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Assessing the Impact of Tax-Benefit Policies on Inequality of Opportunity: Evidence from Brazil and Peru

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Abstract

This paper evaluates how tax and transfer systems in Brazil and Peru affect equality of opportunity. Using detailed household data and tax–benefit microsimulation models, we decompose total income inequality into within-type and between-type components, where types are defined by predetermined circumstances such as parental background. We first measure inequality of opportunity in market incomes and then assess how much redistribution reduces it. The results show that existing fiscal systems achieve only modest reductions in overall inequality: the Gini coefficient falls by 0.02–0.08 points. Their impact on equality of opportunity is even smaller, with the between-types component declining by less than 0.01 Gini points in both countries. The paper also runs counterfactual simulations, including an analysis of the required redistribution to completely eradicate between-type inequality.

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1 Introduction

The equality of opportunity (EOp) approach has emerged as a prominent alternative framework to equality of outcomes for analyzing inequality and designing appropriate policy responses. According to this theory, differences in income arise from two broad sources: effort, which lies within an individual’s control, and circumstances, which are determined by factors beyond individual control. The normative premise is that income differences attributable to circumstances are unjust and should therefore be eliminated, whereas income differences that result from varying levels of effort may be considered acceptable. From a policy perspective, the EOp framework implies that redistributive action should primarily correct income differences that stem from unequal circumstances.

Empirically, research on equality of opportunity typically decomposes total inequality into the components associated with circumstances and with effort. Circumstances are commonly captured by parental background, ethnicity, or place of birth, whereas effort is proxied by choices such as educational attainment or labour supply. This literature has been extended to developing countries, with [Brunori et al. \(2023\)](#) providing influential syntheses of the evidence. However, existing studies generally do not examine how tax and benefit systems alter the extent of inequality that is attributable to circumstances—that is, how fiscal policy affects inequality between types, where types are defined by shared background characteristics.

This paper seeks to fill this gap. We first estimate the extent of inequality of opportunity in market incomes for two Latin American countries, Brazil and Peru. In a second step, we perform a similar decomposition for disposable incomes, allowing us to assess the extent to which taxation and income transfers reduce overall inequality and, crucially, inequality between types. In other words, we evaluate the extent to which redistribution of income (which reflects an *outcome* variable) contributes to improving equality of *opportunity*.

Brazil and Peru are particularly suitable case studies because detailed household microdata are available that allow for reliable estimation of taxes paid and benefits received. The data also allow us include information on parental background and other circumstances relevant for constructing EOp measures. Their tax-benefit policies also differ substantially, with Brazil representing a much more redistributive system. The paper can therefore highlight how well different institutional arrangements perform in reducing inequality of opportunity.

Having assessed the effects of the current fiscal systems on equality of opportunity, we then consider several counterfactual reforms. First, we conduct a policy swap exercise in which Peru is assumed to adopt the Brazilian tax and transfer system. This enables us to

evaluate whether Brazil’s more redistributive system would lead to improved equality of opportunity in a lower-income setting. Second, we present an example, a hypothetical new policy in Peru, which is tailor-made to address inequality of opportunity and assess its success and the associated fiscal costs. Third, we examine the amount of redistribution that would be required to fully eliminate inequality arising from differences in circumstances and compare this desirable benchmark with actual current redistribution. Methodologically, the paper relies on recently developed tax–benefit microsimulation models for Peru and Brazil. These models allow us to compute household- and individual-level taxes and transfers and to simulate the impacts of the hypothetical policy arrangements described above.

A substantial body of theoretical and empirical work forms the foundation of the equality of opportunity (EOp) approach. The formal structure of EOp was developed, among others, in the work of Roemer, with authoritative modern treatments provided by [Roemer and Trannoy \(2015\)](#) and [Roemer and Trannoy \(2016\)](#). These theoretical contributions are complemented by the welfare-economic foundations developed by [Fleurbaey and Maniquet \(2011\)](#). [Ferreira and Peragine \(2016\)](#) further synthesize how these concepts have been operationalized in empirical inequality research, also in low- and middle-income countries.

There are few earlier papers which examine the linkages between redistribution and equality of opportunity. [Almås et al. \(2011\)](#) propose experimental and normative approaches to distinguishing fair from unfair differences, and, in their empirical application for Norway, demonstrate study that both the pre-tax and the post-tax income distributions have become less fair in Norway. [Roemer et al. \(2003\)](#) provide a multi-country assessment of how different fiscal regimes equalize opportunities for income acquisition. [Dunnzlaff et al. \(2011\)](#) use EU-SILC data to calculate how redistribution affects one particular measure of EOp, the Gini Opportunity index, while [Jäntti et al. \(2026\)](#) offer a more recent analysis of the role of redistribution within the EU countries. In the Latin American context, however, evidence is still scarce. [Figueiredo and da Fonseca Silva \(2014\)](#) provide an evaluation of fairness of Latin American tax policies and find that taxation has a limited impact on equality of opportunity in the countries they study.

This paper contributes to the literature in the following ways. First, it is among the earliest studies to examine how existing tax and transfer systems reduce inequality of opportunity; to our knowledge, only one earlier Latin American study [Figueiredo and da Fonseca Silva \(2014\)](#) has explored this issue. Second, and in contrast to that work, we analyze how a broader set of reforms could attenuate inequality arising from circumstances. We also assess how much these countries ought to redistribute if the policy goal were to fully rectify between-types inequality.

The paper is structured as follows. Section 2 describes the data and explains how individuals are allocated to types based on their circumstances. Section 3 outlines the conceptual framework for decomposing inequality of opportunity and provides a summary of the institutional settings and fiscal architectures in Brazil and Peru. Section 4 presents the main findings on the extent to which current systems reduce inequality of opportunity. Section 5 reports the results of the counterfactual simulations, including the policy swap, comparisons between actual and required redistribution, and the effects of alternative tax–benefit proposals. Section 6 concludes.

2 Data, Measurement, and Modelling

Our empirical analysis relies on harmonized microdata from two nationally representative household surveys: the *Pesquisa Nacional por Amostra de Domicílios* (PNAD) for Brazil and the *Encuesta Nacional de Hogares* (ENAH) for Peru. These datasets provide the detailed micro-level data required to measure exogenous circumstances, capture intergenerational linkages, and observe labour market outcomes.

Crucially, both survey environments are integrated with tax-benefit microsimulation models—BRASMOD for Brazil and PERUMOD for Peru. This integration is essential for evaluating the redistributive impact of fiscal systems on inequality of opportunity. While standard survey data provides either only market or net income, the microsimulation models allow us to precisely compute direct taxes, social insurance contributions, and cash transfer entitlements, thereby constructing a harmonized post-tax-and-transfer (disposable) household income baseline. Incomes are subsequently adjusted using standard equivalence scales to ensure comparability.

We use tax-benefit microsimulation models for the two countries, BRASMOD (Bottega et al., 2024) and PERUMOD (Torres and Chang, 2025)¹. Both are arithmetic models, implying that they do not themselves contain behavioural reactions to policies. These models combine household level microdata and detailed modelling of most relevant direct tax and benefit policies, social security contributions, as well as several indirect taxes. In PERUMOD, social social protection policies, such as the FISE programme are simulated, as well as child benefits and old-age social assistance pensions. In BRASMOD, Bolsa Familia and several other cash benefits, such as Salario Familia and emergency benefits, are simulated. Both models have been used in prior research and they have also been benchmarked and compared with external macro data.

The models are used for calculating gross incomes from reported net incomes and

¹PERUMOD is part of the SOUTHMOD project of UNU-WIDER, see <https://www.wider.unu.edu/project/southmod-simulating-tax-and-benefit-policies-development-phase-3>

for simulating taxes and benefits. Both models utilize formality as information when simulating certain policies, e.g. mandatory social security contributions are only levied on formal workers. The models are also used for policy swap analysis to examine how the more redistributive Brazilian system would influence total inequality and inequality of opportunity in Peru as well as in counterfactual analysis in testing the potential role of not-yet existing policies.

2.1 Brazil: PNAD 2014

For the Brazilian context, our analysis is strictly confined to the 2014 wave of the PNAD.² A pervasive challenge in the empirical literature on inequality of opportunity is the accurate observation of parental background. Neither the standard PNAD nor the subsequent continuous surveys (*PNAD Contínua*) field retrospective questions regarding parents' education or occupation. In standard waves, parental background can only be inferred if the parents co-reside in the same household as the adult respondent—a constraint that introduces severe truncation bias by fundamentally over-representing younger adults and specific household structures.

To circumvent this limitation, we exploit the 2014 PNAD, which included a specialized supplement on Social Mobility and Education. This module directly asked respondents to recall their parents' highest level of education and primary occupation when the respondent was 15 years old. The presence of these retrospective variables makes the 2014 wave uniquely suited for our analysis, allowing for the direct and unbiased observation of parental background for the adult working-age population. Post-fiscal incomes for this cohort are simulated utilizing the BRASMOD framework.

2.2 Peru: ENAHO

For Peru, we utilize the 2014 and 2022 waves of ENAHO, administered by the National Institute of Statistics and Informatics (INEI). Unlike the standard Brazilian surveys, ENAHO consistently collects retrospective data on parental characteristics across multiple cross-sections. Furthermore, ENAHO explicitly records self-identified ethnicity, maternal language, and geographic origins, allowing us to deeply incorporate ethnic and spatial circumstances into the opportunity sets.

The selection of the 2014 and 2022 waves facilitates a comparative static analysis over nearly a decade, capturing structural economic shifts within the country. As direct information on taxes and contributory payments in ENAHO is incomplete, we apply the PERUMOD microsimulation model. This framework computes personal income taxes

²Summary statistics for the data for both countries are provided in Tables [A1](#) and [A2](#).

and entitlements from major social programs, such as *Juntos* and *Pensión 65*, ensuring our gross and net income concepts are strictly harmonized with the Brazilian sample.

2.3 Circumstances and Intergenerational Linkages

Following the established literature, we define circumstances as exogenous characteristics determined before individuals exercise meaningful economic agency. The vector of observed circumstances is selected based on theoretical relevance and strict data availability.

For the Peruvian cohort, the circumstance vector comprises four variables:

- **Parental education:** The highest educational attainment of the most educated parent.
- **Place of birth:** Categorized to capture spatial inequalities and urban/rural divides in early-life infrastructure.
- **Gender:** Self-reported by the respondent.
- **Ethnicity:** Self-identified Indigenous or minority status.

For the Brazilian cohort, the circumstance vector includes the same four foundational variables—utilizing standard IBGE racial classifications (White, Black, Brown, Indigenous, and Asian)—with the addition of a fifth variable:

- **Parental occupation:** The main occupational sector of the highest-earning parent when the respondent was 15 years old.

The inclusion of parental occupation in the Brazilian model provides a highly granular proxy for early-life socioeconomic status, household wealth, and latent network effects that parental education alone may not fully capture.

