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DESIGNING ALTERNATIVE INEQUALITY MEASURE USING EUROPEAN ASSOCIATION OF TAX LAW PROFESSORS (EATLP) 2024 INEQUALITY CONGRESS COUNTRY REPORTS AND AI

DESENVOLVENDO UMA MEDIDA ALTERNATIVA DE DESIGUALDADE USANDO OS RELATÓRIOS NACIONAIS DO CONGRESSO SOBRE DESIGUALDADE DE 2024 DA ASSOCIAÇÃO EUROPEIA DE PROFESSORES DE DIREITO TRIBUTÁRIO (EATLP) E IA

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Abstract

This study presents a novel method for approximating inequality by converting expert qualitative data from 32 EATLP country reports into quantitative indicators with the help of large language models (LLMs). Nine sub-indicators—covering aspects such as economic rights, judicial enforcement, tax policy, and anti-discrimination—are aggregated to build an overall indicator. Validation against the World Inequality Database's Gini coefficients shows that the composite index explains more than half of the variation in post-tax Gini, validating the role of legal and institutional factors in shaping inequality outcomes. A sub-index based solely on tax-specific metrics, the Tax Equality Score, also displays a positive association with Gini differentials before and after taxation. While it suffers from some limitations, such as potential model biases and no temporal dimension, this approach shows the potential of LLMs to supplement traditional socioeconomic data. It offers a scalable and cost-effective way to capture complex policy and institutional dimensions of inequality.

Keywords: AI-Driven Inequality Metrics. Taxation and Socioeconomic Disparities. Institutional Effectiveness. Global Governance Assessment. LLMs in Public Policy.

Resumo

Este estudo apresenta um método inovador para aproximar a desigualdade, convertendo dados qualitativos de especialistas de 32 relatórios de países do EATLP em indicadores quantitativos com o auxílio de modelos de linguagem de grande escala (LLMs). Nove subindicadores — abrangendo aspectos como direitos econômicos, aplicação da lei, política tributária e antidiscriminação — são agregados para construir um indicador geral. A validação com base nos coeficientes de Gini do Banco de Dados Mundial de Desigualdade mostra que o índice composto explica mais da metade da variação do Gini pós-impostos, validando o papel dos fatores legais e institucionais na formação dos resultados de desigualdade. Um subíndice baseado exclusivamente em métricas específicas de impostos, o Índice de Igualdade Tributária, também apresenta uma associação positiva com as diferenças de Gini antes e depois da tributação. Embora apresente algumas limitações, como potenciais vieses do modelo e ausência de uma dimensão temporal, esta abordagem demonstra o potencial dos LLMs para complementar os dados socioeconômicos tradicionais. Ela oferece uma maneira escalável e econômica de capturar as complexas dimensões políticas e institucionais da desigualdade.

Palavras-chave: *Métricas de Desigualdade Impulsionadas por IA. Tributação e Disparidades Socioeconômicas. Eficácia Institucional. Avaliação da Governança Global. Mestrados em Políticas Públicas.*

1 INTRODUCTION AND RESEARCH QUESTION

Inequality data such as Gini is famous for being inconsistent across countries having different definitions in almost each of them. Differences in the quality and availability of sources and methods for assembling global databases of inequality are substantial, both between different countries and within the same country across various times (Atkinson and Brandolini, 2001). There has been much research trying to create a measure that does not rely on income data attempting to overcome the issue of reliance on national statistical institutes for data. For example, by using nightlights data from satellites (Galimberti *et al*., 2021).

The purpose of this research is to create a novel way to approximate inequality by using semi-structured qualitative data transformed in quantitative one and combined in an index with the aim to initiate a scientific discussion on the usefulness of such a measure. A group of 32 country reports based on standard questionnaire on the topic of “Taxation and Inequalities: Constitutional Underpinnings” from the annual European Association of Tax Law Professors (EATLP) 2024 congress are used as a data source. Each report will be summarised based on a common pre-defined framework and then fed into Large Language Model (LLM) for each of the sections and sub-sections of the framework to be transformed into a quantitative measure. Afterward each value will be combined into a composite index that can be compared to Gini inequality index as a validation procedure.

Even though this approach has some limitations such as the biases that are inherent in LLM models and the difficulties of capturing temporal dynamics, it is a promising strategy for advancing the way such indices are developed and applied. Current indices like the Worldwide Governance Indicators (WGI) and Corruption Perceptions Index (CPI) of Transparency International mostly rely on structured questionnaire data which is often time-consuming to collect and process. On the other hand, LLMs have the capability of simplifying this process because they can process qualitative data effectively, combine different data sources and update themselves frequently. For instance, an LLM-based system could also help in the identification of insights from the expert opinions, legal texts or policy papers which would drastically cut down the time and human resources needed for the conventional index development. In addition, using advancements in natural language processing, such systems could emerge with better ways of measuring and capturing the dynamics of development-related issues in various countries and regions. The issue of bias and the need for proper validation will continue to be important even as the capabilities of LLM expand, however there is room for transformative change. With proper application, these tools have the potential of not only enhancing the existing methodologies but also creating new ways of developing relevant and more effective global indices on governance and inequality at a faster, cheaper and efficient manner.

2 LITERATURE REVIEW

Inequality is an elusive concept which is commonly associated with economic terms such as an imperfect distribution of income. In common parlance, inequality is defined as the fact that some people have much more than others and, when it comes to tax, the general perception is that tax policies fail to tax the handful of individuals that own the most wealth (Ranchordás, 2025). According to Limberg (2021) wealth concentration is indeed one of the key sources of inequalities worldwide. Economic inequality is typically measured through Gini coefficients that show the percentage of income to be redistributed at national level to achieve a perfectly equal income distribution. While inequality is layered and intersectional, resulting often from the overlap of multiple differences, economic inequality remains key because it gives rise to many other inequalities. Furthermore, inequalities are not always evident as direct or indirect discrimination of taxpayers or economic disparities between individuals. (Ranchordás, 2025).

Globally, significant tax policies or measures with negative impacts on equality have been identified. Firstly, in low and middle-income countries, and over the past four decades, most OECD economies have faced rising inequality, challenging budget conditions, and a decline in the share of income tax (Islam *et al*. 2018).

