is particularly clear in the range $R \in [2, 4[$, where there is is a wide variation of progressivity and aggregate tax rates, all leading to similar redistributive capacities. A lesson from this analysis is that it is important for policy advisers to rely on a clear diagnostic on the drivers of PIT redistribution in a given economy – progressivity or policy size? – in order to offer relevant advice on how to improve it.

Figure 6. PIT Redistributive Capacity as a Function of Progressive Capacity and the Aggregate Tax Rate
(In percent)



Sources: authors' calculations, IMF, EY, SWIID 9.1

Notes: Transplant-and-compare Indicators for 2018. Each point represents a country.

The Kakwani decomposition is examined by country group and through time in Figure 7. The upper left panel shows that the trend of progressive capacity in AEs and EMEs has been downwardly in the recent period – much in accordance with recent studies using different methodologies (Gerber et al. 2020). Despite a slightly increasing aggregate average tax rate

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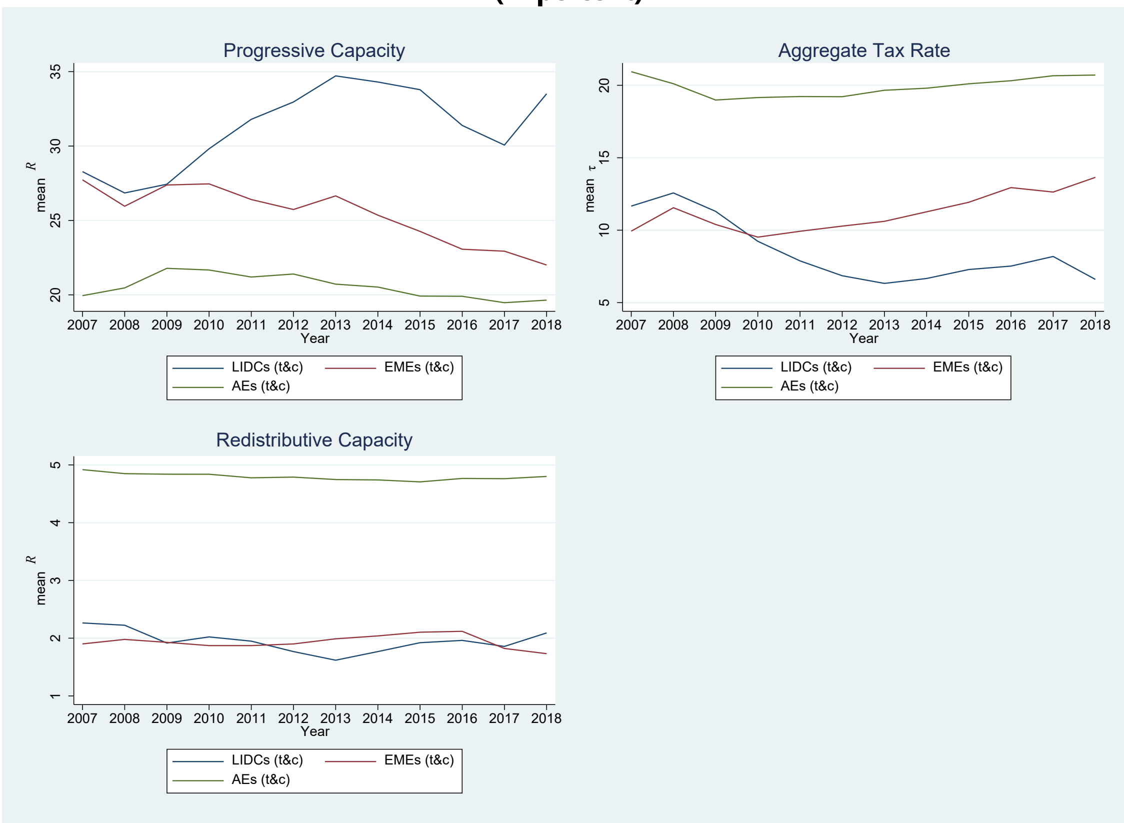
[25] Individual indices are given in Appendix II.

(upper right panel), the redistributive capacity (lower left panel) is either stagnant (AEs) or decreasing in recent years (EMEs).

Figure 7. Average PIT Progressive and Redistributive Capacities by Country Group (In percent)