3 Conceptual Framework and Empirical Estimation

3.1 Decomposing Inequality of Opportunity

To quantify the extent of inequality of opportunity (IOP), we adopt an *ex-ante* approach, comparing overall observed inequality to the counterfactual inequality that would persist if every individual within a specific circumstance group (a “type”) received the exact same outcome. For additively decomposable inequality indices, such as the Mean Log Deviation (MLD) or generalized entropy $GE(0)$ class commonly utilized in this literature, this approach effectively decomposes total inequality into a within-group (“equitable”) component and a between-group (“inequitable”) component.

Because the groups are defined by circumstances strictly beyond individual control—such as parental education, spatial origins, and ethnicity—the between-group component represents the inequitable share of total inequality. We proceed in two analytical steps to estimate this metric.

First, we estimate the conditional expectation of the outcome variable, y , given the vector of strictly exogenous circumstance variables, C :

$$\hat{y} = \mathbb{E}(y \mid C) \quad (1)$$

For any given circumstance type, $\hat{y}$ corresponds to the mean income of that specific group. For instance, if the circumstance vector consisted solely of biological sex and region of birth, $\hat{y}$ would assign each individual the average income of their specific gender-region cohort. By replacing actual incomes with this conditional expectation, we eliminate within-type variation—effectively smoothing out differences driven by individual effort or random shocks.

Second, we calculate absolute inequality of opportunity by applying a chosen inequality measure, $I(\cdot)$, to this smoothed counterfactual distribution:

$$I_B = I(\hat{y}) \quad (2)$$

Because the variation in $\hat{y}$ is exclusively determined by inherited circumstances, I_B isolates the extent of inequality of opportunity. To contextualize this magnitude, we compute total inequality by applying the same index directly to the actual, un-smoothed outcome distribution, $I(y)$. The relative share of inequality of opportunity is simply the ratio of the between-group inequality to the total inequality.

3.2 The Redistributive Impact of Fiscal Policy

To evaluate how fiscal systems mitigate or exacerbate these disparities, we apply this decomposition across different stages of the income generation and redistribution process. Leveraging the microsimulation frameworks (BRASMOD and PERUMOD), we distinguish between three progressive income concepts:

- **Market Income** (y_M): Pre-tax and pre-transfer income.
- **Gross Income** (y_T): Market income plus direct cash transfers, prior to direct taxation.
- **Disposable Income** (y_D): Post-tax and post-transfer income.

For each income concept, we compute both total inequality and the corresponding inequality of opportunity:

$$I(y_M), \quad I(\hat{y}_M) \quad (3)$$

$$I(y_T), \quad I(\hat{y}_T) \quad (4)$$

$$I(y_D), \quad I(\hat{y}_D) \quad (5)$$

Standard redistribution, representing the total reduction in overall inequality achieved by the tax-benefit system, is measured as the absolute difference between inequality in market and disposable incomes:

$$R_T = I(y_M) - I(y_D) \quad (6)$$

Correspondingly, the targeted redistribution that specifically reduces the structural inequality of opportunity—the “fairness” effect of the fiscal system—is captured by the reduction in between-type inequality:

$$R_B = I(\hat{y}_M) - I(\hat{y}_D) \quad (7)$$

Ultimately, to evaluate the efficiency of the state in leveling the playing field, we calculate the share of total redistribution that actively mitigates unfair, circumstance-driven inequality: R_B/R_T . The complete analytical framework for a single cross-section is summarized in Table 1. In the empirical analysis, our key interest is in the absolute redistribution R_B and the relative reduction R_B/R_T , as well as how taxes and benefits contribute to the relative reduction.

Table 1: Analytical Framework for a Single Cross-Section

	Total Inequality	Between-Types Inequality	Between Share
Market income (pre)	$I_{M,T} = I(y_M)$	$I_{M,B} = I(\hat{y}_M)$	$\frac{I(\hat{y}_M)}{I(y_M)}$
Disposable income (post)	$I_{D,T} = I(y_D)$	$I_{D,B} = I(\hat{y}_D)$	$\frac{I(\hat{y}_D)}{I(y_D)}$
Absolute Redistribution	R_T	R_B	$\frac{R_B}{R_T}$
Redistribution (%)	$\frac{R_T}{I_{M,T}}$	$\frac{R_B}{I_{M,B}}$	

We use both the Gini index as well as the Mean Logarithmic Deviation (MLD, or GE(0)) to measure inequality. The choice of index dictates the exactness of the opportunity decomposition. Unlike the MLD, which is perfectly additively decomposable into strictly within- and between-group components, a conventional, exact decomposition of the standard Gini index is mathematically constrained by an overlapping residual. To

circumvent this limitation and maintain comparability with broader macroeconomic literature, we estimate the inequality of opportunity utilizing a “smoothed Gini” approach. By computing the Gini coefficient exclusively over the distribution of conditional expectations (the group-average incomes), we neutralize within-group variance. This yields a robust measure of “inequitable inequality” that is driven entirely by structural differences in exogenous circumstances.

3.3 Institutional Context: Fiscal Architectures in Brazil and Peru

Brazil (2014): The Higher-Tax, Higher-Transfer Model During the 2014 baseline, Brazil operated a relatively expansive welfare state for a middle-income economy, raising taxes equivalent to approximately 32% of GDP (Table 2). However, the system relied heavily on indirect consumption taxes, while broad personal income tax (PIT) exemptions—most notably the non-taxation of distributed corporate dividends—substantially limited the progressivity of direct taxation at the top of the income distribution.

Consequently, the equalizing capacity of the Brazilian state was almost entirely relegated to the expenditure side. The structural mitigation of poverty and inequality depended heavily on massive cash transfer architectures, primarily *Bolsa Família* (a targeted conditional cash transfer) and the *Benefício de Prestação Continuada* (BPC, a non-contributory pension for the elderly and disabled).

Table 2: Macro-Fiscal and Social Protection Context (2014)

	Peru (2014)	Brazil (2014)
Total Tax Revenue (% of GDP)	16.56	31.76
Direct Taxes	7.53	7.8
Indirect Taxes	9.03	15.61
Social Contributions	0	8.35
Social Assistance Spending (% of GDP)	1	2.4
Social Insurance Spending (% of GDP)	2.3	9.8
Coverage of Poorest Quintile (%)	88	80.6

Peru (2014–2022): High Informality and Constrained Fiscal Capacity In sharp contrast, Peru exemplifies a constrained fiscal model. The Peruvian state operates with significantly lower tax revenues and is structurally hampered by pervasive labor informality, which persistently encompasses roughly 75% of the active workforce. This massive informal sector limits the direct tax base, forcing a heavy reliance on the Value Added Tax (VAT) and severely limiting the redistributive capacity of the PIT.

On the expenditure side, Peru’s targeted social safety net—anchored by programmes such as *Juntos* (conditional cash transfers for impoverished households) and *Pensión 65* (non-contributory elderly assistance)—operates on a substantially smaller absolute scale than its Brazilian counterpart.

Furthermore, the macro-fiscal environment shifted drastically between the 2014 and 2022 waves of the ENAHO. By 2022, the Peruvian economy had suffered severe scarring from the COVID-19 pandemic, which disproportionately affected informal workers and forced women out of the workforce at higher rates due to caregiving responsibilities. Subsequent inflationary pressures, combined with broad, untargeted policy responses (such as allowing universal early withdrawals from private pension funds), eroded the real purchasing power and the targeting efficiency of the state’s traditional cash transfer programmes.

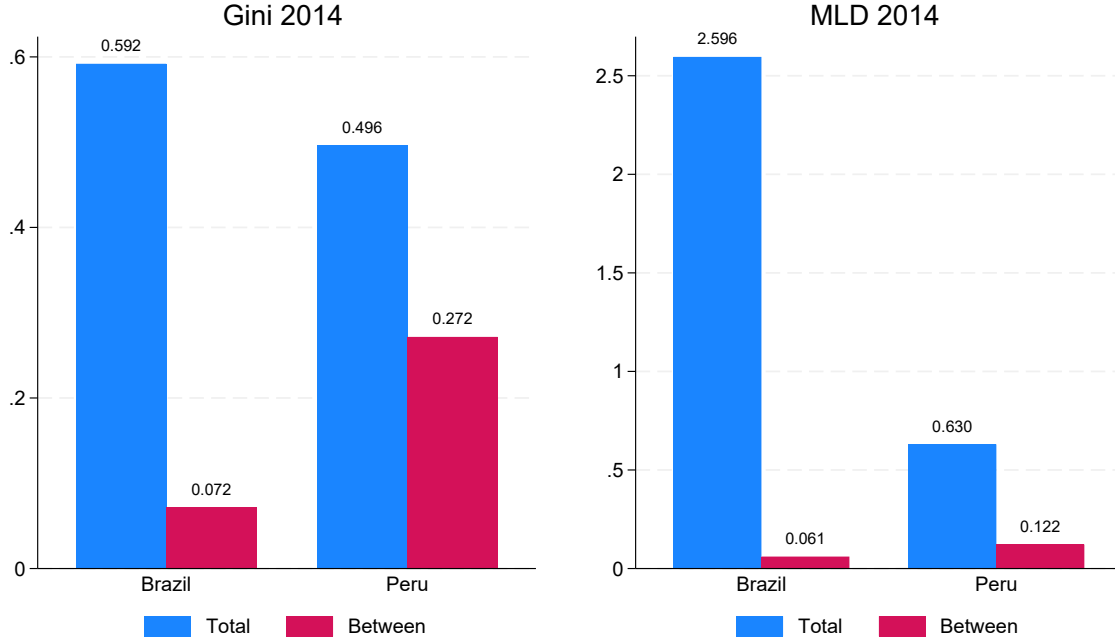
4 Results

4.1 Baseline Market Inequality and Opportunity Gaps

Figure 1 presents baseline estimates of total ($I_{M,T}$) and between-type ($I_{M,B}$) inequality for pre-tax market income across Brazil (2014) and Peru (2014, 2022). Opportunity types are defined by parental education, gender, ethnicity, and geographic region.

Over the analyzed decade, Peru experienced a modest reduction in both total and between-group inequality. By 2022 (see Appendix Figure A1), the total market Gini fell slightly below 0.47 alongside a proportional contraction in the between-type component. This indicates an overarching, systemic compression in the Peruvian market income distribution that concurrently mitigated circumstance-driven economic disparities.

Figure 1: Inequality of Market Income in Brazil and Peru (2014): A Comparison of Gini and MLD Indices ($I_{M,T}$ & $I_{M,B}$)



Notes: The figure displays the decomposition of market income inequality into total and between-group components. Total ($I_{M,T}$) represented by blue bars, and Between-group ($I_{M,B}$) by red bars. The between-group component measures “inequality of opportunity” by partitioning the population into “types” based on circumstances such as - parents’ highest level of education, gender, ethnicity, and region of birth. For the case of Brazil, the circumstances also include parental occupation.