The development of income inequality over the past decades has attracted considerable attention in the public debate and spurred a surge in research trying to understand the causes of inequality. Interest in the role of tax systems in addressing inequality has increased in recent years (Rubolino and Waldenström, 2020). Tax is an important policy tool, among others, for governments that wish to address inequality. A broad array of policy tools can help mitigate inequality. Non-tax policies including the removal of barriers to labour market participation, minimum wages, and in-kind social transfers such as education and healthcare are essential to reducing inequality, especially at the lower end of the income distribution (OECD 2024). According to Ennis, Gonzaga and Pike (2019) competition policies that reduce market power can also help mitigate rising wealth concentration at the top. Tax measures can complement these policies. Tax policy can influence inequality across the income and wealth distributions, including at the higher end where other policy tools may have more limited reach. Much of the literature addresses the macroeconomic implications of high inequality, including a potential increase in financial fragility, political instability and a slowdown of economic growth (Ulrich and Qualo, 2023). The most influential theory explaining wage inequality is probably the race between technology and skills. According to this theory, technology increases the productivity gap between highly skilled workers and low skill workers. If the number of highly skilled workers does not keep up with their demand, their pay premium will rise above average earnings and pay inequality widens (Cantante, 2020). Kierzenkowski and Koske (2012) define the theory as a "nuanced view", according to which globalisation fosters the opposition between the highly qualified workforce and the routine manual workers, because the tasks performed by the later can be done in low wage countries.

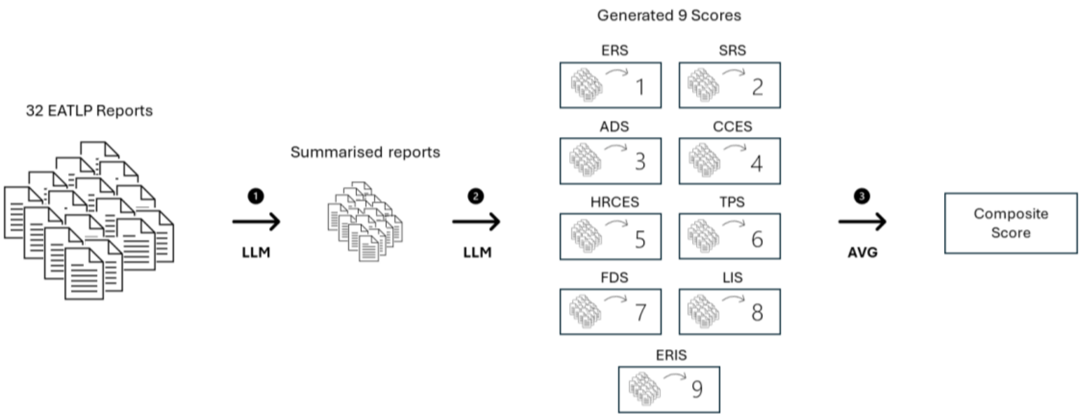
3 METHODOLOGY

This study explores the use of large language models (LLMs) to convert qualitative legal and institutional data into a structured quantitative framework for assessing inequality. LLMs are especially well-suited for this purpose, as they can efficiently analyse vast amounts of unstructured or semi-structured text, identify key insights aligned with a predefined framework, and produce consistent quantitative scores across various types of textual data.

An overview of the steps in the methodology are design of a common framework with main sections and subsections, summarisation of each report's contents into the framework (1), definition of the indices framework, quantification of the qualitative results in the indices framework (2), creation of a composite index (3), and validation with Gini index using correlation metrics and regression analysis. The above numerated steps can be illustrated with Figure 1 which displays the process with a comprehensible overview.

Figure 1

Index Creation Process



Source: prepared by the authors

3.1 EATLP congress

The European Association of Tax Law Professors (EATLP) is an organisation comprising tenured and full professors who specialise in teaching tax law at European universities. Each year the association organises congresses. They have a different topic each year for which a guiding questionnaire is prepared and each country member prepares a report on the topic specific to its country legal and institutional environment. The purpose is to learn about the regional specificities, collecting understanding of what works and what not and why. The topic of the congress in 2024 was "Taxation and Inequalities: Constitutional Underpinnings". There were 32 countries, the majority 27 from Europe, 2 representatives from Asia (Japan, China), 2 from North America (USA and Canada), and 1 from South America (Brazil).

The three main goals of the EATLP reports are (1) to examine how constitutional principles of equality and non-discrimination influence tax systems, exploring whether legal frameworks adequately address systemic inequalities and support equitable tax policies, (2) to evaluate the effectiveness of national tax policies in reducing income inequality, promoting gender and intergenerational equity, balancing progressivity with economic efficiency, and considering the role of tax incentives and preferential regimes in addressing broader social disparities, (3) to investigate the impact of tax enforcement practices on inequality, including the use of technology, discretionary measures, and tax amnesties, while identifying strategies to ensure fair and inclusive enforcement for vulnerable groups. The questionnaire of 2024 congress can be provided upon request.

3.2 LLMs

The research focuses on using advanced LLMs to come up with a quantitative representation based on the qualitative information drawn from country expert reports. These models are particularly useful for that since they can capture the sentiment in the text which is what powers them to understand the prompts and present answers. Additionally, summarisation is integral part of the process and of large language models. This is due to several indispensable characteristics of the model. One is that it is trained on massive and diverse datasets such as books, articles, and social media where sentiment is embedded naturally. Additionally, they can be fine-tuned for a specific context, which is what is done in this research with the provision of expert developed reports on the topic of inequality with their own specific structure. This step enhances the ability of the model to generate consistent scores with fairly accurate results. Other inherent characteristics of models like GPT and BERT are that they have self-attention mechanisms, which means that they have weights assigned to each word in relation to every other word in a sentence or paragraph (Vaswani *et al*., 2017). For example, in a general sentence like "I didn't like the movie because it was boring", the model understands that the word "boring" is connected to the word "movie". In other words, a LLM will assign higher weights to the connection of these words. All of this makes summarisation and sentiment analysis innate part of these models. And sentiment analysis is similar to the process of quantifying text information.

The summary is performed by OpenAI 4o model. This model is powerful and well-suited for the task since it is more efficient and capable of handling long texts due to the significant increase in the number of parameters when compared to its previous version[1].

