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# Does income inequality affect greenhouse gas emissions? Evidence from brazilian states using dynamic panel data models

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# Resumo | Abstract

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Este artigo investiga a relação entre desigualdade de renda e emissões de gases de efeito estufa (GEE) no Brasil, um país marcado por alta desigualdade e por um perfil de emissões dominado por mudanças no uso da terra e desmatamento. Utilizando um modelo de dados em painel dinâmico para os 27 estados brasileiros entre 2012 e 2022, avaliamos os efeitos da desigualdade de renda, medida tanto pelo coeficiente de Gini quanto pela participação da renda do topo de 10%, sobre as emissões de GEE. A análise se baseia em três hipóteses teóricas: os mecanismos de agregação, de composição do consumo e de economia política. Os resultados mostram uma associação positiva e estatisticamente significativa entre o aumento da desigualdade e as emissões de GEE. As evidências sugerem que o consumo orientado por status e o enfraquecimento da ação coletiva em sociedades desiguais parecem contribuir para maiores emissões. Este estudo oferece a primeira evidência subnacional dessa relação no Brasil, destacando a importância de enfrentar a desigualdade nas políticas climáticas.

**PALAVRAS-CHAVE:** Desigualdade de Renda; Emissões de Gases de Efeito Estufa; Brasil; Dados em Painel Dinâmico; Economia Política Ambiental.

**CÓDIGOS JEL:** Q56, Q54, O44, C23, D31.

This paper investigates the relationship between income inequality and greenhouse gas (GHG) emissions in Brazil, a country with high inequality and an emissions profile dominated by land-use change and deforestation. Using dynamic panel data for Brazil's 27 states from 2012 to 2022, we assess the effects of income inequality, measured by both the Gini coefficient and the income share of the top 10%, on GHG emissions. The analysis draws on three theoretical hypotheses: the aggregation, consumption composition, and political economy mechanisms. Results show a positive and statistically significant association between increased inequality and GHG emissions. The findings suggest that status-driven consumption and weakened collective action in unequal societies seem to contribute to higher emissions. This study offers the first subnational evidence on this relationship in Brazil, highlighting the importance of addressing inequality in climate policy.

**KEYWORDS:** Income Inequality; Greenhouse Gas Emissions; Brazil; Dynamic Panel Data; Environmental Political Economy.

**JEL CODES:** Q56, Q54, O44, C23, D31.

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## 1. Introduction

Growing concerns about climate change have heightened the need to understand the socioeconomic factors influencing greenhouse gas (GHG) emissions. Among these factors, the relationship between income inequality and emissions is particularly relevant. Despite prominence in academic debates, no consensus exists regarding its nature or the theoretical mechanisms underlying it. This lack of agreement reflects both the complexity of the transmission channels involved and the heterogeneity of the contexts studied.

This study seeks to advance the debate by examining the Brazilian case at the subnational level, testing the effect of income inequality, measured by the Gini index and the income appropriation by the top decile, on GHG emissions. We use three theoretical hypotheses to help explain the inequality-emissions relationship based on: (1) the aggregation hypothesis, (2) the consumption composition hypothesis, and (3) the political economy hypothesis. To isolate these effects, our empirical strategy controls for other variables representing indirect channels, such as sectoral composition, deforestation, and energy intensity, that might influence the inequality-emissions nexus.

Brazil provides a particularly compelling setting for this analysis. The country not only exhibits one of the world's highest levels of income inequality (with a Gini coefficient of approximately 0.53, compared to the global average of 0.38 across 165 countries[1]) but also has a distinct emissions profile compared to the global pattern. Unlike most countries, where emissions are primarily driven by energy, in Brazil, approximately 70% of net[2] GHG emissions stem from land-use change and agricultural activities[3], sectors deeply shaped by historical land inequality. Furthermore, recent evidence shows that carbon footprints in Brazil are highly concentrated: the top 10% emit more than the bottom 30% combined, with particularly stark disparities in sectors such as air travel and durable goods consumption. This distinctive context indicates that the relationship between inequality and emissions in Brazil may follow different dynamics than those observed in other countries.

This paper contributes to the literature in three key ways. First, we provide the first subnational analysis of the inequality-emissions nexus across Brazil's 27 federative units (2012-2022), uncovering critical regional heterogeneities obscured in cross-country studies. Second, our dynamic panel approach (system GMM) addresses endogeneity concerns while accounting for unobserved state-level characteristics. Third, through control variables (GDP per capita, deforestation, agricultural sectoral share, energy intensity), we are able to isolate inequality's effects from other indirect factors that may also determine GHG emissions in Brazil.