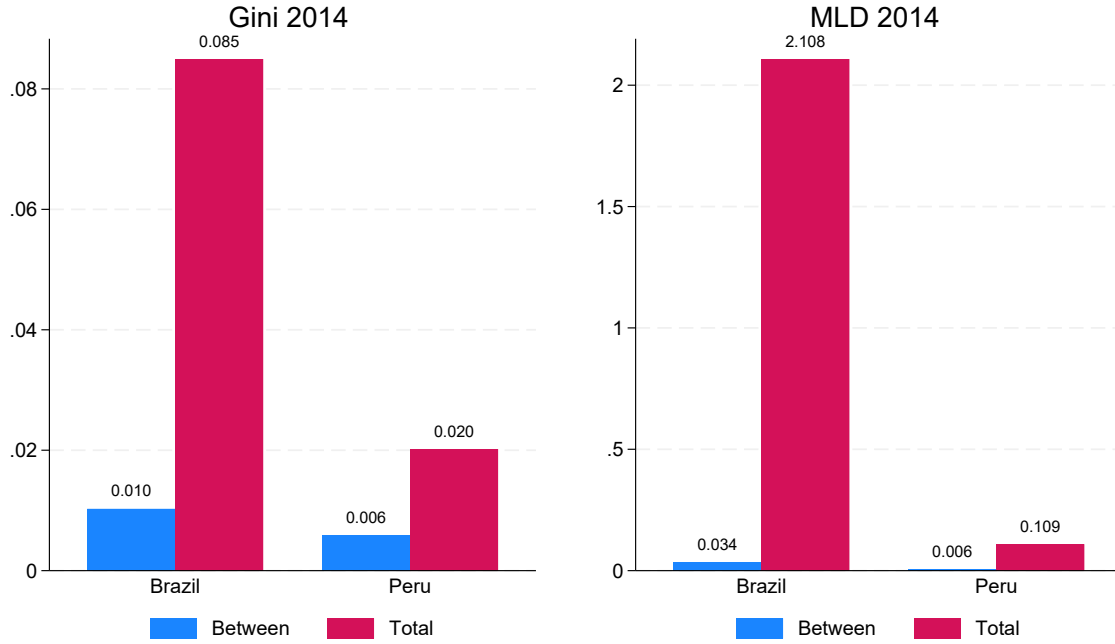
Source: Authors’ calculations based on PNAD-BRASMODO (Brazil) and ENAHO-PERUMOD (Peru).

4.2 The Redistributive Impact on Inequality of Opportunity

Figure 2 illustrates the absolute redistributive effect of the tax-benefit systems, capturing both the reduction in overall inequality (R_T) and the targeted reduction in circumstance-driven, between-type inequality (R_B).

The 2014 Brazilian data show a clear divergence between aggregate redistribution and EOp outcomes. The fiscal system (simulated via BRASMODO) produces a sizable aggregate redistributive effect, reducing the total Gini coefficient by almost 0.09 points and lowering the MLD by approximately 2.0 points. By contrast, the absolute reduction in between-group inequality (R_B) is very small across both measures. This pattern suggests that, although the Brazilian state plays an active role in income redistribution, its redistributive mechanisms are weakly aligned with reducing inequality linked to observable circumstances. The system primarily reduces within-group dispersion—such as income fluctuations arising from temporary shocks or labor market volatility—while largely preserving inequality between groups defined by structural conditions.

Figure 2: Redistribution of Total and Between-Group Inequality in Brazil and Peru (2014): A Comparison of Gini and MLD Indices (R_T & R_B)



Notes: The figure displays the redistribution of income inequality, decomposed into total and between-group components. Total redistribution (R_T) is represented by red bars, and Between-group redistribution (R_B) by blue bars. The between-group component measures the extent to which the tax-benefit system reduces “inequality of opportunity” among population “types” defined by circumstances: parents’ highest level of education, gender, ethnicity, and region of birth. For the case of Brazil, the circumstances also include parental occupation.

Source: Authors’ calculations based on PNAD-BRASMODO (Brazil) and ENAHO-PERUMOD (Peru).

In comparison, Peru’s tax–benefit system (simulated via PERUMOD) exhibits a more limited redistributive impact. In 2014, the reduction in the overall Gini coefficient is modest (around 0.02), accompanied by only a slight reduction in between-type inequality. This outcome is consistent with the more constrained scope of fiscal policy instruments in Peru to modify market income distributions through taxation and cash transfer mechanisms.

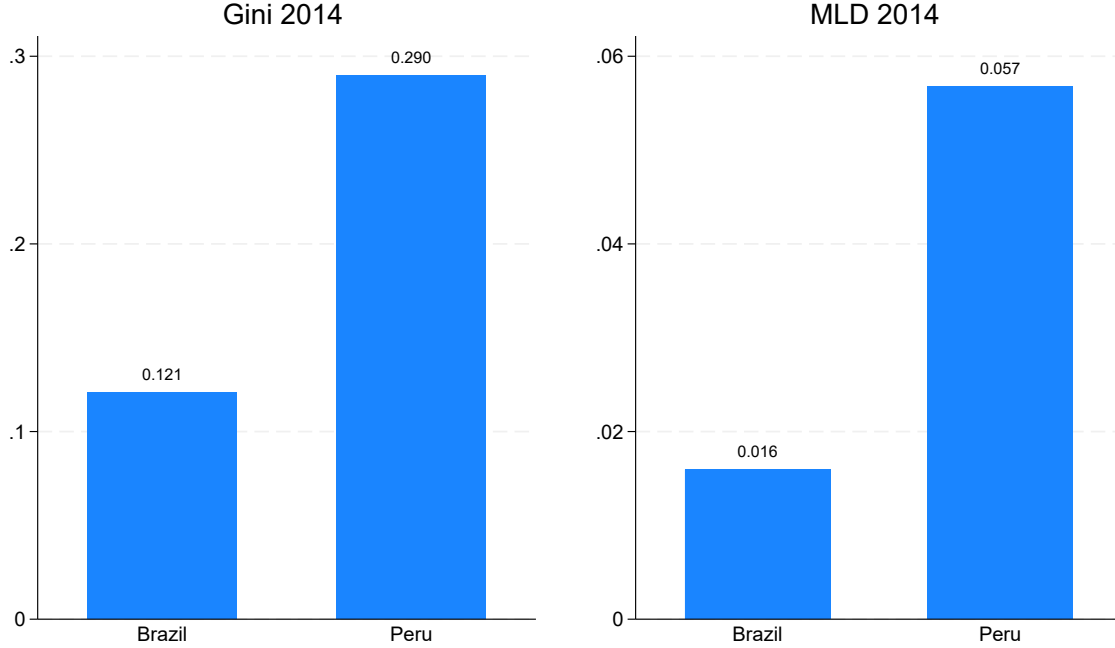
The temporal evolution of the Peruvian system yields a concerning finding regarding the trajectory of state capacity, illustrated in Appendix Figure A2. By 2022, the total redistributive impact of the state contracted visibly, with the overall reduction in the Gini index (R_T) falling from 0.020 to 0.015. Crucially, this aggregate contraction was accompanied by a severe erosion in the system’s ability to mitigate circumstance-driven inequality. The absolute reduction in between-group inequality (R_B) fell from an already modest 0.006 Gini points in 2014 to a negligible 0.002 points in 2022. While the 2022 tax-benefit system maintained a nominally progressive fairness effect—meaning

state interventions still marginally leveled the playing field rather than amplifying disparities—its functional capacity to correct for initial, exogenous circumstances was almost entirely hollowed out over the intervening decade.

4.3 Relative Redistribution and the “Fairness Share” (R_B/R_T)

Figure 3 illustrates the relative redistribution of the between-group component, defined as the ratio of circumstance-driven redistribution to total redistribution (R_B/R_T). This metric effectively serves as a “fairness share,” quantifying the exact proportion of the state’s fiscal intervention that actively levels the playing field versus the proportion that smooths idiosyncratic, within-group income shocks.

Figure 3: Relative Redistribution of the Between-Group Component in Brazil and Peru (2014): A Comparison of Gini and MLD Indices ($\frac{R_B}{R_T}$)



Notes: The figure displays the relative redistribution of the between-group component, calculated as the ratio of between-group redistribution to total redistribution ($\frac{R_B}{R_T}$). This ratio indicates the share of total redistributive effort that specifically targets “inequality of opportunity” among population “types” defined by circumstances: parents’ highest level of education, gender, ethnicity, and region of birth. For the case of Brazil, the circumstances also include parental occupation.

Source: Authors’ calculations based on PNAD-BRASMOD (Brazil) and ENAHO-PERUMOD (Peru).

The 2014 cross-country comparison reveals a critical nuance regarding fiscal efficiency. As established in Figure 2, Brazil’s tax-benefit system reduces overall inequality quite strongly. However, Figure 3 demonstrates that its *relative* efficiency in tackling inequality of opportunity is surprisingly low. Based on the Gini index, only about 12% of

Brazil’s total redistribution mitigates between-group gaps, compared to approximately 29% in Peru. When evaluated through the Mean Logarithmic Deviation (MLD)—which is sensitive to the bottom of the income distribution—the fairness share declines sharply in both nations. In 2014, only roughly 2% of Brazil’s, and 6% of Peru’s, total reduction in inequality can be attributed to dismantling circumstance-driven, between-types, disadvantages. This observation reinforces the conclusion that these Latin American welfare systems achieve only limited correction to inherited socioeconomic opportunity gaps.

4.4 Decomposing Fairness: The Role of Taxes vs. Transfers

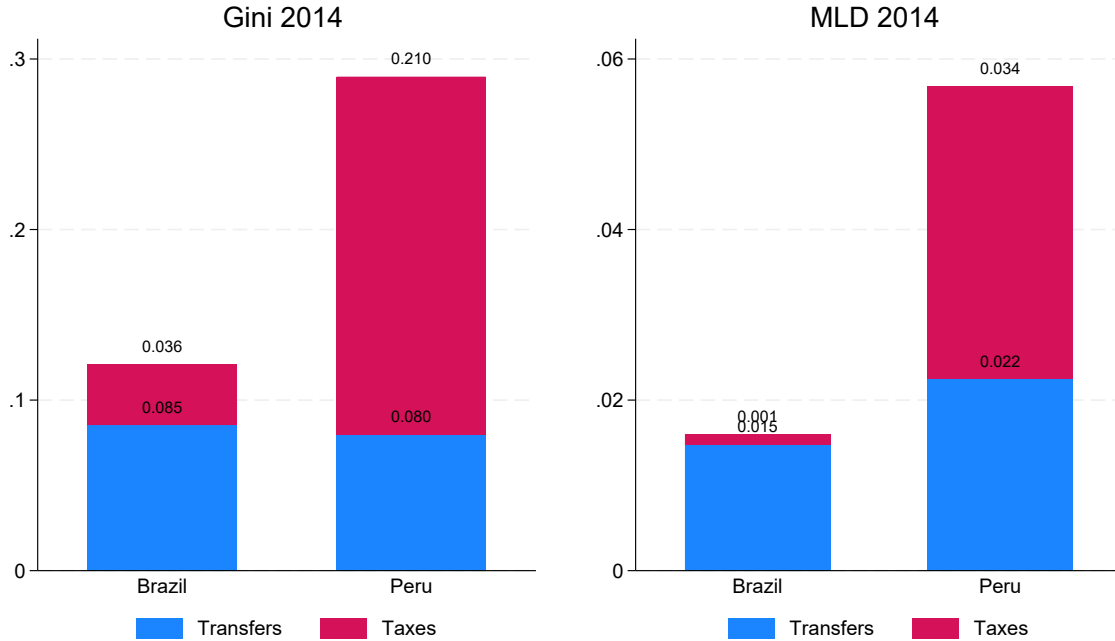
Figure 4 splits the relative redistribution of the between-group component (R_B/R_T) identified in Figure 3, decomposing the net “fairness share” into its fiscal instruments: direct taxes and direct cash transfers.