The sentiment analysis is done by o1 (omega 1) – OpenAI's best model by the time of this paper being written[2]. This model is their first to use chain-of-thought functionality which is a structured reasoning process that increases their ability to solve complex problems by explicitly generating intermediate steps. This improves accuracy, explainability, and capability in tasks requiring logical and contextual depth.

3.3 Summarisation framework

The summarisation structure used for analysing the national reports is designed to reflect the framework and its objectives outlined in the EATLP Congress 2024 questionnaire. It provides a synthesis of constitutional and legal principles, regional contextual factors, and practical applications of taxation in addressing inequalities. These sections within are explained in more detail below.

The first one focuses on basic information about the country, such as the date of constitution adoption and/or its most recent amendments and the political system. The introduction assesses the general constitutional environment shaping tax law and policy.

The structure then examines constitutional provisions related to inequality, such as economic rights, social rights, and anti-discrimination clauses. It investigates how these principles are integrated into legal systems and supported by international treaties, domestic legislation, or judicial interpretations. Economic rights sub-section explores the property rights, labour rights, and access to resources through the lenses of taxation, redistribution, and equality. The sub-section on social rights delves into education, healthcare, and social security. For example, it considers whether progressive taxation systems or welfare policies effectively support marginalised groups. This reflects the questionnaire's objective of examining how tax policies impact income inequality and other social disparities. To address anti-discrimination, the structure includes legal protections for groups based on gender, race, religion, or other identities. It assesses the

[1] Release notes of the model by OpenAI: https://openai.com/index/hello-gpt-4o/
[2] Release notes: https://openai.com/index/openai-o1-system-card/

effectiveness of these protections and their enforcement, responding to the questionnaire's focus on which inequalities are addressed in national law and how tax policy and broader legal frameworks engage with them.

The next section, judicial enforcement mechanisms, analyses the role of constitutional courts, human rights commissions, and other bodies in upholding equality and non-discrimination. Additionally, it observes important principles and policies regarding property laws, taxation laws and provisions, and financial and taxation (de)centralisation. This section aligns with the congress' exploration of legal remedies and enforcement tools used to address inequality, particularly through the tax system. As a subsection, "implementation and impact" is included to examine the legislative outcomes and their practical effects on inequality, evaluating whether policies achieve their intended goals. The goal is to understand how the high-level underpinnings translate into specific case law examples, derived legislation, and institutional enactment.

Finally, the framework incorporates contextual factors that are affecting the equality and/or taxation in the countries such as historical background (wars and revolutions, unions, religion, and other influences), economic status, cultural and societal norms (e.g., focus on generational wealth preservation). It is also designed to capture any recommendations made by the responsible country reporters and familiar challenges.

This outline provides a common and structured way to review all the 32 reports enabling an organised way to analyse and compare. The framework together with example countries is displayed in Appendix A.

3.4 Indices framework

The indices, which are 9 in total, are derived from the summarisation structure and thus from the questionnaire and the EATLP reports' structure. They are an integral part of the process to create a composite score.

The Economic Rights Index (ERS) measures effectiveness and compliance with property, labour, and access to resources in terms of equality. The Social Rights Index (SRS) gauges availability and access to social rights, for instance, in education, medical care, and social security.

The Anti-Discrimination Score (ADS) considers constitutional and national legislative anti-discrimination protections in terms of such factors as gender, religion, and race. It considers both constitutional provisions and national legislation. The Constitutional Court Effectiveness Score (CCES) part of the subsection of the judicial enforcement mechanisms in the summarisation framework. It considers constitutional courts' success in safeguarding equality principles. For example, there are nations, such as China, with no constitutional court and thus rely on alternative courts such as labour and civil courts or specialist commissions. Part of the same section is the Human Rights Commission Effectiveness Score (HRCES) which assesses whether an independent administration (e.g., an Ombudsman, a Human Rights Commission, etc.) is responsible for values of equality and how effective it is.

The Legislation Implementation Score (LIS) which combines the legislation derived from the constitutional underpinnings such as specific anti-discrimination laws, progressive tax laws, etc. together with case law examples and the institutional framework such as revenue agencies or tax administrations. This is one of the indices that can be considered as related to taxation since it encapsulates tax law and enforcement. Then, there is a designated index on tax policy, existing implementation or discussion of progressive tax and specific allowances for low-income groups which is named Tax Policy Score (TPS). TPS can be used for a subindex to compare the taxation effect on Gini. The Fiscal Decentralisation Score (FDS) assesses the extent of regional autonomy in tax policy versus central government control. Countries like the United States and Switzerland score highly due to their ability to set taxation levels independently, providing flexibility to address regional inequalities. TPS, FDS, and LIS collectively form a sub-index that can be compared to the difference between pre-tax and post-tax Gini coefficients.

The Effectiveness in Reducing Inequality Score (ERIS) measures a country's success in minimising inequality, based on national report findings and suggestions. Common suggestions include "bridging gaps between regions," "enforcing anti-discrimination laws," and "raising access to justice for disadvantaged groups."

Each index is rated between 1 and 5, with 5 being most effective. Individual ones for each one are averaged together to produce a composite index.

3.5 Measure validation

To validate this newly created measure, there is a need for a commonly accepted measure of inequality. The one that this research will leverage is Gini on pre-tax equal-split national income of adults from the World Inequality Database (WID). In WID, the term "equal-split" refers to a methodological approach for measuring income distribution where the individual serves as the primary unit of analysis, rather than the household. To account for shared resources within members of a household, the total income of the household is divided equally among all members[3]. The latest data that is available for all 32 countries in the study is from 2023 for this measure. This data is directly assessed against the total composite index which includes the tax related indices.

The other data points that are utilised are the Gini post-tax equal-split adults' national income again coming from the WID for which the latest available data for all countries is only from 2022. While there is a one-year difference between the two measures, it should not create significant measurement errors because the Gini does not have significant movements year over year. Based on performed analysis of the 32 countries from the period of 2000-2022 of the same post-tax Gini measure, only in 3 percent of all possible cases (25 out of 704) have a year over year change of more than 5% whether positive or negative. 15 of those 25 occurrences have happened between 2000 and 2010 with the majority from countries like North Macedonia, Kosovo, Serbia, which can be treated as outliers during this period due to turbulent historical events after the war in Yugoslavia. In the last 5 YoY values there is only one example of more than 5% change which is Portugal from 2020 to 2021, with overall average of -0.3%. In summary, this one-year difference in both measures should not create a significant measurement error when both indices are used together.