Our results indicate that: (i) both the Gini coefficient and the top 10% income share exhibit a positive and statistically significant relationship with state-level GHG emissions per GDP; (ii) this effect persists even after controlling for potential indirect channels; and (iii) the magnitude and patterns align more closely with the consumption composition and political economy hypotheses.

The paper is structured as follows: Section 2 reviews the theoretical and empirical literature; Section 3 details the methodological approach and database; Section 4 presents and discusses the results in light of competing hypotheses; and Section 5 concludes with policy implications and directions for future research.

## 2. Literature review on the income inequality-emissions nexus

### 2.1. Some theoretical hypotheses

The relationship between income inequality and emissions remains an open question in the environmental economics literature. While a growing number of empirical studies have explored this nexus, the theoretical mechanisms through which inequality influences environmental outcomes are still subject to debate. Three primary theoretical hypotheses have been proposed to explain the direct relationship between income inequality and GHG emissions, as follows.

[1] See Haddad *et al.* (2024).
[2] Land use, land use-change and forestry (LULUCF) is both a source and sink of emissions.
[3] Climate Watch, 2024. Washington, DC: World Resources Institute (WRI). Available online at: https://www.climatewatch.org

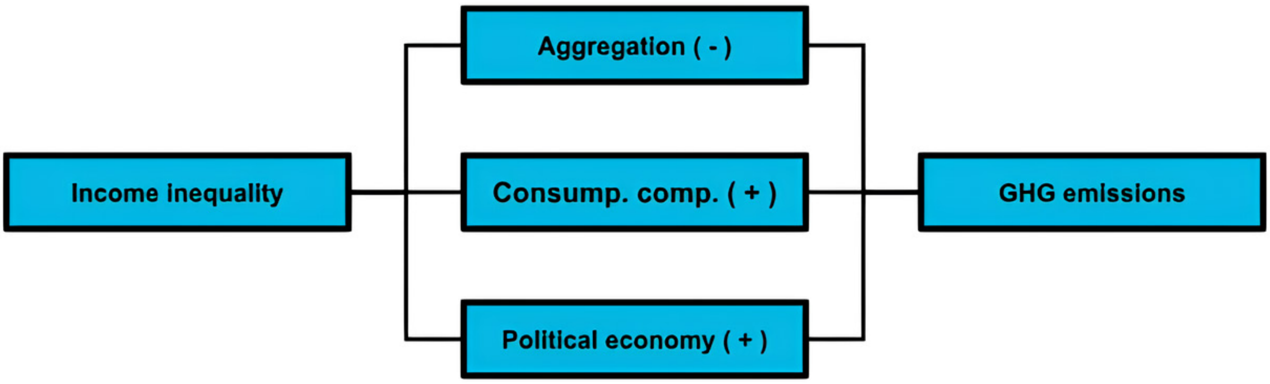
**H1. Aggregation hypothesis (-):** this hypothesis focuses on the marginal effects of income distribution on emissions via consumption. As the marginal propensity to consume (MPC) generally declines with income, redistributing income from the rich to the poor tends to raise aggregate consumption (Ravallion *et al*., 2000). Since most consumption activities, either directly (through consumption) or indirectly (through production), lead to increased emissions, the marginal propensity to emit of lower-income groups tends to be higher than that of wealthier individuals. As a result, when income becomes more equally distributed, the level of aggregate emissions is likely to increase.

**H2. Consumption composition hypothesis (+):** the second hypothesis is based on the idea that, at lower income levels, consumption is constrained to subsistence goods which have low income elasticity. As income rises, households do not merely consume more, but also shift their consumption toward carbon-intensive luxury goods, such as private transportation and aviation (Wilkinson and Pickett, 2009). In this case, higher income inequality, by increasing carbon intensive consumption, could contribute to higher aggregate GHG emissions.

**H3. Political economy hypothesis (+):** the third approach builds on the notion that the effect of inequality on emissions depends on the distribution of political influence and the environmental preferences of different social groups. In particular, Boyce (1994) argues that in highly unequal societies, the wealthy are both more capable of capturing rents from environmentally damaging economic activities and of imposing the associated costs onto poorer, less politically empowered groups. On top of that, income inequality may foster social fragmentation, undermining collective action for public goods provision and reinforcing present-oriented preferences that delay environmental protection efforts. Consequently, higher inequality is associated with weaker environmental governance and higher degradation and GHG emissions.