In Brazil, the mitigation of circumstance-driven inequality relies heavily on the cash transfer system. Of the roughly 12% relative reduction in the Gini between-group component, transfers account for approximately two-thirds of the effect (roughly 8.5 percentage points), with direct taxation contributing the remaining 3.6 percentage points.

This asymmetry becomes even more pronounced when viewed through the MLD. The fractional 1.6% reduction in opportunity gaps is almost entirely generated by transfers ($\sim 1.5\%$), with taxes playing a negligible role. This indicates that the Brazilian tax code does virtually nothing to level the playing field for the absolute poorest opportunity types, leaving that structural burden entirely to cash transfer programmes (such as *Bolsa Família*).

In Peru, by contrast, taxes are responsibly to a greater share of IEOp reduction than transfers, when using the Gini index. The two instruments have a roughly equal role in the between-types redistribution when inequality is measured using the MLD index.

Figure 4: Decomposition of Between-Group Redistribution by Taxes and Transfers in Brazil and Peru (2014): A Comparison of Gini and MLD Indices (R_B)



Notes: The figure displays the decomposition of between-group redistribution (R_B) into the contributions of direct taxes and social transfers. Blue bars represent the redistributive effect of Transfers, and red bars represent the redistributive effect of Taxes. The between-group component measures the reduction in “inequality of opportunity” among population “types” defined by circumstances: parents’ highest level of education, gender, ethnicity, and region of birth. For the case of Brazil, the circumstances also include parental occupation.

Source: Authors’ calculations based on PNAD-BRASMODO (Brazil) and ENAHO-PERUMOD (Peru).

4.5 Robustness

We verify the robustness of our baseline estimates through two sensitivity exercises. First, we examine how the treatment of missing data in parental circumstances affects the opportunity decomposition. Second, we relax the parametric ex-ante decomposition by applying a data-driven machine learning (ML) approach to partition the circumstance types.

Sensitivity to Missing Parental Education

In our primary specification, we retain the full sample of observations to maximize statistical power, absorbing individuals with missing retrospective data on parental education into a baseline category. However, grouping completely unobserved circumstances in this manner risks artificially compressing the estimated between-group variance. To assess the sensitivity of our results to this choice, Figure A3 compares the baseline decomposi-

tion of market income inequality with estimates derived from a trimmed sample, which is restricted strictly to individuals for whom at least one parent’s educational attainment is observed.

The restricted sample indicates that our baseline estimates effectively serve as a lower bound for inequality of opportunity. Excluding observations with entirely unobserved parental education nearly doubles the between-group Gini ($I_{M,B}$) for Brazil, from 0.072 to 0.140. In Peru, the between-group Gini similarly rises from 0.272 to 0.339. Consequently, the absolute reduction in between-type inequality (R_B) is also estimated to be higher in the trimmed sample, reaching 0.015 in Brazil and 0.010 in Peru (Figure A4). Despite these level shifts, the qualitative conclusion is unchanged: the proportion of total fiscal redistribution that mitigates inequality of opportunity remains strictly marginal.

Machine Learning-Based Identification of Types

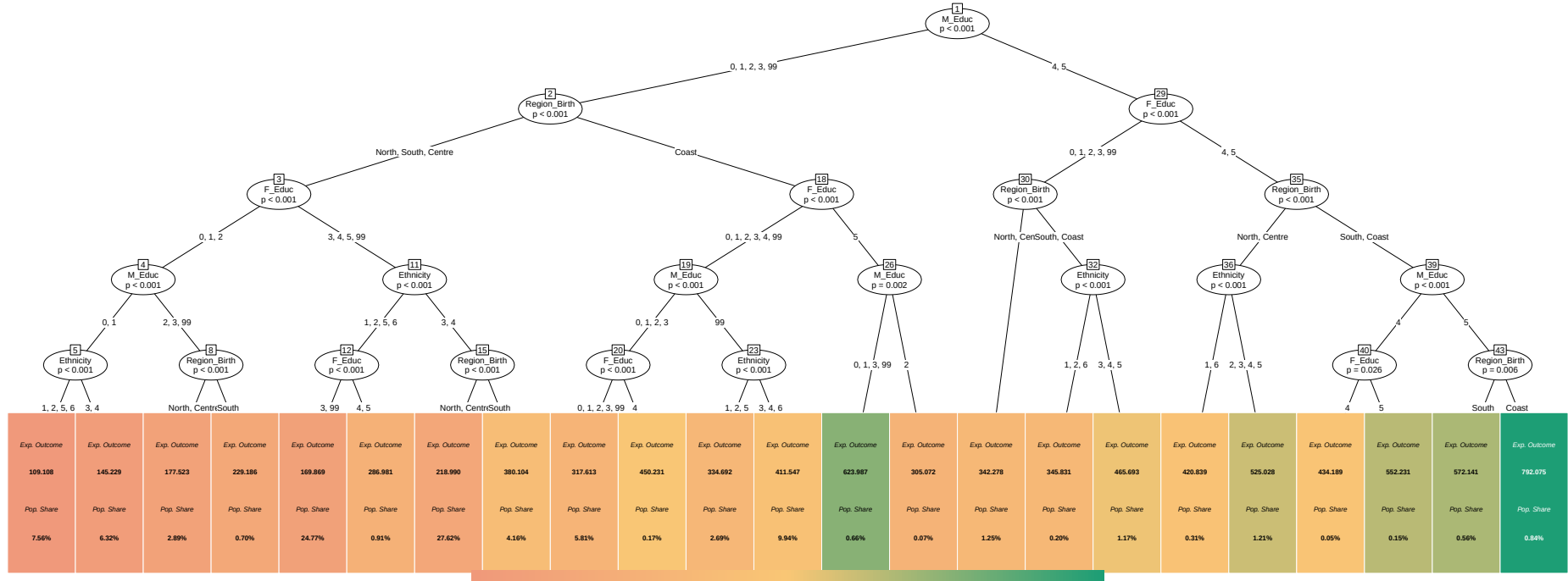
The standard decomposition relies on a partition of the population into all possible types that the background variables allow. As a robustness check, we employ conditional inference trees—following the methodology established by Brunori et al. (2023)³—to systematically identify the most significant circumstance-driven splits in the income distribution (Figure 5).

Applying this ML approach to Peru⁴ in 2014 (Figure A5) yields a between-group Gini of 0.246, which is slightly more conservative than the 0.272 baseline estimate. Furthermore, the absolute between-group redistribution (R_B) identified via the ML tree is 0.007 (Figure A6), which tightly mirrors the baseline estimate of 0.006 (Figure 2). This indicates that the limited impact of the tax-benefit system on equality of opportunity is robust to the choice of partition, and is not driven by our baseline categorization.

³We are grateful to the authors for generously sharing their code.

⁴The corresponding code for Brazil did not converge in our replication.

Figure 5: Conditional Inference Tree for Peru: Ex-Ante Inequality of Opportunity Identification



Notes: The figure presents a conditional inference tree used to partition the Peruvian population into mutually exclusive “types” based on circumstances. Following the methodology of Brunori et al. (2023), the tree identifies the most significant splits in market income, where each terminal leaf represents a specific type with a distinct mean income (Exp. Outcome) and population share (Pop. Share). This machine learning approach allows for a data-driven identification of the groups most affected by inequality of opportunity. The circumstances used include: parents’ highest level of education (M_Educ and F_Educ), gender, ethnicity, and region of birth. Node values indicate p-values for the hypothesis of independence between the circumstance and income.

Source: Authors’ calculations based on ENAHO-PERUMOD (Peru).

5 Counterfactual Simulations

The analysis above highlighted the relatively minor role the tax/benefit policies in these countries have in reducing inequality of opportunity. Armed with microsimulation modelling, in this section we therefore examine three counterfactual scenarios to understand how equality of opportunity could be further improved.

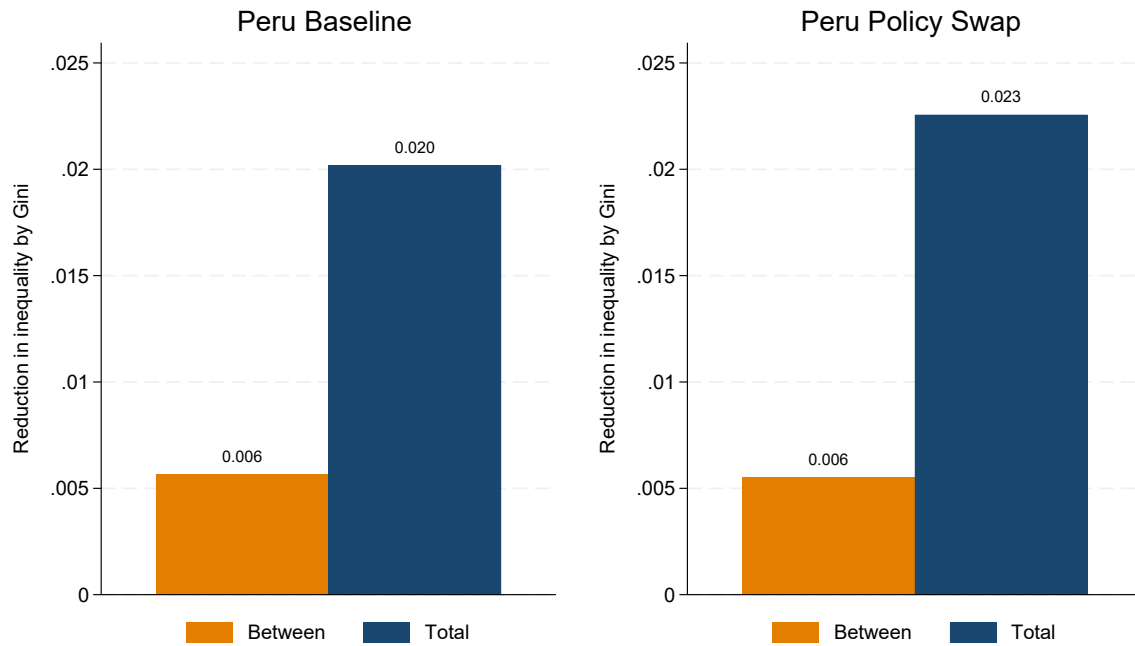
5.1 Cross-National Policy Swap

We start with a policy swap analysis, in which Peru is assumed to adopt the Brazilian tax and transfer system. This exercise identifies whether Brazil’s more redistributive, high-tax, high-transfer model would lead to improved equality of opportunity when constrained by a lower-income macroeconomic baseline.