As discussed above, there are three scores that can be directly linked to the setup and the effectiveness of taxation and its redistribution. Those are LIS, FDS, and TPS, which are combined in a separate index attempting to represent the efficacy of tax law and its implementation. On the other hand, we have the Gini pre-tax and Gini post-tax, the difference of which provides the effects of taxation on income inequality distribution. An additional validation is to compare this sub-index with the difference of Gini pre-tax

[3] A reference to the methodology and measure types of WID: https://wid.world/codes-dictionary/

and Gini post-tax. The results of this will provide a more nuanced evaluation of the index creation approach and the possibility to approximate different variations of Gini.

The validation is based on standard ordinary least squares regression which provides residual information per country that can inform where the measure fails to mimic Gini which in turn can instigate a deep dive. The composite index (CS) is the only variable that will explain Gini, which is expressed with the below simple formula:

$$GINI_{post-tax} = \beta_0 - \beta_1 CS_c + \varepsilon_c \qquad (1)$$

where c represents each country and ε_c is the error term. The expected relationship is negative since the higher the index, the better the country scores on its legal principles and provisions related to safeguarding equality whereas Gini ranges from 0 to 1, with 0 being a perfect equality – all income is spread equally between the units, and 1 being a perfect inequality – one unit holds all income. In other words, the higher the composite index the lower the Gini should be.

To validate the created index, derived from sub-indices (LIS, FDS, TPS) related to tax law and tax enforcement and referred to here as the Tax Equality Score (TES), a regression analysis is conducted using the Gini Tax Effect (GTE) – defined as the difference between the post-tax Gini coefficient and the pre-tax Gini coefficient. In mathematical terms this can be represented as:

$$GTE_c = \beta_0 + \beta_1 TES_c + \varepsilon_c \qquad (2)$$

The relationship between the variables is expected to be positive since with the increase in the Tax Equality Score the expectation is that a more effective redistribution would appear, thus the gap between pre-tax Gini and post-tax Gini should become wider resulting in lower inequality.

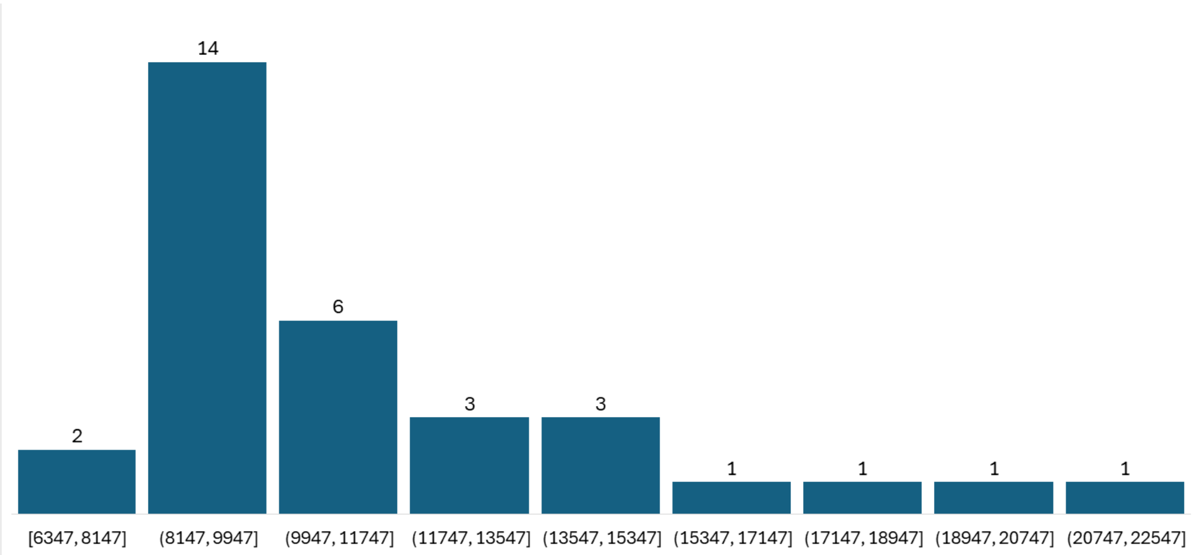
4 DATA

In the research there are two main data sources: the 32 EATLP country reports on inequality and the World Inequality Database's Gini coefficient post and pre taxation. Out of the former, 9 individual indices have been extracted, and two comprising indices have been created, the Composite Score from all 9 indices and the Tax Equality Score. Out of the latter, a Gini Tax Effect measure has been conceived out of the subtraction of Gini pre-tax and Gini post tax data.

The questionnaire on which the reports are based on has a threshold on the number of words that each report should have written which is 8000 words. However, most of the reports have overachieved and their word count is above the limit with only 2 countries (Norway and Brazil) having a word count that is below. More than half (22) have a word count from 8000 to 12000. Below in Figure 2 a histogram is presented where each bin represents 1800 words.

Figure 2

EATLP reports word count histogram



Source: prepared by the authors

France, Sweden and Australia are the outliers to the right of the graph when it comes to word count of EATLP reports. The median is 10076 words, which as a count for an input of a LLM prompt is on the higher side. In LLMs, there is a shared word capacity between the input provided and the output. In other words, if the prompts are text-intensive the model will generate a shorter output. With higher number of words passed to a LLM prompt the possibility of primacy and recency biases to occur are higher. These biases are related to the attention the model put to the text in the beginning and the end and the extent to which it considers the middle part of the prompt (Guo *et al*., 2024). Like human psychology, we tend to consider more the beginning and the ending of a text.

However, a way to overcome these limitations of the models is to point in the prompt of the model to what it should pay attention to (Guo *et al*., 2024), which is the approach undertaken in this research especially in the summarisation task where this is mostly relevant.