Figure 1 shows the main transmission mechanisms linking income distribution and GHG emissions highlighted in the literature.

**Figure 1. Transmission channels through which income inequality impacts emissions**




Source: Authors' own elaboration.

## 2.2. The empirical debate

Empirically, the coexistence of alternative theoretical explanations for the relationship between income inequality and greenhouse gas (GHG) emissions has yielded mixed and often inconclusive results in the literature (Table 1). Jorgenson *et al*. (2017) argue that different measures of income inequality reflect different mechanisms and, as such, correspond to different theoretical arguments. For example, Hailemariam *et al*. (2020) argue that income inequality as measured by the Gini index better describes the aggregation approach, as it highlights disparities between low- and middle-income households. On the other hand, measures such as the income share of the top decile are better aligned with the composition hypothesis, as they reflect the concentration of resources among the wealthiest segments of society and the resulting patterns of luxury consumption (Jorgenson *et al*., 2017).

In addition, many papers argue for a nonlinear relationship between income inequality and emissions, inspired by the Environmental Kuznets Curve[4]. For example, Grunewald *et al*. (2017) find that the direction and magnitude of the inequality-emissions nexus depend on the country's income level: while higher inequality (measured by the Gini index) tends to reduce GHG emissions in low-income countries, it acts as a driver of GHG emissions in high-income contexts. Moreover, Lamperti *et al*. (2024) point out that the stage of economic development, measured by the relative weight of services in the economic structure, is a crucial factor shaping the relationship between inequality and emissions. This strand of the literature overlaps two distinct debates: the effects of per capita income and development stages on emissions trajectories, and the impact of income distribution on emissions, conditional on aggregate income levels. Most of this literature relies on cross-country panel data studies, which inherently encompass wider heterogeneity in income levels and economic structures.

Unlike most studies shown in Table 1, the present study focuses on a single country, Brazil, characterized by lower interstate variation in income inequality relative to global cross-country datasets. Given this more homogeneous context, we adopt a linear specification for the relationship between income inequality and GHG emissions in line with Hao *et al*. (2016) and Jorgenson *et al*. (2017). While the potential for nonlinear interactions between income levels and inequality remains theoretically relevant, investigating such dynamics falls beyond the scope of this paper.

**Table 1. Recent empirical literature on the income inequality-emissions nexus**

| Study | Data sample | Method | Inequality measure | Impact of inequality on emission |
|---|---|---|---|---|
| Grunewald *et al*. (2017) | 158 countries (1980-2008) | Group fixed effects | Gini index | Nonlinear |
| Hao *et al*. (2016) | 23 Chinese provinces (1995-2012) | Generalized Mean Methods (GMM) | Gini index | Positive |
| Jorgenson *et al*. (2017) | 51 U.S. states (1997-2012) | Prais-Winsten model with panel-corrected standard errors | Gini index; Income share of top 10%, 5% and 1% | Non significant; Positive |
| Mittmann and Mattos (2020) | 16 LATAM countries (1970-2013) | GMM | Gini index | Nonlinear |
| Hailemariam *et al*. (2020) | 17 OECD countries (1945–2010) | Dynamic Common Correlated Effects based on mean group | Gini index; Income share of top 10% and 1% | Negative; Positive |
| Lamperti *et al*. (2025) | 160 countries (1980-2018) | Fixed effects | Gini index, Palma ratio, the 20:20 ratio, income share of 20% and 10% | Nonlinear |
| Cappelli (2025) | 107 countries (1990-2019) | GMM and Dynamic Panel Threshold Model | Income share of top 10%, middle 40% and bottom 50%. | Nonlinear |

Source: Authors' own elaboration.

Unlike most studies shown in Table 1, the present study focuses on a single country, Brazil, characterized by lower interstate variation in income inequality relative to global cross-country datasets. Given this more homogeneous context, we adopt a linear specification for the relationship between income inequality and GHG emissions in line with Hao *et al*. (2016) and Jorgenson *et al*. (2017). While the potential for nonlinear interactions between income levels and inequality remains theoretically relevant, investigating such dynamics falls beyond the scope of this paper.

[4] For a discussion on the Environmental Kuznets Curve and inequality see Heerink *et al*. (2001).