To conduct the analysis, we have used the Brazilian benefit amounts directly and converted them into the Peruvian currency. However, because of the underpinning data set does not contain the necessary information to fully simulate the Brazilian system, the policy swap exercise is admittedly imperfect. The policies we were not able to simulate include business owner and manager social insurance contributions, formal unemployment benefits, and the *Benefício de Prestação Continuada* (BPC), a targeted benefit for the poor elderly and disabled.

Figure 6 demonstrates that the Brazilian policies achieve only marginal improvement in the overall reduction in inequality, and the share of between redistribution out of all redistribution even declines somewhat (see Figure 7). The results in Figure 8 suggest that the simulated Brazilian benefit policies appear to be less well targeted at the disadvantaged groups in Peru.

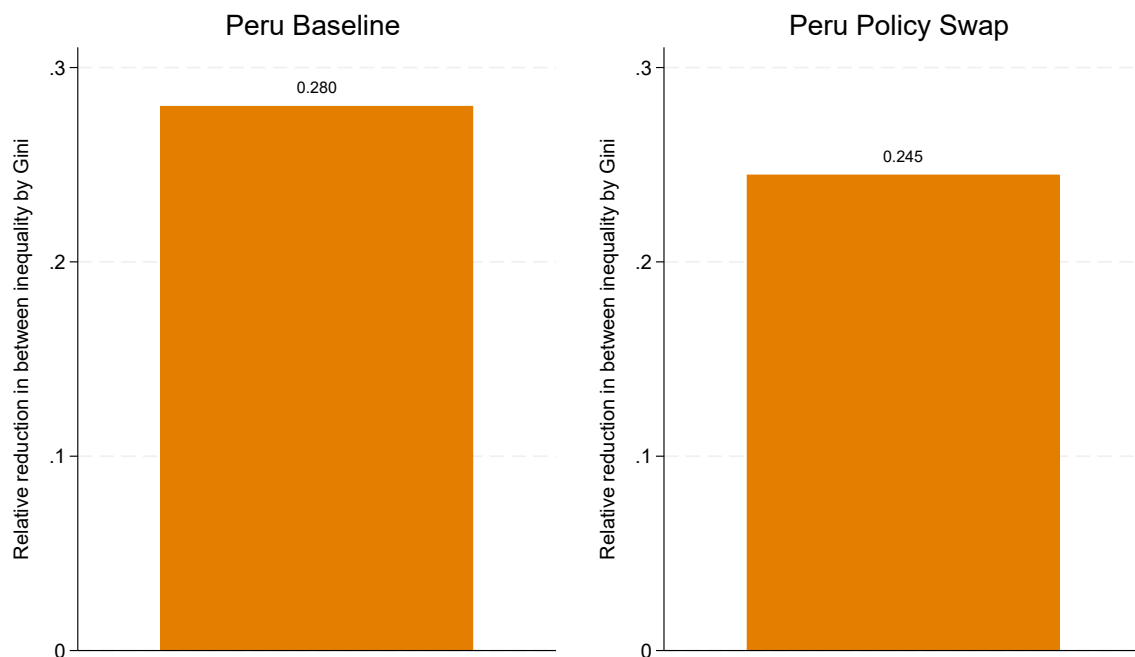
Figure 6: Counterfactual Analysis of Redistribution in Peru (2014): Baseline vs. Policy Swap (R_B & R_T)



Notes: The figure compares the redistribution of income inequality in Peru under the baseline scenario and a counterfactual policy swap scenario, measured by the Gini index. Total redistribution (R_T) is represented by dark blue bars, and Between-group redistribution (R_B) by orange bars. The between-group component measures the reduction in “inequality of opportunity” among population “types” defined by circumstances: parents’ highest level of education, gender, ethnicity, and region of birth.

Source: Authors’ calculations based on ENAHO-PERUMOD (Peru).

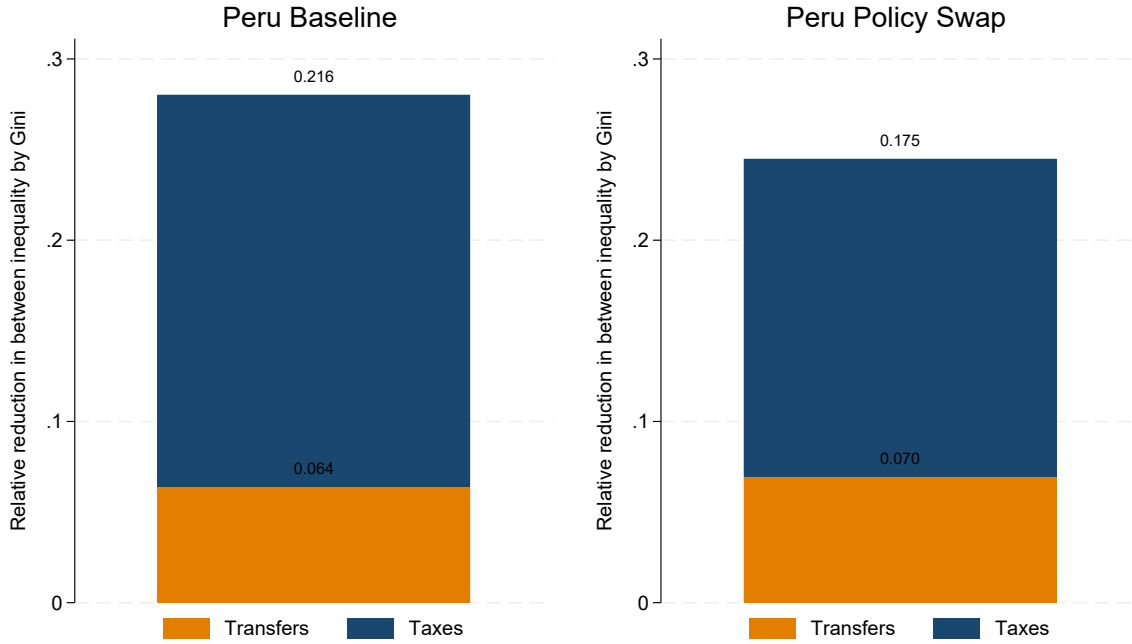
Figure 7: Relative Redistribution of the Between-Group Component in Peru (2014): Baseline vs. Policy Swap ($\frac{R_B}{R_T}$)



Notes: The figure compares the relative redistribution of the between-group component in Peru under the baseline scenario and a counterfactual policy swap scenario, measured by the Gini index. The values represent the ratio of between-group redistribution to total redistribution ($\frac{R_B}{R_T}$), indicating the share of total redistributive effort targeting “inequality of opportunity.” Population “types” are defined by circumstances: parents’ highest level of education, gender, ethnicity, and region of birth. For the case of Brazil (used in the underlying model framework), the circumstances also include parental occupation.

Source: Authors’ calculations based on ENAHO-PERUMOD (Peru).

Figure 8: Decomposition of Between-Group Redistribution in Peru (2014): Baseline vs. Policy Swap (R_B)



Notes: The figure displays the decomposition of between-group redistribution (R_B) in Peru into the contributions of direct taxes and social transfers under the baseline and policy swap scenarios, measured by the Gini index. Orange bars represent the redistributive effect of Transfers, and dark blue bars represent the redistributive effect of Taxes. The between-group component measures the reduction in “inequality of opportunity” among population “types” defined by circumstances: parents’ highest level of education, gender, ethnicity, and region of birth.

Source: Authors’ calculations based on ENAHO-PERUMOD (Peru).

5.2 Benefit Policy Simulation

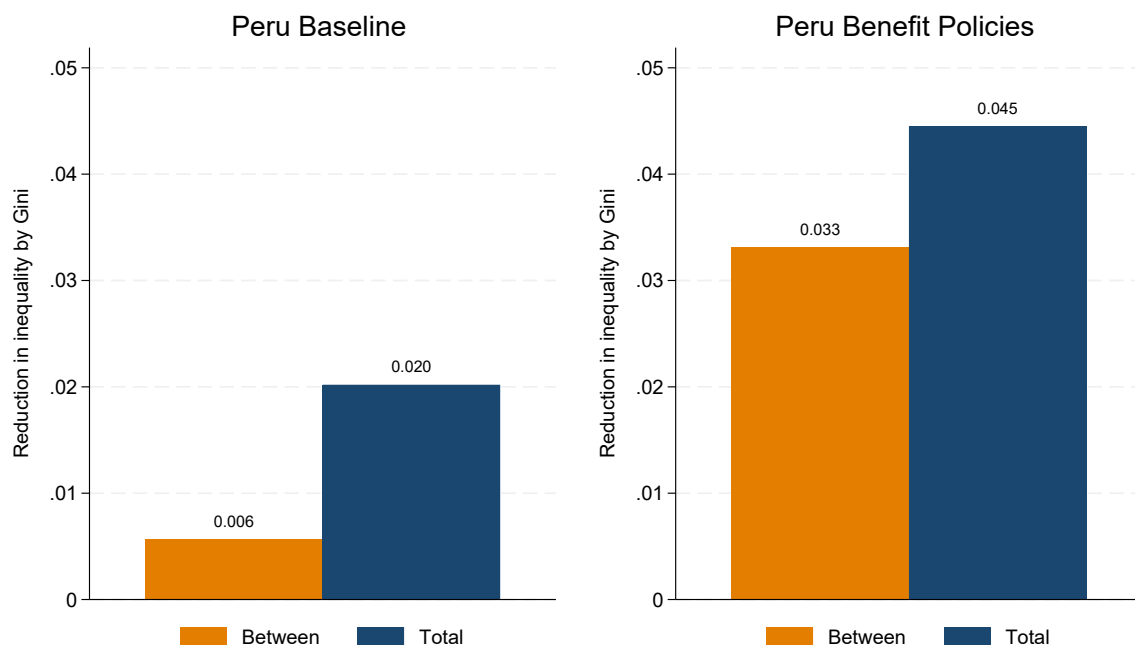
A natural question to ask is whether there are policies that could fare much better in the Peruvian context as tools to reduce between-types inequality. Examining mean incomes between different types reveals that those whose parents are from rural areas in the Northern or the Central region and whose parents have the lowest education level have themselves low mean group incomes. Given that actual policies are seldom targeted by parental background, we examine if a benefit policy which is given to those who themselves reside in these regions or have low education level⁵ would achieve significant IEOp reduction. This idea is operationalized by a policy that gives a hundred Peruvian sol all individuals aged 18 or above living in the North and Centre region and having primary or below primary education as well as living in rural areas.