In Table 1 summary statistics for all 14 variables part of this research are presented. Overall, social (SRS) and anti-discrimination (ADS) scores are the most highly scored across most regions. However, some of the implementation mechanisms, such as the constitutional courts (CCES) and human rights commissions (HRCES) or any other legal body responsible for adherence to the equality principles, have significantly lower scores. Interestingly, the model did not score any of the indices with a score that is below 2. FDS with the highest variance is inconsistent, indicating significant differences of the fiscal setup across the countries. The TPS is relatively strong, suggesting that taxation frameworks are designed with equity considerations reflecting the fact that there is room for improvements. This could be the case since most of the countries in the sample have some form of progressive taxation, which to this day is the major tax-based redistribution lever available to policy makers. For example, Bulgaria which does not have any progressive taxation in place is scored with 2. It is also important how effectively do these taxes benefit the disadvantaged. The rather low score of the ERIS reveals that there is an overall disconnect between the policy design and the enforcement to address inequality.

Table 1

Summary statistics of variables

	ERS	SRS	ADS	CCES	HRCES	TPS	FDS	LIS	ERIS	Composite Score	TES	23 Gini Pre-Tax	22 Gini Post-Tax	Gini Tax effect
mean	3.38	4.34	4.31	3.47	3.72	4.00	2.66	3.94	3.28	3.74	3.53	0.48	0.36	0.12
std	0.87	0.75	0.78	0.84	0.81	0.84	1.04	0.80	0.77	0.57	0.70	0.07	0.11	0.07
min	2	3	3	2	2	2	2	3	2	2.78	2.33	0.33	0.17	-0.07
25%	3	4	4	3	3	3	2	3	3	3.22	2.92	0.44	0.27	0.07
50%	3	4.5	4.5	3.5	4	4	2	4	3	3.78	3.50	0.46	0.36	0.12
75%	4	5	5	4	4	5	3	5	4	4.14	4.00	0.50	0.42	0.17
max	5	5	5	5	5	5	5	5	5	4.56	5.00	0.69	0.65	0.25

Source: prepared by the authors

When it comes to Gini, the distribution mimics a normal one with the median and the mean almost being identical. The highest values for both are from Brazil, with 0.69 and 0.65 for 2023 pre-tax and 2022 post-tax respectively, as opposed to Norway that has the lowest ones. One interesting observation is that taxation appears to be creating greater inequality since the Gini Tax effect metric's minimum value is a negative one. This is the case for Japan and Ukraine, both having negative values and thus can be considered as outliers.

Exploring further the variables, a high level of intervariable correlation is visible from Table 2, where the dark blue signals high positive correlation and intense orange – high negative correlation. This should come as no surprise, as the variables are either inherently interconnected or assumed to exist in a causal hierarchy. For instance, the ERS and the SRS are presumed to establish the groundwork for the TPS, with correlations of 0.79 and 0.77, respectively. Moreover, it is plausible to consider the presence of an unobserved factor, such as countries' level of education, which might underlie and account for some of these correlations. Exploring the causality between the variables would be a challenging exercise which can be the focus of other research's efforts.

Table 2

Correlation matrix of variables

	ERS	SRS	ADS	CCES	HRCES	TPS	FDS	LIS	ERIS	Composite Score	TES	2023 Gini Pre-Tax	2022 Gini Post-Tax	Gini Tax effect
ERS														
SRS	0.690													
ADS	0.772	0.808												
CCES	0.545	0.558	0.654											
HRCES	0.519	0.644	0.703	0.435										
TPS	0.792	0.771	0.785	0.546	0.613									
FDS	0.219	0.116	0.297	0.598	0.227	0.222								
LIS	0.821	0.740	0.807	0.571	0.567	0.861	0.285							
ERIS	0.894	0.724	0.813	0.635	0.593	0.843	0.327	0.812						
Composite Score	0.849	0.786	0.837	0.714	0.651	0.891	0.453	0.877	0.917					
TES	0.736	0.646	0.765	0.728	0.571	0.835	0.689	0.863	0.806	0.912				
23 Gini Pre-Tax	-0.478	-0.409	-0.316	-0.224	-0.458	-0.459	0.232	-0.413	-0.436	-0.384	-0.227			
22 Gini Post-Tax	-0.741	-0.659	-0.694	-0.432	-0.565	-0.751	0.058	-0.780	-0.736	-0.723	-0.568	0.764		
Gini Tax effect	0.631	0.580	0.731	0.426	0.382	0.667	0.158	0.761	0.668	0.704	0.633	-0.110	-0.726	

Source: prepared by the authors

The correlation between the Composite Score and Gini post-tax is high (-0.72) and with the expected sign. Overall, almost all indices have a negative correlation with both Gini pre- and post-tax signalling that higher rights, effectiveness, and policy scores are associated with lower inequality. The TES exhibits a more moderately high correlation (0.63) with the Gini tax effect variable, and it is again with the initially predicted sign.

5 RESULTS AND DISCUSSION

In this section the results from the two regressions will be presented where it will become evident to what extent the Composite score explains Gini post-tax and thus inequality and to what extent does the TES explain the Gini tax effect measure.

5.1 Composite score regression

First, the results of the Composite score regression on the 32 observations are presented below in Table 3.

Table 3

Composite Score Gini post-tax regression results

	Coefficients	Standard Error	t Stat	P-value	R Square	Adjusted R Square
Intercept	0.86743	0.08987	9.65240	1.0361E-10***		
Composite Score	-0.13636	0.02377	-5.73671	2.916E-06***	0.52313	0.50723

Source: prepared by the authors

The results reveal that the Composite score demonstrates a statistically significant negative association with the post-tax Gini coefficient which is in line with the initial model specification. More specifically, the coefficient for the variable is estimated to be -0.136, indicating that an increase in the Composite score corresponds to a reduction in the post-tax Gini coefficient, suggesting that it correctly reflects laws, policies, institutions among other factors that correspond to income inequality mitigation. With a high statistical significance of this relationship, highlighted by a t-statistic of -5.74 and a very small p-value of 2.9E-06, the H_0 of no relationship between the Composite score and post-tax inequality can be firmly rejected.