Brazil represents a particularly distinctive case within this debate, as its emissions profile diverges significantly from the global pattern. Whereas in most countries GHG emissions are primarily driven by energy, Brazil´s emissions, as aforementioned, are overwhelmingly driven by land-use change, deforestation, and agribusiness, which account for approximately 70% of its net CO2e emissions. We believe that these emission sources may be deeply intertwined with regional economic structures, patterns of land ownership, and social inequality. By employing subnational panel data, this study seeks to contribute to the literature by investigating the heterogeneity of these dynamics across Brazilian states, allowing for a potentially more precise examination of how income inequality interacts with local economic and environmental processes to shape emissions outcomes.

**2.3 Carbon inequality in Brazil**

Before presenting our methodological approach, it is useful to provide an overview of the relationship between inequality and greenhouse gas (GHG) emissions in Brazil. Following Rodrigues *et al*. (2025), we use household budget microdata from the 2018–2019's *Pesquisa de Orçamentos Familiares* POF) and sectoral emission coefficients from an environmentally extended input-output matrix to estimate the GHG footprint of Brazilian households. Note that this method derives GHG footprint estimates from household consumption and, therefore, does not capture emissions footprints from other components of final demand. As a result, the sum of all calculated household GHG footprints represents only a fraction of total Brazilian emissions.[5] Table 2 summarises our estimates for the average GHG footprint by household position at the income distribution. The GHG footprint is further disaggregated by the economic sectors that contribute most significantly to the total footprint.

Our estimates reveal substantial inequalities in GHG emissions that reflect the country's underlying income distribution. We observe that greenhouse gas emissions are heavily concentrated among high-income households, while low- and middle-income groups exhibit more similar GHG footprints. Households with higher incomes have significantly larger average per capita GHG footprints as greater income enables higher levels of consumption. The top 1% of income earners in the population have an average per capita GHG footprint of 2.48 tons CO2e, which is approximately five times greater than that of the poorest 10%, at 0.49 tons CO2e. Furthermore, the aggregate emissions of the top 10% exceed those of the bottom 30%, underscoring the highly skewed nature of emissions in Brazil.

We can also analyse the consumption composition of households across different income levels, as the type of goods and services consumed influences their footprints. Products from the agricultural and livestock sectors account for the largest share of GHG emissions across all income groups, averaging 376 kg of $CO_2$ equivalents annually. Despite representing only 2.5% of the average household budget, they contribute to over half (54%) of the total carbon footprint, underscoring both the sector's disproportionate total emissions and its high carbon intensity in Brazil. The second-largest contributor to the carbon footprint is household consumption of electricity, gas, water, sewage, and urban sanitation, with an average footprint of 244 kg of CO2e per year. This is notable given Brazil's relatively high share of renewable energy sources and the modest share of these items in the average household budget. Transport-related goods and services comprise the third main component, contributing an average of 124 kg of $CO_2$ equivalents annually. However, note that among the top 1% of the income distribution, transport emissions increase significantly and become the second-largest source of household emissions (655 kg of CO2e annually), signalling a shift in the composition and drivers of carbon footprints at higher income levels. This result is relevant as it reflects an intensification of high-income consumption led by transport-related goods, in particular, aviation.[6]

Overall, we see that carbon inequality in Brazil is closely tied to the underlying income inequality, manifesting in disproportionately high per capita GHG emissions among the top income households. Since the two most carbon-intensive products are food and energy related, despite their high contribution to the overall GHG footprint, their consumption remains similar across deciles and takes low shares of household budgets. It is the intensity and volume of expenditure among high-income households, particularly in emissions-intensive luxury consumption, that drive the unequal distribution of household carbon footprints. We provide further analysis when discussing the results of our model. The next section presents the methodology and data sources used.

[5] For the empirical model estimated in the paper, we use total GHG emissions estimates from a supply perspective. See Section 3.2. for a detailed discussion.
[6] For a further discussion on aviation, see Bergamin *et al*. (2025).