⁵Given the intergenerational linkages, individuals who themselves belong to these groups are more likely to have such parental background.

The results are reported in Figures 9 and 10. In comparison with the actual Peruvian overall redistribution, such a benefit policy would achieve twice as high redistribution on the whole. The policy would be especially effective in mitigating inequality of opportunity, with the absolute reduction rising to about 0.03 Gini points. As expected, transfers would then bring the greatest contribution to between-types inequality reduction.

The costs of this hypothetical policy would be high, amounting to 58.08% of existing social assistance budget in 2014, and 41.85% of direct income taxes and social contributions. The point is not to propose Peru adopt the policy as such; the goal is rather to showcase that there is potential to reduce between-groups inequality, and it would be interesting to study different – arguably more realistic – options along those lines.

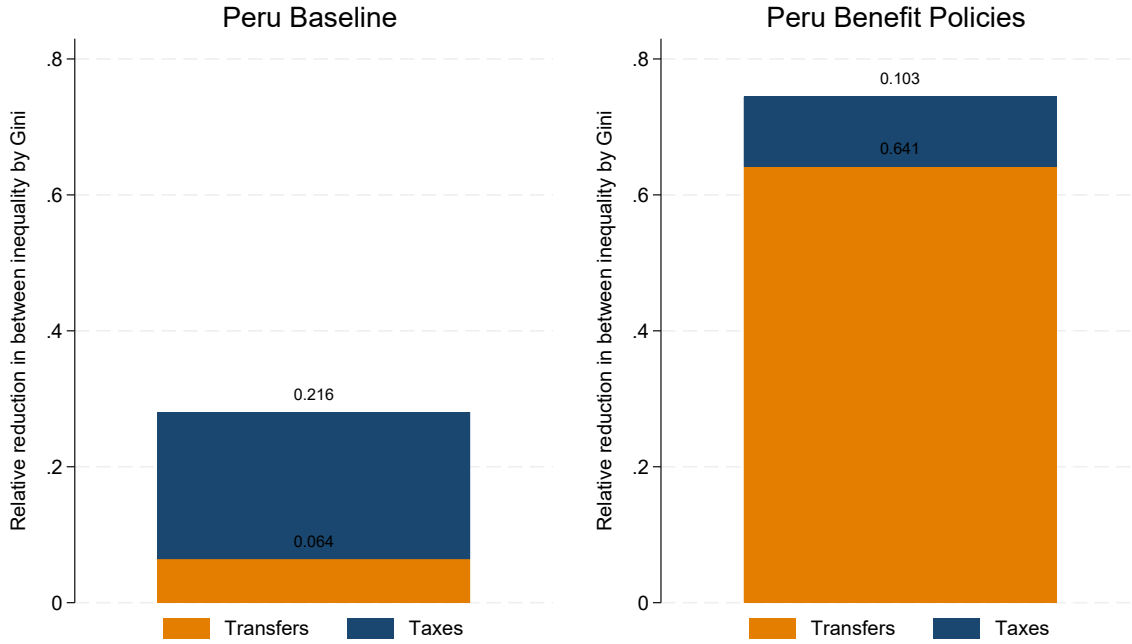
Figure 9: Counterfactual Analysis of Benefit Policy Simulation in Peru (2014): Baseline vs. Benefit Policies (R_B & R_T)



Notes: The figure compares the redistribution of income inequality in Peru under the baseline scenario and a hypothetical benefit policy simulation, measured by the Gini index. The simulated policy targets individuals aged 18 or above in rural areas of the North and Centre regions with primary or below primary education. Total redistribution (R_T) is represented by dark blue bars, and Between-group redistribution (R_B) by orange bars. The between-group component measures the reduction in “inequality of opportunity” among population “types” defined by circumstances: parents’ highest level of education, gender, ethnicity, and region of birth.

Source: Authors’ calculations based on ENAHO-PERUMOD (Peru).

Figure 10: Decomposition of Between-Group Redistribution in Peru (2014): Baseline vs. Benefit Policies (R_B)



Notes: The figure displays the decomposition of between-group redistribution (R_B) in Peru into the contributions of direct taxes and social transfers under the baseline and benefit policy simulation scenarios, measured by the Gini index. Orange bars represent the redistributive effect of Transfers, and dark blue bars represent the redistributive effect of Taxes. The between-group component measures the reduction in “inequality of opportunity” among population “types” defined by circumstances: parents’ highest level of education, gender, ethnicity, and region of birth.

Source: Authors’ calculations based on ENAHO-PERUMOD (Peru).

5.3 Lump-sum Transfers

One key idea in Equality of Opportunity theories is that the income differences that do not arise from differences in effort should be compensated for. In fact, one of the features of the approach suggested by Fleurbaey and Maniquet (2011) is that transfers should be uniform within a type (or a group) when types are formed based on circumstances.

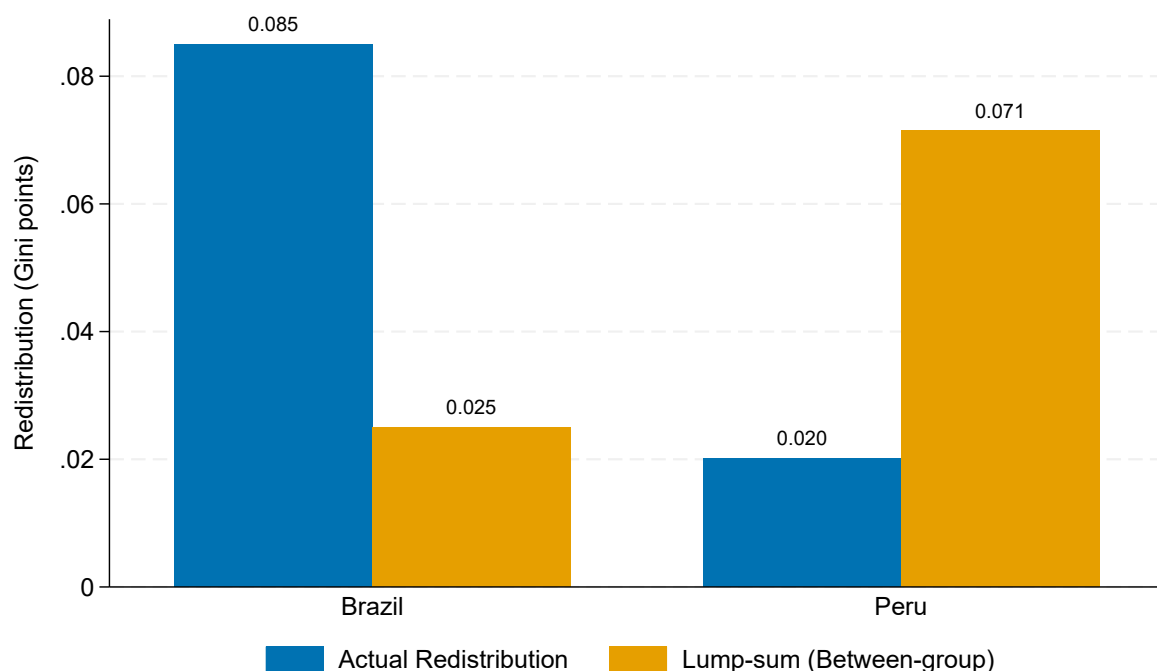
We follow this idea and calculate type-specific lump-sum transfers, which bring each type’s mean income to the level of the mean income of the entire society. We then compute how large redistributive flows such a transfer would represent and compare them with actual redistribution. In other words, we examine how much market income inequality is reduced when transfers are set to equalize mean incomes of groups. This represents the desirable degree of redistribution, viewed from the EOp angle.

These results are presented in Figure 11. The figure compares the actual redistribution, when measured using the Gini index, with the yardstick-level of redistribution.

The results indicate that hypothetical redistribution, which would completely eliminate between-types inequality, exceeds the actual redistribution in the case of Peru, whereas the opposite holds for Brazil. This reflects the greater absolute extent of between-types inequality, observed in Figure 2.

Of course, there can be other reasons for redistribution, but these results still provide, we believe, an interesting comparison to the ongoing redistributive effort in the two countries we examine.

Figure 11: Actual vs. Lump-sum Redistribution in Brazil and Peru (2014): A Comparative Yardstick Analysis (R_T)



Notes: The figure compares actual redistribution with a hypothetical yardstick-level of redistribution based on Equality of Opportunity (EOp) theory, measured in Gini points. Actual Redistribution is represented by blue bars. Lump-sum (Between-group) redistribution, represented by yellow bars, indicates the redistributive flow required to completely equalize mean incomes across population “types.” These types are defined by circumstances: parents’ highest level of education, gender, ethnicity, and region of birth. For the case of Brazil, the circumstances also include parental occupation.

Source: Authors’ calculations based on PNAD-BRASMODO (Brazil) and ENAHO-PERUMODO (Peru).

6 Conclusion

The role of the modern welfare state extends beyond reducing absolute poverty to addressing inequalities associated with predetermined circumstances. This study presents empirical evidence suggesting that the existing tax–benefit systems in Brazil and Peru—despite substantial differences in scale and scope—do achieve some reduction in inequality of op-

portunity. This implies that redistributing outcomes also improves somewhat equality of opportunity, a point which has gone largely unnoticed by the otherwise broad empirical work on equality of opportunity, including in the Latin American context. But the actual extent of advancement in equality of opportunity is limited in the countries we study.

In Brazil, a large fiscal framework produces significant compression in overall income inequality, yet it shows limited effectiveness in reducing disparities linked to demographic characteristics and family background. While aggregate redistribution is substantial, the system appears weakly targeted with respect to the structural factors that shape opportunity. In Peru, while the share of between-types redistribution is substantial, the overall reduction in inequality of opportunity is limited because of the very small redistributive effort overall. Our policy swap analysis indicates, quite surprisingly, that despite these differences in the tax/benefit policies, the extent of inequality reduction that could be achieved in Peru if it implemented Brazilian policies would still not be much larger. However, further simulations reveal that it could be possible to arrange a more redistributive system and one that targets especially group-based inequalities also in Peru, albeit with very significant fiscal implications.

Certain caveats need to be borne in mind when interpreting the results. Chief among those is that the actual extent of circumstances may well be greater than what this research can observe, since the datasets that we use, and which are typical in the developing country context, have a fairly limited number of circumstance variables. If the share of market-income inequality attributed to circumstances were higher, it is likely that the actual extent of redistribution that manages to reduce between-type inequality could also be greater, even if its share out of total redistribution remained the same or declined somewhat. Another concern is that the tax-benefit simulation may be imperfect, and this was a particularly severe issue in the policy swap exercise, which was complicated by the lack of required information in the survey data in Peru.