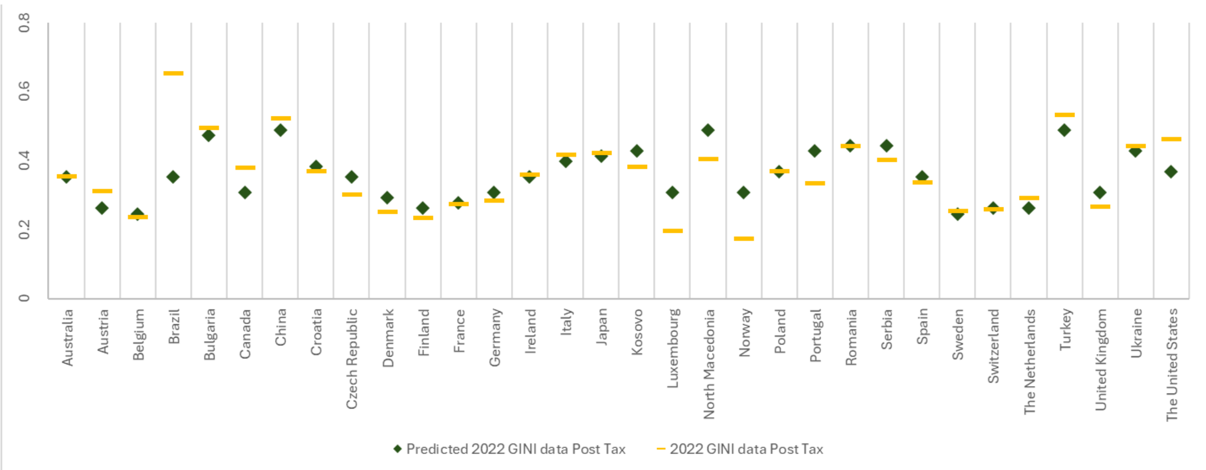
In terms of model fit, the R^2 value indicates that the newly created index explains approximately 52% of the variation in the post-tax Gini. More than half of the variation in post-tax inequality is attributable to this score, which points to a substantial explanatory power whereas the other half is related to unobserved factors to this model.

Overall, the findings suggest that the Composite score serves as a meaningful predictor of post-tax income inequality. The explanatory power of the variable is significant. For example, in other papers (Bourguignon *et al*., 1990) have models' results that range between 0.53 and 0.69 explanatory power measured by R^2 with the difference that there are many more variables such as factor endowments (e.g., labour, capital, export-specific land, mineral resources, etc.), ownership structure (e.g., distribution of agriculture land, concentration of human capital) among others, which are all important and significant variables affecting inequality. Additionally, the models attempt to explain specific income shares (e.g., 20%, 40%) rather than the entire range of income distribution. And this is one of the papers that presents the highest explanatory power.

Below in Figure 3 a comparison between the predicted Gini post-tax 2022 values and the actual ones are presented following the model estimation. This view helps in identifying for which countries the model's prediction is not close, supporting the thought process behind what could be the reason.

Figure 3

Predicted Gini post-tax vs. Gini post-tax



Source: prepared by the authors

The top countries that the model's prediction is off are Brazil, Norway, Luxembourg, the US and Portugal. It is worth mentioning that both Brazil and Norway are the ones that are on the bottom ranks for word count of their reports. In addition, Norway and Luxembourg are with a notoriously low inequality since their Gini post-tax coefficient is below the 0.2 mark and no other country can share a similar achievement, making them noticeable outliers. Regarding the bias of US and Portugal, the reasons explaining it can be numerous, ranging from the information in the reports, LLM's bias, unobserved factors among other reasons.

5.2 Tax equality score regression

The regression results presented below in Table 4 investigate the relationship between the TES and the Gini tax effect coefficient. This analysis attempts to evaluate whether the process for index creation can be used in a flexible way and capture the different inequality measures' dynamics. The model is again straightforward since it incorporates only one explanatory variable.

Table 4

Tax Equality Score and Gini Tax Effect regression results

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*R Square*	*Adjusted R Square*
Intercept	-0.1033	0.0503	-2.0548	0.0487***		
Tax Equality Score (TES)	0.0626	0.0140	4.4800	0.0001***	0.4008	0.3809

Source: prepared by the authors

The results reveal a positive and statistically significant association between TES and the Gini tax effect, which aligns to the initial expectations. The estimated coefficient for TES is 0.0626, implying that an increase in the independent variable is associated with a greater positive impact of taxation in reducing income inequality. The significance of this relationship is strongly supported by the t-statistic of 4.49 and a p-value of 0.0001, which rejects the H_0 that TES has no effect on the Gini tax effect measure.

In terms of the model's explanatory power, the R^2 value is 0.4, indicating that approximately 40% of the variation in the Gini tax effect coefficient can be explained by the TES, which is again a relatively high explanatory power for a model with only one variable.

Considering the comparison in Figure 4 which is between the predicted Gini tax effect and the actual one, we are presented with insights requiring further reflection.

Figure 4

Predicted Gini Tax Effect vs. Gini Tax Effect

Source: prepared by the authors

In this case, we have a few countries that can be considered as outliers for different reasons. On one hand, Japan and Ukraine as already mentioned above are one of the few that their inequality increases after taxation is applied. With standard OLS regression models, such extremes cannot be taken into consideration, and the model completely misses their values and overshoots them. Ukraine both in 2022 and 2023 was in war. When it comes to Japan, there might be several reasons for this such as regressivity in some of their taxes (e.g., consumption tax), their limited redistribution through social spending and the available tax deductions and exemptions for companies that favour high-income individuals (Inoue, 2020). On the other hand, there are Denmark and Luxembourg which decrease their level of inequality by almost 0.25 through taxation which is by far the most in the sample. Even though the model performs worse than the previous one, it shows reasonable and significant results.

Overall, this approach's results present an interesting use case of LLMs where purely qualitative data is transferred successfully into quantitative one, contributing to the discussion of utilising AI in social sciences.

5.3 Limitations

While this research provides an insightful analysis of laws, taxation and inequality within diverse national contexts using an innovative method, it is important to acknowledge the inherent limitations of the approach.

Firstly, it is worthwhile to discuss the bias that LLMs can have. It is true that the model could have already been trained on some information regarding the inequality in some of the countries which might affect the models' outcome. In this case, the countries of the sample were mostly from the developed ones, so it would be interesting for further research to attempt and do a similar analysis but for countries in the developing world. However, there is no apparent hurdle for the approach in this research where detailed expert information is passed through a framework to not work for the developing countries.