Sources: authors' calculations, IMF, EY, SWIID 9.1

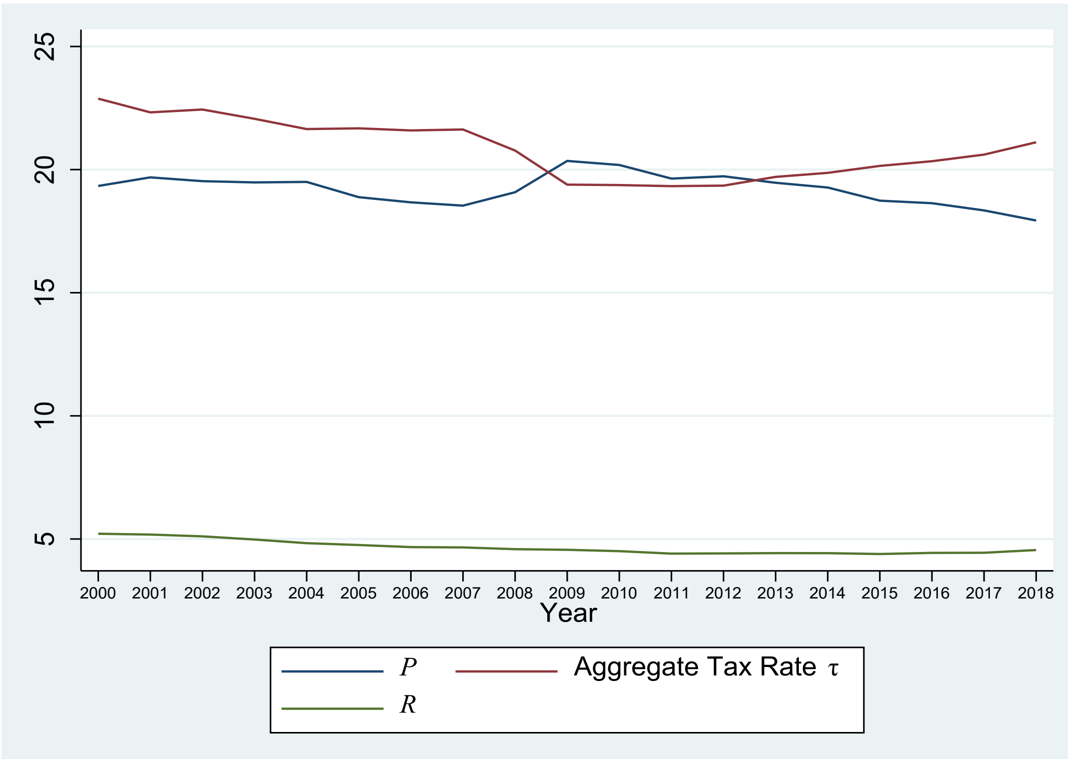
Note: Unweighted averages of transplant-and-compare indicators.

Turning to LIDCs, it is observed that the low and declining aggregate tax rate (upper right panel) is the key driver of the relatively low redistributive capacity in these countries (lower left panel), which is broadly consistent with the evolution of the bottom and top PIT rates reported above (Figure 4). Notice that at about 2 Gini points this redistributive capacity is low but far from negligible and is in fact close to what the EME country group achieves. Again, this is an interesting finding for the applied policy analyst: more than the (ascertained) progressivity of PIT schedules, this result suggests that it is the aggregate tax rate that matters in many LIDCs. This is consistent with what we know of that country group: PIT is often unequivocally progressive since it is only levied on a small group of, mostly, high income individuals; but these taxpayers pay a low average tax rate, which in turn results in a low, but not negligible, redistributive capacity.

Finally, Figure 8 focuses on OECD countries (with a longer time series), where similar trends as reported for AEs generally. Progressive capacity is declining while the aggregate tax rate is almost flat, leading to slightly diminishing redistributive capacity over time.

Figure 8. Average Progressive and Redistributive Capacities in the OECD

(In percent)



Sources: authors' calculations, IMF, EY, SWIID 9.1

Note: Unweighted averages of transplant-and-compare indicators.

V. Conclusions

Building on the transplant-and-compare method, we have presented a simulation-based technique to produce indices of progressive and redistributive capacities of tax policy adjusted for differences in pre-tax income distributions, allowing for meaningful international and intertemporal comparisons. Because it uses aggregate information on the shape and scale of the pre-tax distribution which is often available (namely, Gini coefficients of pre-tax income and GDP per capita), this approach can be implemented in countries where microdata is otherwise missing or cannot be used. While the paper focuses on income taxes, the technique can be similarly applied to transfers and wealth taxes.

Using a sample of 108 countries over the 2007-2018 period, we have illustrated the approach with an analysis of the redistributive capacity of the PIT worldwide. We first find that even controlling for differences in pre-tax distributions, there is no evidence of a cross-country

"Robin-Hood" paradox – countries with more income inequality do tend to implement more redistributive PITs. We also find that the size of the PIT (as measured by its aggregate tax rate, or the ratio of revenue over GDP) is more of a constraint to redistribution in many LIDCs than the progressivity of tax rates and schedules, suggesting that developing the right diagnostic of the true drivers of redistributive capacity matters to applied policy work in specific country situations.

It is hoped that this technique can be of use to policy analysts wishing to benchmark the redistributive capacity of tax (or transfer) policies and reforms, especially when microdata is not available.