**Table 2. Sectoral GHG emissions and income distribution**

| Sector | Average annual per capita emissions (CO2 equivalent, in kg) by position at the per capita income distribution | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0-10 | 10-20 | 20-30 | 30-40 | 40-50 | 50-60 | 60-70 | 70-80 | 80-90 | 90-95 | 96-99 | 99-10 |
| **Agriculture and livestock products** | 262.7 | 305.3 | 295.5 | 338.0 | 334.3 | 341.0 | 360.7 | 362.1 | 454.8 | 571.3 | 706.2 | 824.9 |
| **Electricity, gas, water, sewage and urban sanitation** | 130.9 | 175.1 | 179.6 | 210.7 | 216.2 | 228.1 | 246.5 | 271.4 | 314.8 | 377.5 | 442.9 | 574.1 |
| **Transport, storage, and postal services** | 44.2 | 64.6 | 73.1 | 80.7 | 95.1 | 105.0 | 119.4 | 140.6 | 140.6 | 167.3 | 324.7 | 655.7 |
| **Foods and beverages** | 25.0 | 31.3 | 31.5 | 36.0 | 38.9 | 37.9 | 44.8 | 45.6 | 54.4 | 69.5 | 82.1 | 100.0 |
| **Oil** | 10.4 | 13.9 | 15.7 | 18.8 | 22.5 | 26.0 | 30.2 | 35.9 | 47.9 | 62.0 | 85.1 | 114.3 |
| **Paper products** | 3.4 | 3.3 | 3.8 | 3.5 | 4.0 | 4.4 | 4.3 | 4.7 | 5.3 | 5.8 | 6.6 | 7.9 |
| **Hygiene products** | 2.2 | 2.7 | 3.2 | 3.4 | 3.9 | 4.0 | 4.6 | 5.0 | 6.1 | 6.6 | 7.9 | 10.0 |
| **Machinery, equipment, furniture and other industrial products** | 1.9 | 2.2 | 2.6 | 2.9 | 3.3 | 3.9 | 4.5 | 5.2 | 6.5 | 9.3 | 12.1 | 21.7 |
| **Cement and other non-metallic mineral products** | 1.5 | 2.0 | 2.4 | 2.1 | 2.7 | 2.6 | 3.4 | 3.5 | 5.1 | 7.3 | 8.7 | 14.3 |
| **Other extractive industries products** | 1.0 | 1.3 | 0.9 | 1.0 | 1.4 | 1.0 | 1.6 | 1.2 | 1.5 | 3.2 | 1.0 | 1.7 |
| **Others** | 3.0 | 11.8 | 13.5 | 15.1 | 17.4 | 18.8 | 22.4 | 25.8 | 33.8 | 43.2 | 58.5 | 94.4 |
| **TOTAL** | 486.5 | 613.7 | 621.8 | 712.2 | 739.5 | 772.8 | 842.5 | 901.1 | 1097.5 | 1353.3 | 1735.7 | 2419.1 |

Source: Rodrigues *et al.* (2025). Authors' own elaboration.

## 3. Methodology and data sources

### 3.1 Model specification

Most empirical works in the literature consider the GHG emission per capita as the target variable. It is worth mentioning that this measure can be decomposed as follows: $\frac{GHG}{N} = \left(\frac{GHG}{GDP}\right)\left(\frac{GDP}{L}\right)\left(\frac{L}{N}\right)$, where: $GHG$ is greenhouse gas; $GDP$ is domestic output; $L$ is the level of employment; and $N$ is total population. Therefore, the greenhouse gas emission per capita ($\frac{GHG}{N}$) can be decomposed in the emission intensity $\left(\frac{GHG}{GDP}\right)$, labor productivity $\left(\frac{GDP}{L}\right)$ and the labor force participation rate $\left(\frac{L}{N}\right)$. Provided that the participation rate remains relatively unchanged over time and that the relationship between labor productivity and income inequality is widely explored in a different strand of the literature, in the present work we focus on the emission intensity $\left(\frac{GHG}{GDP}\right)$ since it can be seen as a metric for the environmental efficiency of an economy. A declining GHG intensity indicates that an economy is decoupling its growth from emissions, meaning it is becoming more carbon-efficient through better technology or a shift toward less energy-intensive sectors.

$$log(GHG/GDP) = \beta_0 + \beta_1 log(GHG/GDP)_{it-1} + \beta_2 Inequal_{it} + X_{it}\beta + \nu_i + \kappa_t + u_{it} \quad (1)$$

where subscripts $i$ and $t$ account for state and time-period. respectively; $GHG/GDP$ is the level of greenhouse gas emission as a share of GDP; *Inequal* accounts for the income distribution variable measured by the percentage of total income appropriated by the top 10% or the Gini index; $X$ is the matrix of control variables and $\beta$ is the vector of corresponding coefficients; $v$ and $k$ are the state and time fixed effects, respectively; and $u$ is the error term. In this study, we consider as controls the sectoral share of agriculture and livestock in GDP; the GDP per capita; the total final consumption of electricity as a share of GDP; and deforestation in thousands of square kilometres.