Secondly, the content provided by the EATLP reporters is crucial for this research. The inherent human behaviour biases that everyone possesses, and expresses will be passed through the model, and they will affect the results. It is plausible that aspects of the endowment effect may have influenced the reporters, leading them to speak more favourably about their country due to their inherent emotional attachment and sense of ownership (Thaler, 1980). However, trained experts tend to handle bias better (Shepperd *et al*., 2018). The supposition is that law professors can distance themselves from their countries and discuss the problem objectively.

Another limitation is that the analysis does not consider any temporal dimensions. It is curious to see whether the model will find the semantic differences and how would it evaluate them when for example a legal or institutional improvement relating to inequality is implemented.

Importantly, there are recent papers that discuss causality in the opposite direction where high income inequality undermines the quality of the institutions (Posner, 2024) which could to some degree cause a reverse causality issue. While institutions are important part of the generated index, they are function of the laws and policies in a country which is the main topic of the EATLP congress.

Since there is only one variable in the models, there will be an omitted variables bias. Considering other variables might affect the coefficient of the generated indices, but not to the extent that will change their sign. In this research the purpose is not to come up with the best model that explains inequality but rather to validate the novel approach.

6 CONCLUSION

This research explores an innovative methodology to quantify inequality through a composite index derived from qualitative data synthesised via LLMs. By leveraging country-specific reports from the EATLP, the study addresses some of the challenges in conventional inequality measures, such as reliance on incomplete or inconsistent economic data.

The proposed framework demonstrates potential in capturing multidimensional facets of inequality, such as economic rights, judicial enforcement, fiscal decentralisation, and social policies, and converts them into quantifiable scores. These indices, validated against established measures like the Gini coefficient, reveal substantial explanatory power. Moreover, by segmenting the indices to include only tax-specific metrics, thus coming up with Tax Equality Score, and validating it against the effect of taxation measured through Gini, the study proves that this approach captures granular nuances and successfully quantifies them.

The methodology is not without limitations. The inherent biases of LLMs, the dependency on subjective expert inputs, and the static nature of the reports are some of the limitations of the framework. The shortcoming of lack of temporal dynamics cannot support the conversion on causality. Nevertheless, the validation outcomes underscore the robustness of the composite index as a meaningful approximation of inequality.

In a world increasingly reliant on AI for data manipulation, this study contributes to the discourse on integrating LLMs into social science research. It offers a scalable, cost-effective, and adaptable approach to inequality assessment that can complement traditional economic measures and can be comparable to the approaches by organisations such as the Transparency International for creating indices. By addressing some of the existing limitations such as the lack of temporal dimension of the measure, future research can support the development of a procedure that is even more scalable and useful and possibly broaden the scope of its application's academic contexts.

This approach invites further exploration into AI-driven methodologies that are valuable, meaningful and supportive to the existent domain knowledge and theory.