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Appendix I. The Kakwani Decomposition

As shown by Kakwani (1977), R_i can be decomposed into its size and progressivity components. Noting the means of pre-tax income and taxes as μ_{X_i} and μ_{T_i}, and the aggregate tax rate as $\tau_i \equiv \frac{\mu_{T_i}}{\mu_{X_i}}$, the Kakwani decomposition reads as:

$$R_i = \frac{\tau_i}{1-\tau_i} P_i$$

This expression shows that the global redistributive power of tax policy depends not only on progressivity P_i but also on a multiplicative term $\frac{\tau_i}{1-\tau_i}$ which is increasing in the aggregate tax rate τ_i. That term is the amplitude, or size, of tax policy. The Kakwani decomposition captures the simple fact that the redistributive power of taxation depends not only on the progressivity of tax schedules and rates, but also on total tax collection as a proportion of aggregate income.

This decomposition assumes no income reranking, which is appropriate for any tax policy where the marginal tax rate is below unity (which is empirically always the case, excluding rare pathological situations), but may not hold for transfers. Extending the Kakwani decomposition to include a reranking term is straightforward (Kakwani 1984; Vellutini 2021).

Appendix II. Progressive and Redistributive Capacities of the PIT

(2018, in percent)

Country	ISO Code	Progressive Capacity (*P*)	Aggregate Tax Rate (τ)	Redistributive Capacity (*R*)
Netherlands	NL	28.70	25.80	9.98
Austria	AT	18.34	32.84	8.97
Belgium	BE	14.85	36.93	8.69
Australia	AU	18.23	27.29	6.84
Italy	IT	20.87	24.38	6.73
Israel	IL	26.56	19.19	6.31
Argentina	AR	17.67	26.22	6.28
Malta	MT	20.03	23.70	6.22
France	FR	22.78	21.29	6.16
United Kingdom	GB	26.28	18.54	5.98
Luxembourg	LU	13.70	30.20	5.93
Slovenia	SI	13.77	30.01	5.90
Ireland	IE	14.44	28.38	5.72
Germany	DE	39.08	12.35	5.51
Portugal	PT	13.13	28.63	5.27
Croatia	HR	23.15	18.15	5.13
Cyprus	CY	34.44	12.94	5.12
Finland	FI	27.55	14.49	4.67
Mexico	MX	23.48	16.19	4.54
United States	US	23.76	15.21	4.26
Uruguay	UY	30.53	11.61	4.01
New Zealand	NZ	11.68	25.54	4.01
Canada	CA	15.80	19.32	3.78
Korea	KR	13.28	22.01	3.75
Sweden	SE	35.31	9.36	3.65
Poland	PL	13.16	21.24	3.55
Norway	NO	20.11	14.62	3.44
China	CN	34.50	9.07	3.44
Dominican Republic	DO	37.27	8.30	3.37
Greece	GR	7.61	28.23	2.99
Turkey	TR	7.86	27.38	2.96
Malaysia	MY	34.18	7.97	2.96
Denmark	DK	16.10	15.45	2.94
Panama	PA	31.58	8.51	2.94
Estonia	EE	13.84	17.09	2.85
Philippines	PH	41.30	6.33	2.79
Nigeria	NG	22.87	10.82	2.77
Brazil	BR	40.79	6.32	2.75
Singapore	SG	25.11	9.76	2.71
Spain	ES	19.33	11.80	2.59
Moldova	MD	21.06	10.73	2.53
Slovak Republic	SK	9.27	21.40	2.52
Vietnam	VN	43.82	5.26	2.43
Seychelles	SC	4.53	33.62	2.30
Sierra Leone	SL	41.79	5.03	2.21

Country	ISO Code	Progressive Capacity (*P*)	Aggregate Tax Rate (*τ*)	Redistributive Capacity (*R*)
Czech Republic	CZ	13.59	13.34	2.09
Thailand	TH	37.45	5.23	2.07
Armenia	AM	3.87	33.16	1.92
Indonesia	ID	38.60	4.69	1.90
El Salvador	SV	41.38	4.30	1.86
Switzerland	CH	28.60	5.79	1.76
Peru	PE	39.05	4.25	1.73
Costa Rica	CR	40.47	3.71	1.56
Lao P.D.R.	LA	26.21	5.43	1.50
Honduras	HN	44.79	2.84	1.31
Romania	RO	39.72	3.02	1.24
Bolivia	BO	5.04	16.00	0.96
Angola	AO	4.52	15.18	0.81
Venezuela	VE	1.00	43.40	0.77
Latvia	LV	2.03	24.31	0.65
Belarus	BY	2.41	19.52	0.59
Iran	IR	2.22	20.41	0.57
Mongolia	MN	3.55	13.05	0.53
Kazakhstan	KZ	2.70	14.40	0.45
Colombia	CO	46.80	0.84	0.40
Paraguay	PY	46.57	0.76	0.36
Serbia	RS	47.59	0.70	0.33
Montenegro, Rep. of	ME	2.48	9.92	0.27
Pakistan	PK	46.66	0.53	0.25
Ecuador	EC	47.30	0.50	0.24