In addition to the primary theoretical mechanisms from hypotheses H1 to H3, income inequality may also influence GHG emission intensity indirectly through a number of confounding factors listed as control variables in our model.

First, income inequality can shape the trajectory of economic growth and GDP per capita. Empirical evidence suggests that high levels of inequality can dampen long-term economic growth by constraining aggregate demand, reducing human capital accumulation, and increasing social instability (Castelló-Climent, 2010; Halter, Oechslin and Zweimüller, 2014; Hasparyk, Ribeiro and Bottega, 2023; OECD, 2015). As GDP per capita is a well--established driver of emissions, the impact of inequality on economic growth may have indirect consequences for GHG emissions (Liu *et al*., 2019; Shahiduzzaman, 2015).

Second, the sectoral composition of economic activity, particularly the share of agriculture in total value added, is another potential channel. According to Ceddia (2019), for a sample of 10 Latin American countries over 1990-2010, higher inequality can promote agricultural expansion. These activities are major sources of GHG emissions in Brazil (see Table 5). Consequently, inequality may indirectly affect emissions by shaping the relative importance of agriculture in regional economies.

Third, income inequality can affect deforestation rates. Highly unequal societies often feature weaker regulatory institutions, lower enforcement capacity, and greater influence of economically powerful actors over land-use decisions, which may undermine community-based forest management, conservation initiatives, and sustainable land-use practices (Koop and Tole, 2001; Mikkelson, Gonzalez and Peterson, 2007). Therefore, the relationship between income inequality and deforestation is particularly relevant to our research question since large-scale deforestation driven by commercial agriculture and extractive industries, activities influenced by changes in income distribution, is a major source of GHG emissions in Brazil (Koch *et al*., 2019; Stabile *et al*., 2020; Garofalo *et al*., 2022; Rodrigues *et al*., 2024).

Finally, income inequality can influence patterns of energy consumption. Societies with greater inequality may exhibit more uneven access to modern, efficient energy infrastructure, leading to higher energy intensity per unit of GDP (Simionescu and Oancea, 2025; Xu and Zhong, 2023). Moreover, status-driven consumption can result in elevated demand for energy-intensive goods and services among affluent groups, increasing overall energy use and associated GHG emissions (Ramakrishnan and Creutzig, 2021). This reinforces the link between inequality and GHG emissions through the energy-intensity channel.

The next section presents in detail the dataset used in this study.

### 3.2 Database

This study employs balanced panel data to analyze the dynamic effects of income inequality on Brazil's greenhouse gas (GHG) emission intensity. The dataset consists of annual data from 2012 to 2022 for all 27 Federative Units (FUs), totalling 297 observations per variable. The period was selected based on the availability of continuous and comparable time series for all variables relevant to the proposed longitudinal analysis. Table 3 provides detailed descriptions and data sources, while Table 4 presents the descriptive statistics for the variables used in the econometric estimations of this study.

**Table 3. Description of the variables**

| Variable | Unit | Description | Source |
|---|---|---|---|
| GHG emission[1] / GDP[2] | Tonnes per million BRL of GDP | Tonnes of greenhouse gas emissions per million reais at 2015 prices. | Greenhouse Gas Emissions and Removals Estimation System (*SEEG*)[3]/ Brazilian Institute of Geography and Statistics (IBGE) |
| Top 10% appropriation | Percentage ratio | Percentage of total income appropriated by the top decile of the income distribution pyramid. | Continuous National Household Sample Survey (*PNAD Contínua* – IBGE) + Data from Brazilian Tax Authority |
| Gini index | Varies from 0 (perfect equality) to 100 (perfect inequality) | Gini index of the per capita household income, at average annual prices. It is a measure of income inequality within a population. | Continuous National Household Sample Survey (*PNAD Contínua* – IBGE) + Data from Brazilian Tax Authority |
| Agriculture / GDP | Percentage ratio | Sectoral share of Agriculture and Livestock in GDP (percentage) | IBGE, in collaboration with state statistical offices, state government secretariats, and the Superintendence of the Manaus Free Trade Zone (*SUFRAMA*). |
| GDP per capita | Thousands of reais per total population | GDP at 2015 constant prices per estimated population | IBGE |
| Energy / GDP | Megawatt-hours (MWh) per million BRL of GDP | Total final consumption of electricity, in MWh, per million reais at 2015 prices. | Brazilian Ministry of Mines and Energy, National Energy Balance (*MME*) / IBGE |
| Deforestation | Thousands of km$^2$ | Aggregated biome-level data by federative unit: Amazon, Cerrado, Caatinga, Atlantic Forest, Pampa, and Pantanal. | Satellite-Based Deforestation Monitoring Program in the Brazilian Legal Amazon (*PRODES*), TerraBrasilis platformd |