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APPENDIX

Appendix A – Example LLM Summaries A-B Countries

Category / Country	Australia	Austria	Belgium	Brazil	Bulgaria
Basic Information					
Date of Constitution Adoption/Last Amendment	Commonwealth of Australia Constitution Act 1900; no recent amendments specific to inequality.	1920 (Austrian Federal Constitution); last significant amendments in 2021.	1831 (Belgian Constitution); last significant amendments in 2021.	1988 (Constitution of Brazil); amended multiple times, most recently in 2023.	1991 (Constitution of the Republic of Bulgaria); significant amendments addressing EU integration.
Political System	Federal parliamentary democracy.	Federal parliamentary democracy.	Federal parliamentary democracy.	Federal presidential democracy.	Unitary parliamentary democracy.
Constitutional Provisions Related to Inequality					
Economic Rights					
Right to Property	Protected under the Constitution but subject to public interest limitations.	Guaranteed under Article 5 B-VG; subject to public interest and just compensation.	Protected under Article 5 B-VG; subject to public interest limitations.	Protected under Article 5; subject to public interest and just compensation.	Protected under Article 17 of the Constitution; subject to public interest and compensation.
Labor Rights	Strong protections through the Fair Work Act; anti-discrimination integrated in labor laws.	Strong statutory protections; equality emphasized in labor laws and anti-discrimination provisions.	Statutory protections; equality emphasized in labor and anti-discrimination laws.	Protected by statutory frameworks; progressive equality principles enshrined in law.	Equality emphasized in employment laws; labor protections implemented through statutory frameworks.
Access to Resources	Indirectly addressed through welfare programs and progressive taxation.	Addressed indirectly through progressive taxation and welfare benefits.	Addressed indirectly through progressive taxation and welfare benefits.	Addressed through progressive taxation and social contributions.	Indirectly addressed through taxation policies and social security contributions.
Social Rights					
Education	Universally accessible and free; supported under statutory laws.	Universally accessible and free; supported under statutory laws.	Free and universally accessible; equal treatment for all under Article 24.	Universally accessible and free; supported by statutory laws.	Universally accessible and free; primary focus in the Constitution for all citizens.
Healthcare	Universally provided through Medicare funded by taxation; not a constitutional right.	Universally provided through social insurance contributions; not explicitly a constitutional guarantee.	Universally provided through social insurance; not explicitly a constitutional guarantee.	Universal access through public systems; not a constitutional guarantee.	Universal access provided through social security systems; not explicitly a constitutional guarantee.
Social Security	Comprehensive system established under statutory law.	Comprehensive system implemented through statutory measures.	Comprehensive system implemented through statutory measures.	Comprehensive statutory welfare systems.	Comprehensive welfare system covering pensions and unemployment benefits.
Anti-Discrimination Clauses					
Gender	Addressed under the Sex Discrimination Act and other gender-equality initiatives.	Article 7 B-VG emphasizes equality regardless of gender.	Gender equality explicitly guaranteed under Article 11bis.	Constitutional and statutory protections; recent laws mandate equal pay for men and women.	Explicitly protected under Article 6 of the Constitution and reinforced by anti-discrimination laws.
Race	Protected under the Racial Discrimination Act, aligned with international conventions.	Protected under constitutional principles; no discrimination on grounds of race.	Protected under constitutional principles; no discrimination on racial grounds.	Article 3 and anti-discrimination laws protect against racial prejudice.	Strong legal protections against racial discrimination; linked to EU human rights directives.
Religion	Freedom guaranteed under constitutional and statutory law.	Freedom guaranteed under constitutional law.	Freedom guaranteed under constitutional law.	Freedom of religion protected under Article 5.	Freedom guaranteed under constitutional law and national legislation.
Other Marginalized Groups	Statutory protections for LGBTQ+, disabilities, and age discrimination.	Statutory protections for LGBTQ+, disabilities, and other vulnerable groups.	Statutory protections for LGBTQ+, disabilities, and minority groups.	LGBTQ+ protections and anti-discrimination laws for disabilities in place.	Protections for persons with disabilities, Roma communities, and other vulnerable groups.
Judicial Enforcement Mechanisms					
Constitutional Courts	No specific constitutional court; equality principles enforced through general courts.	Austrian Constitutional Court ensures compliance with equality principles.	Constitutional Court ensures compliance with equality principles.	Supreme Federal Court oversees enforcement of equality principles.	Ensures compliance with equality principles and constitutional provisions.
Human Rights Commissions	Australian Human Rights Commission oversees equality-related issues.	Ombudsman monitors and enforces human rights protections.	Monitors and enforces human rights protections.	Monitors and enforces compliance with anti-discrimination laws.	Commission for Protection Against Discrimination oversees enforcement of anti-discrimination measures.
Other Relevant Provisions					
Land Reform	Minimal focus in constitutional provisions.	Minimal focus in constitutional provisions; addressed in fiscal and tax law.	Minimal focus; addressed through tax policy and fiscal measures.	Limited focus; property rights intertwined with fiscal measures.	Limited focus in the Constitution; addressed through secondary legislation and EU programs.
Taxation Policies	Progressive taxation system; debates on reforms to address regressive impacts of GST.	Article 18 ensures tax equity; progressive taxation system in place.	Progressive taxation system; equality in taxation emphasized in Article 172.	Articles 145 and 150 emphasize progressivity and fairness in taxation.	Flat tax system with limited progressivity; debates on introducing progressive taxation persist.
Decentralization	Fiscal policies centralized at the Commonwealth level; states rely on grants.	Fiscal policies centralized, with limited autonomy at the state level.	Strong fiscal decentralization; distinct taxation systems in regional governments.	High fiscal decentralization; states manage significant portions of tax revenue.	Centralized fiscal policies with minimal autonomy for municipalities.
Implementation and Impact					
Legislation Derived from the Constitution	Anti-Discrimination Acts, Fair Work Act, and tax reforms such as the Medicare levy.	Anti-Discrimination Laws, progressive tax laws, and wealth taxation measures.	Anti-Discrimination Laws, Gender Equality Laws, and progressive tax laws.	Anti-Discrimination Laws, progressive income tax regulations, and equality statutes.	Anti-Discrimination Act, Income Tax Act, and Child Protection Act.
Institutional Framework	Australian Taxation Office (ATO) enforces compliance; AHRC monitors equality measures.	Austrian Tax Administration ensures compliance; Ombudsman monitors rights enforcement.	Tax authorities manage compliance; human rights commissions monitor equality efforts.	Brazilian Tax Administration enforces compliance; Human Rights Commission monitors equality.	National Revenue Agency ensures compliance; the Ombudsman monitors public equality issues.
Case Law Examples	Cases address workplace equality, tax fairness, and human rights violations.	Cases include wealth tax equity, inheritance tax fairness, and anti-discrimination enforcement.	Cases include inheritance tax equity and anti-discrimination measures.	Cases focus on racial discrimination, gender pay equity, and tax fairness.	Cases include discrimination in tax compliance and access to public services.
Contextual Factors					
Historical Background Influencing Constitution	Federation model influenced by UK legal traditions; incremental legislative approach to equality.	Post-war focus on welfare and equality; influenced by EU directives and international norms.	Transition from unitary to federal state structure since the 1970s shaped equality measures.	Transition from military rule to democracy influenced equality-focused principles.	Transition from socialism to a market economy influenced the adoption of equality-focused measures.
Economic Status	Developed economy with a highly progressive tax-transfer system.	Developed economy; challenges in wealth redistribution and addressing rural-urban disparities.	Developed economy with persistent wealth inequality and high tax burden on labor.	Emerging economy with significant inequality and high poverty rates.	Developing economy with persistent income and regional disparities.
Cultural/Societal Norms Affecting Inequality	Persistent gender and racial disparities influence equality policies.	Persistent traditional roles and increasing public debates on wealth inequality.	Cultural diversity and linguistic divisions influence policy development.	Persistent regional disparities and societal norms affect equality measures.	Traditional gender roles and systemic biases impact the implementation of equality measures.
Report Findings					
Summary of Main Conclusions	Tax policies reduce income inequality; wealth inequalities remain significant.	Tax policies address income inequality; significant gaps in wealth redistribution remain.	Progressive taxation reduces income inequality; structural wealth gaps remain.	Progressive taxation addresses income inequality; wealth inequalities remain largely unaddressed.	Tax policies have limited redistributive effects; challenges remain in addressing income inequality and enforcing anti-discrimination laws.
Identified Challenges and Successes	Success in anti-discrimination laws; challenges in addressing wealth and gender gaps.	Success in education and labor rights; challenges in tax equity and addressing wealth disparities.	Success in education and healthcare equality; challenges in tax equity and wealth disparities.	Success in expanding social programs; challenges in enforcing wealth tax laws and tackling regional disparities.	Success in EU-aligned human rights legislation; challenges in implementing progressive tax reforms and addressing regional disparities.
Recommendations Made in the Report	Increase wealth taxes, enhance progressive taxation, and improve gender-responsive budgeting.	Strengthen wealth taxes, reform inheritance laws, and improve fiscal redistribution mechanisms.	Reform wealth taxation, enhance progressivity in tax systems, and address regional disparities.	Strengthen progressive taxation, enhance enforcement of anti-discrimination laws, and address regional inequalities.	Introduce progressive taxation, improve access to justice for marginalized groups, and enhance enforcement mechanisms for anti-discrimination laws.

Authors' Contribution

All authors contributed equally to the development of this article.

Data availability

All datasets relevant to this study's findings are fully available within the article.

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