From a policy perspective, these findings point to the importance of complementing broad-based income redistribution with more explicitly targeted, circumstance-sensitive instruments, maybe on top of achieving greater redistribution in countries where the current tax-benefit system remain limited in scope. Reducing inequality of opportunity in Latin America may require adjustments to direct taxation that better reflect disadvantage across observable types, as well as systematic evaluation of cash transfer programs to ensure that benefits are effectively directed toward groups facing structural constraints rather than disproportionately accruing to already advantaged populations.

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7 Appendix

Tables

Table A1: Mean Income Components (USD PPP)

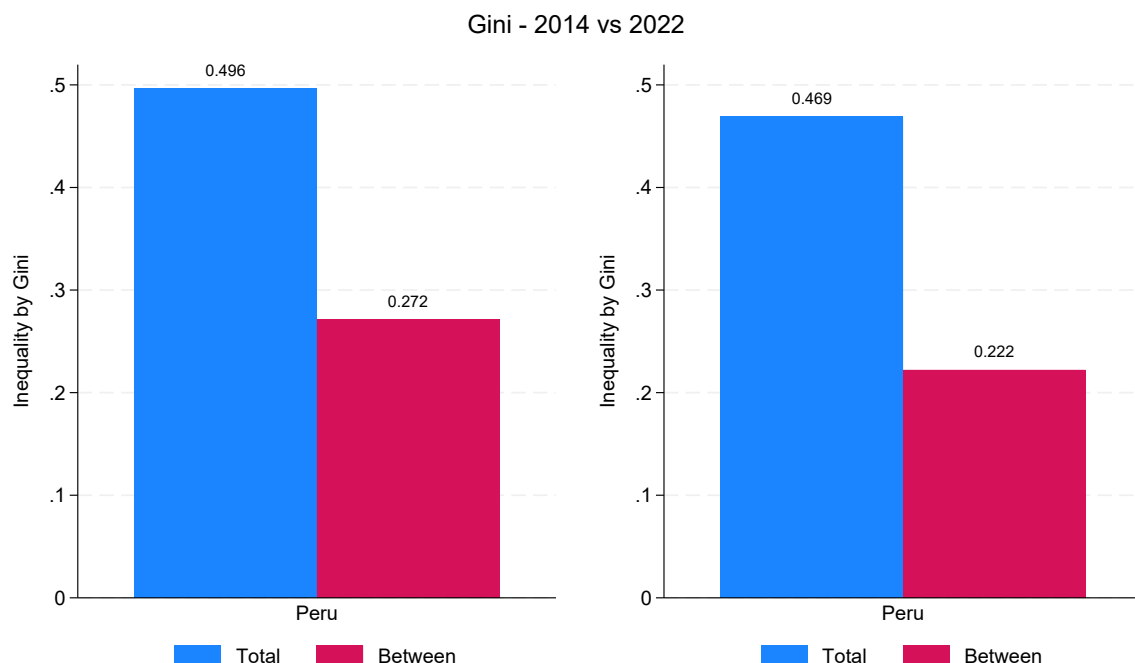
	(1)	(2)
	Peru	Brazil
	mean	mean
Employment Income	215.51	281.96
Self-Employment Income	127.91	123.79
Direct Taxes	6.62	17.50
Social Contributions	18.33	41.83
Benefits Received	17.98	106.46
Disposable Income	400.06	469.62

Table A2: HH Demographic Composition (2014)

	(1)	(2)
	Peru	Brazil
	mean	mean
Urban Household Share	0.79	0.86
Rural Household Share	0.21	0.14
HH has at least one Formal worker	0.73	0.60
HH has at least one Informal worker	0.85	0.53
Average Household Size	3.66	3.02
Number of Children (<18)	1.04	0.81
Number of Working Age (18-64)	2.24	1.93
Number of Elderly (65+)	0.39	0.28

Graphs

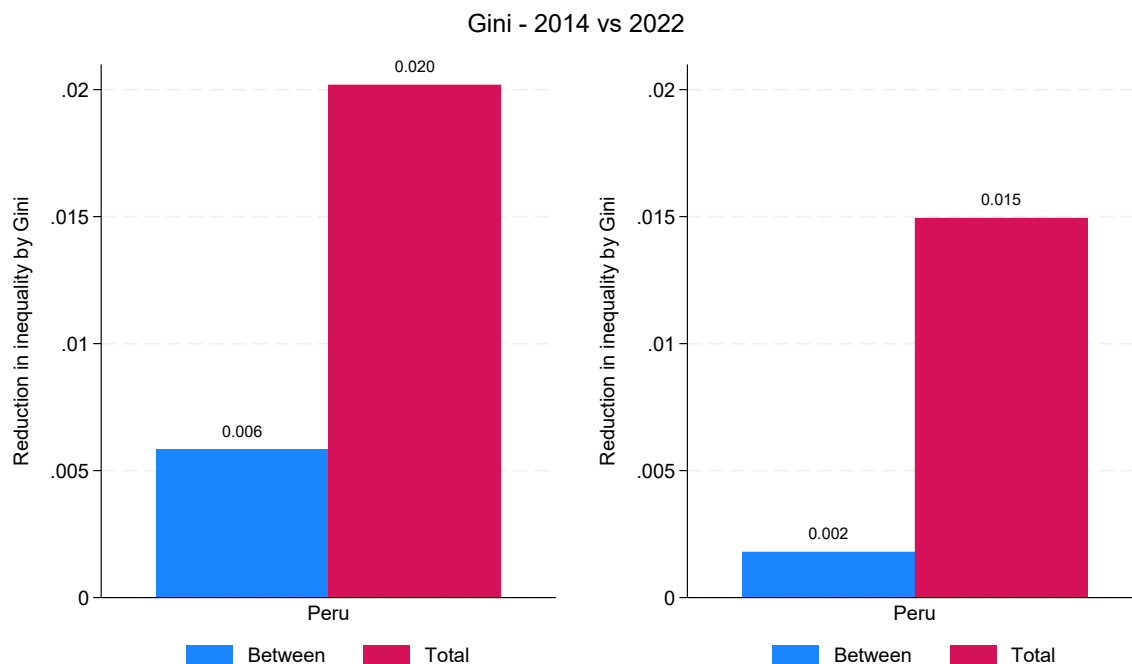
Figure A1: Inequality of Market Income in Peru (2014 vs. 2022): Evolution of Total and Between-Group Components ($I_{M,T}$ & $I_{M,B}$)



Notes: The figure compares the decomposition of market income inequality in Peru for the years 2014 (left) and 2022 (right), measured by the Gini index. Total inequality ($I_{M,T}$) is represented by blue bars, and Between-group inequality ($I_{M,B}$) by red bars. The between-group component measures “inequality of opportunity” by partitioning the population into “types” based on circumstances: parents’ highest level of education, gender, ethnicity, and region of birth. For the case of Brazil (used in the underlying model framework), the circumstances also include parental occupation.

Source: Authors’ calculations based on ENAHO-PERUMOD (Peru).

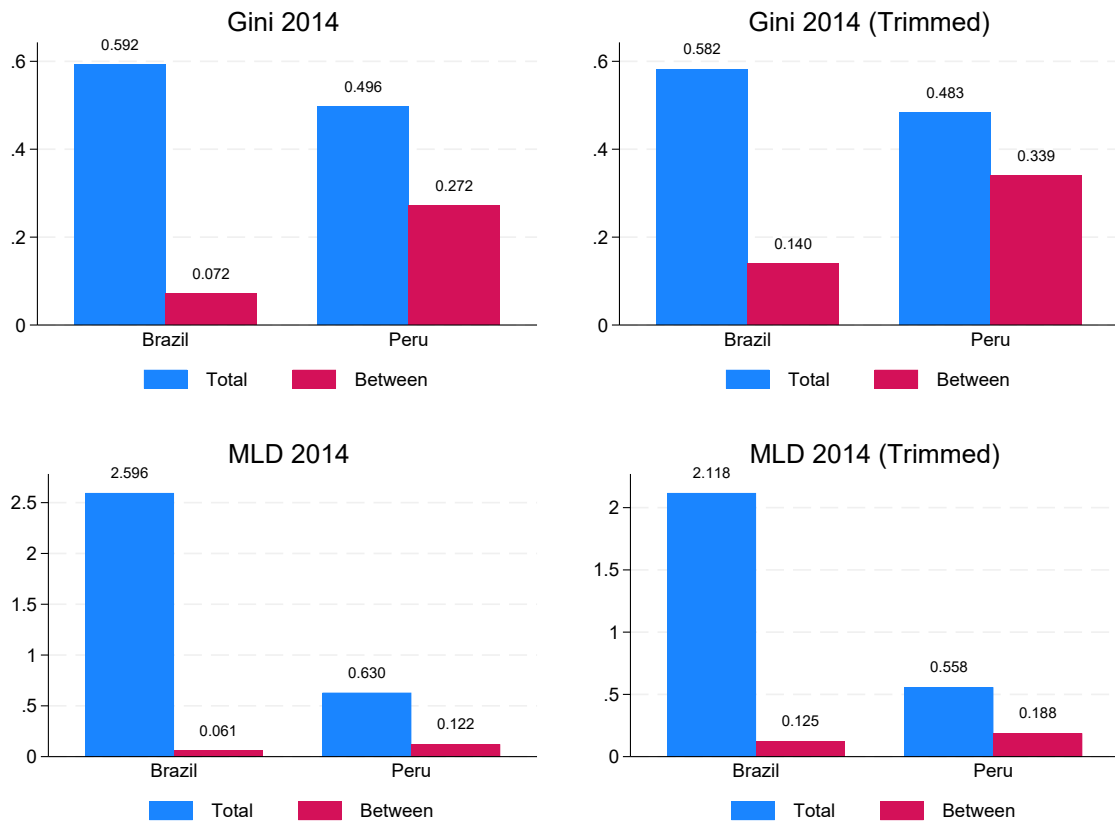
Figure A2: Redistribution of Total and Between-Group Inequality in Peru (2014 vs. 2022): Evolution of Redistributive Effort (R_B & R_T)



Notes: The figure compares the redistribution of income inequality in Peru for the years 2014 (left) and 2022 (right), measured by the Gini index. Total redistribution (R_T) is represented by red bars, and Between-group redistribution (R_B) by blue bars. The between-group component measures the extent to which the tax-benefit system reduces “inequality of opportunity” among population “types” defined by circumstances: parents’ highest level of education, gender, ethnicity, and region of birth. For the case of Brazil (used in the underlying model framework), the circumstances also include parental occupation.

Source: Authors’ calculations based on ENAHO-PERUMOD (Peru).