Note:
1. Emissions, in tonnes, of CO2e GWP-AR6. It refers to the Global Warming Potential (GWP) value of carbon dioxide ($CO_2$) in the AR6 (Sixth Assessment Report) of the Intergovernmental Panel on Climate Change (IPCC). Note that this is a measure of $CO_2$ equivalent, considering the emissions of all greenhouse gases (GHGs).
2. GDP at 2015 constant prices, derived from GDP at current prices and deflated using an index based on the accumulated change in the IPCA (source: IBGE).
3. https://seeg.eco.br/
4. https://terrabrasilis.dpi.inpe.br/

**Table 4. Summary statistics, annual data (2012-2022, Observations = 297)**

| Variable | Mean | SD | Max | Min |
|---|---|---|---|---|
| GHG emission (in tonnes) / GDP (MM Reais) | 732.04 | 875.01 | 3372.89 | 15.43 |
| Top 10% appropriation (in %) | 49.52 | 4.63 | 65.30 | 39.10 |
| Gini index | 56.83 | 4.71 | 73.85 | 46.77 |
| Agriculture / GDP (in %) | 8.58 | 6.37 | 38.00 | 0.30 |
| GDP per capita (thsd. Reais) | 32.73 | 21.89 | 160.49 | 7.15 |
| Energy (MWh) / GDP (MM Reais) | 74.31 | 32.55 | 241.24 | 13.74 |
| Deforestation (thsd. km$^2$) | 112.14 | 108.37 | 391.73 | 2.97 |

Source: Authors' own elaboration

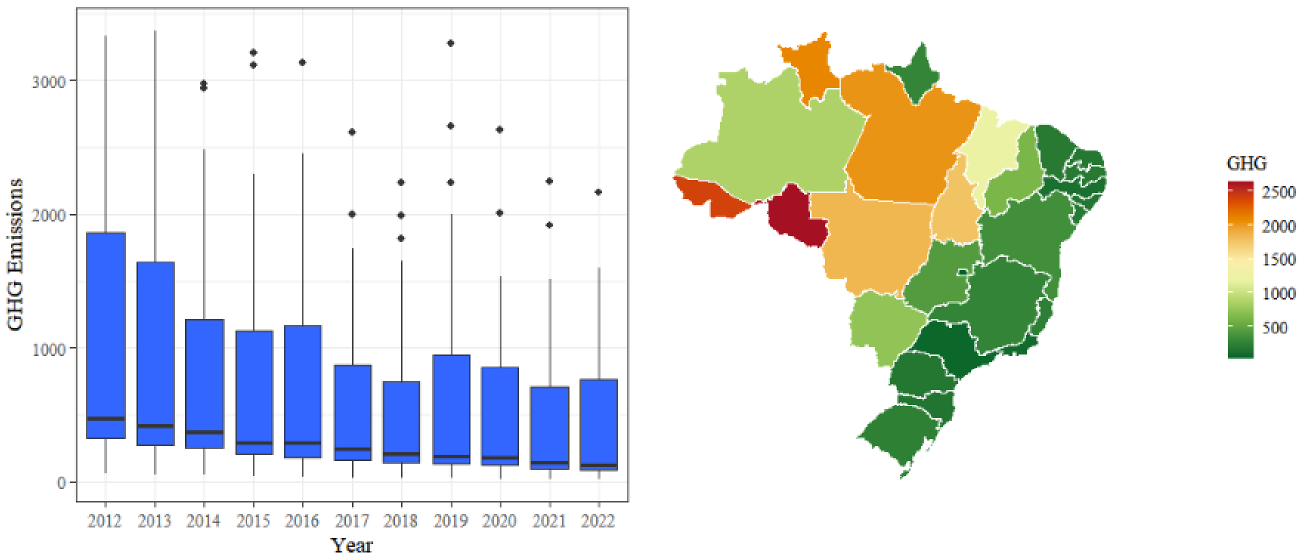
### 3.2.1 Dependent variable: greenhouse gas emission intensity