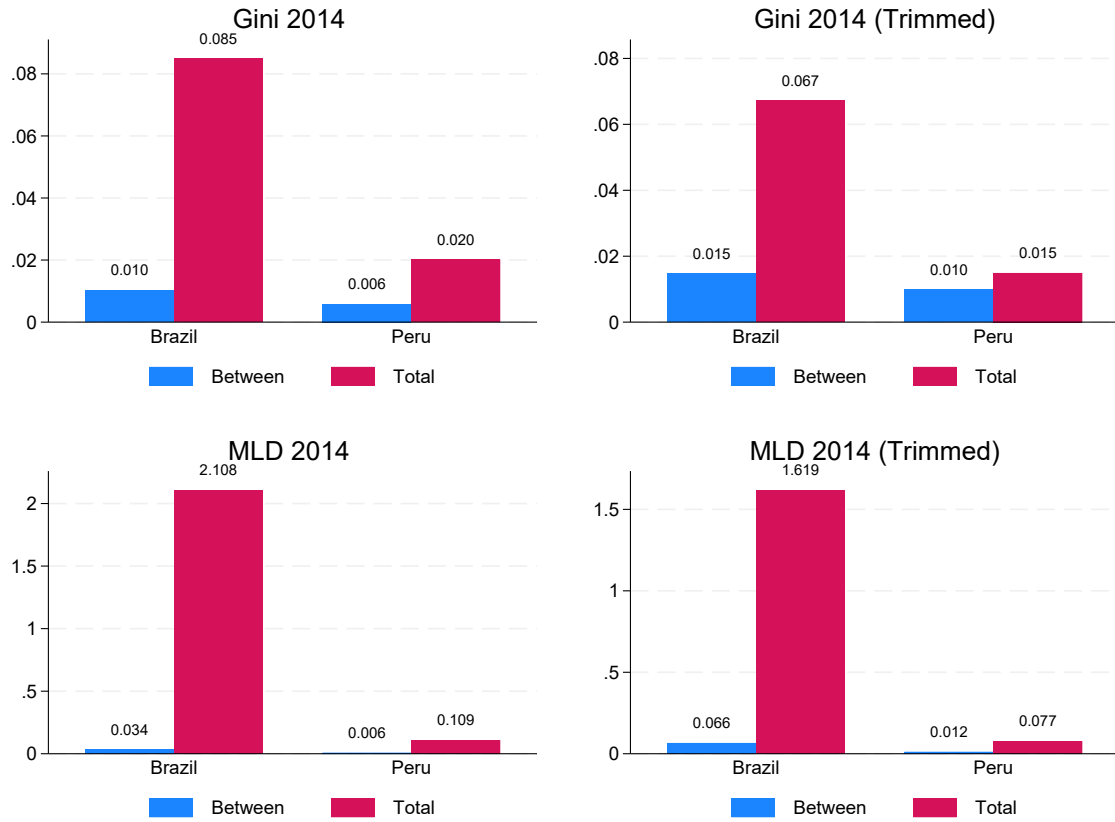
Figure A3: Inequality of Market Income in Brazil and Peru (2014): Sensitivity Analysis with Trimmed Samples ($I_{M,T}$ & $I_{M,B}$)



Notes: The figure presents a sensitivity analysis of market income inequality, comparing results from the full sample (left panels) with a trimmed sample (right panels). Total inequality ($I_{M,T}$) is represented by blue bars, and Between-group inequality ($I_{M,B}$) by red bars. The between-group component measures “inequality of opportunity” among population “types” defined by circumstances: parents’ highest level of education, gender, ethnicity, and region of birth. For the case of Brazil, the circumstances also include parental occupation. Results are shown for both the Gini coefficient and the Mean Log Deviation (MLD).

Source: Authors’ calculations based on PNAD-BRASMOD (Brazil) and ENAHO-PERUMOD (Peru).

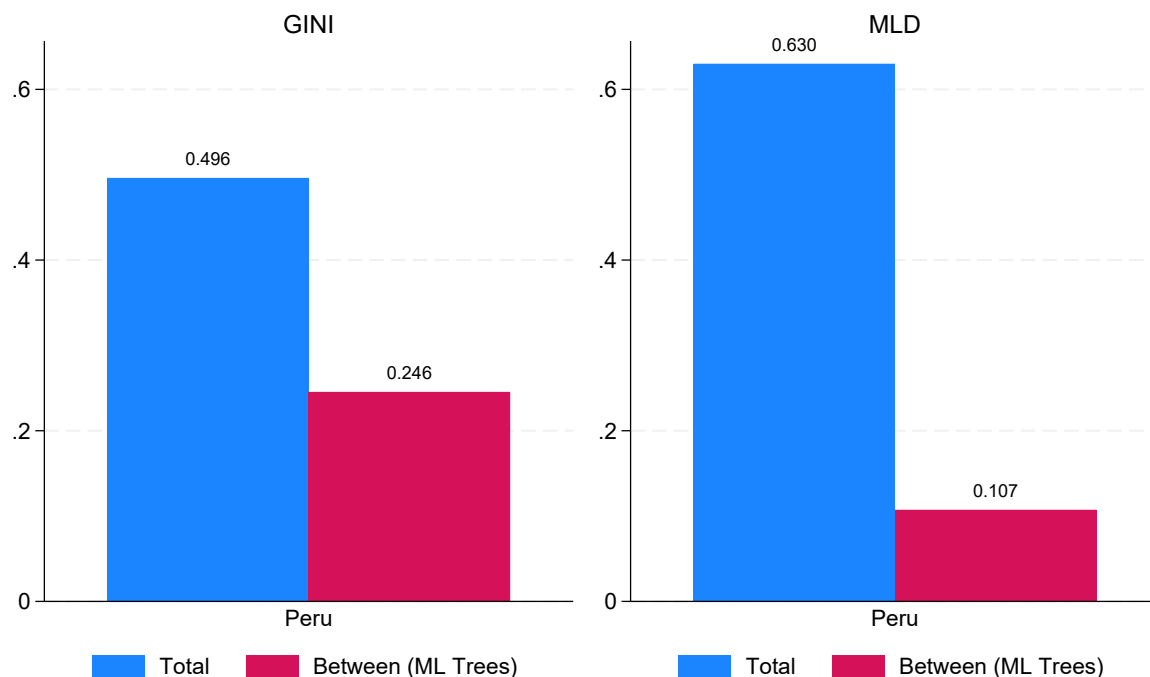
Figure A4: Redistribution of Total and Between-Group Inequality in Brazil and Peru (2014): Sensitivity Analysis with Trimmed Samples (R_B & R_T)



Notes: The figure presents a sensitivity analysis of income redistribution, comparing results from the full sample (left panels) with a trimmed sample (right panels). Total redistribution (R_T) is represented by red bars, and Between-group redistribution (R_B) by blue bars. The between-group component measures the extent to which the tax-benefit system reduces “inequality of opportunity” among population “types” defined by circumstances: parents’ highest level of education, gender, ethnicity, and region of birth. For the case of Brazil, the circumstances also include parental occupation. Results are shown for both the Gini coefficient and the Mean Log Deviation (MLD).

Source: Authors’ calculations based on PNAD-BRASMOD (Brazil) and ENAHO-PERUMOD (Peru).

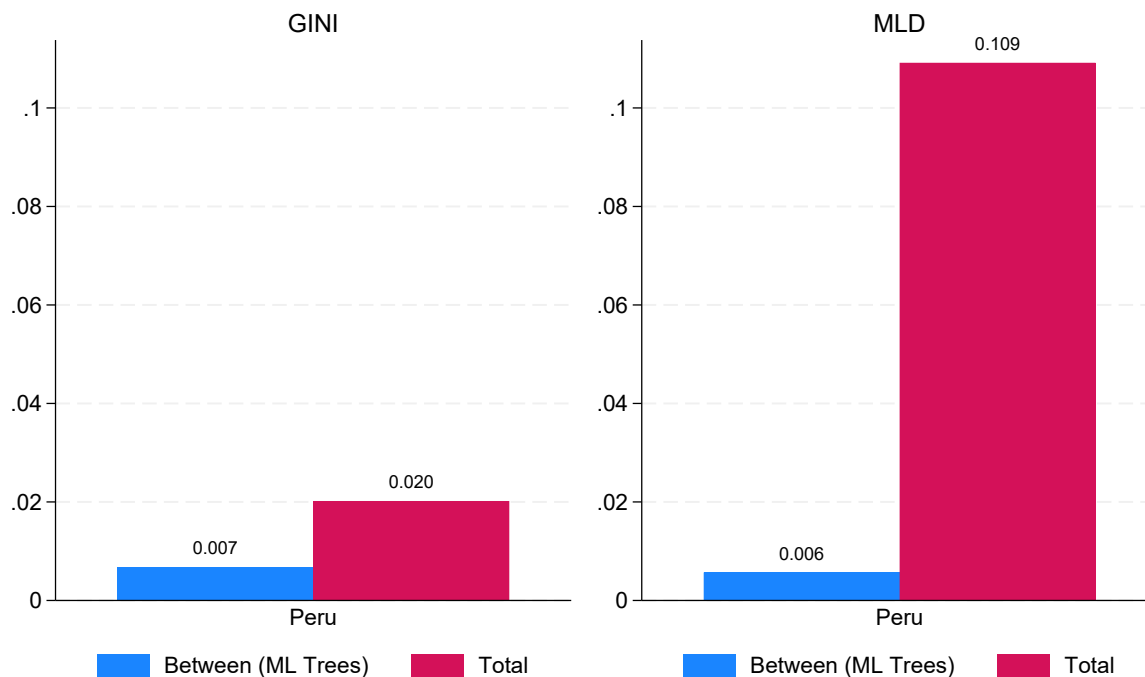
Figure A5: Inequality of Market Income in Peru (2014): Machine Learning-Based Decomposition ($I_{M,T}$ & $I_{M,B}$)



Notes: The figure displays the decomposition of market income inequality in Peru into total and between-group components. Total inequality ($I_{M,T}$) is represented by blue bars, and Between-group inequality ($I_{M,B}$) by red bars. Following the methodology of **Brunori (2023)**, the between-group component is determined via conditional inference trees (ML Trees) to identify population “types” based on circumstances: parents’ highest level of education, gender, ethnicity, and region of birth. For the case of Brazil (used in the underlying model framework), the circumstances also include parental occupation. Results are shown for both the Gini coefficient and the Mean Log Deviation (MLD).

Source: Authors’ calculations based on ENAHO-PERUMOD (Peru).

Figure A6: Redistribution of Total and Between-Group Inequality in Peru (2014): Machine Learning-Based Analysis (R_B & R_T)



Notes: The figure displays the redistribution of income inequality in Peru, decomposed into total and between-group components. Following the methodology of **Brunori (2023)**, the between-group component (R_B) is determined via conditional inference trees (ML Trees) and represented by blue bars. Total redistribution (R_T) is represented by red bars. The between-group component measures the extent to which the tax-benefit system reduces “inequality of opportunity” among population “types” defined by circumstances: parents’ highest level of education, gender, ethnicity, and region of birth. For the case of Brazil (used in the underlying model framework), the circumstances also include parental occupation. Results are shown for both the Gini coefficient and the Mean Log Deviation (MLD).

Source: Authors’ calculations based on ENAHO-PERUMOD (Peru).