The dependent variable is the annual gross emissions of carbon dioxide equivalent (CO2e), measured in tons and weighted by the Gross Domestic Product (GDP) at 2015 constant prices for each Federative Unit (FU). The CO2e estimates were obtained from the Greenhouse Gas Emission Estimation System (SEEG), which estimated the emissions based on the five main sectors: Agriculture, Energy, Land Use Change, Industrial Processes, and Waste. The methodology follows the parameters of the Intergovernmental Panel on Climate Change (IPCC) and the National Inventory, adopting the Global Warming Potential (GWP) conversion factors established in the IPCC's Sixth Assessment Report.

This variable was constructed by dividing CO2e emissions by the GDP of each FU (in millions of reais, 2015 constant prices), yielding a CO2e-to-GDP ratio that measures carbon intensity relative to economic output. This metric facilitates comparisons across states with varying economic structures and emission levels. Significant heterogeneity is evident across FUs: the Federal District averaged just 33.28 tons of CO2e per R$1 million GDP (2012-2022), while Rondônia recorded 2,638.12 tons, a nearly 80-fold difference (see Figure 2). These pronounced disparities mirror the distinct economic structures and sectoral compositions of Brazil's federative units.

It is important to highlight the specificities of the Brazilian case regarding emissions dynamics. According to data from Climate Watch (2024), in 2022, Brazil's CO2e emissions (GWP-AR4) were predominantly driven by Agriculture, Energy, and Land-Use Change and Forestry (LULUCF), in that order. The prominence of LULUCF is particularly notable, as it accounts for net emissions, given that this sector functions both as a source and a sink of greenhouse gases, making it central to achieving net-zero targets. When considering gross emissions data from SEEG for 2022, LULUCF alone was responsible for more than half of Brazil's total CO2e emissions (1.4 out of 2.6 billion tons). In contrast, at the global level, the Energy sector is by far the largest contributor to GHG emissions, followed by Agriculture and Industrial Processes, with LULUCF playing a relatively minor role, despite Brazil accounting for nearly one-third of global LULUCF emissions. Table 5 provides a summary of this comparison.

**Figure 2. GHG Emissions per GDP (2012–2022)**




Note:
Left: Boxplots showing the distribution of data across all states by year. Each box represents the interquartile range (IQR), spanning from the 1st quartile (Q1) to the 3rd quartile (Q3), with the horizontal line inside the box indicating the median. Whiskers extend to the minimum and maximum values within 1.5 times the IQR from the quartiles. Points beyond this range are plotted as outliers.
Right: Map displaying the average values by state over the 2012–2022 period.
Authors' own elaboration.

**Table 5. CO2e Net Emissions (GWP-AR4) by Sector – in MtCO2e and % – 2022**

| Sector | World | | Brazil | |
|---|---|---|---|---|
| | MtCO2e | (%) | MtCO2e | (%) |
| Energy | 38,008.54 | 75.8 | 477.93 | 31.0 |
| Agriculture | 5,905.60 | 11.8 | 551.84 | 35.8 |
| Industrial Processes | 3,208.24 | 6.4 | 39.83 | 2.6 |
| Waste | 1,701.84 | 3.4 | 72.92 | 4.8 |
| Land-Use Change and Forestry | 1,298.76 | 2.6 | 397.22 | 25.8 |
| TOTAL | 50,122.98 | 100 | 1,539.74 | 100 |

Source: Climate Watch, 2024. Washington, DC: World Resources Institute (WRI).

### 3.2.2 Primary explanatory variables: income inequality measures

To examine the link between income inequality and greenhouse gas (GHG) emissions, this study employs two distinct measures of inequality as core independent variables in the econometric models: the Gini coefficient and the income share of the top 10%.

To analyze these variables, we constructed a database that integrates household survey data with administrative fiscal records. Specifically, we combined the annualized Continuous National Household Sample Survey (PNAD Contínua), conducted by the Brazilian Institute of Geography and Statistics (IBGE), which provides comprehensive income data, with aggregate personal income tax tabulations for each fiscal year, provided by the Brazillian fiscal authority.

We combine PNAD Contínua and tax tabulations to mitigate the underestimation of top incomes common in survey-based studies (Lustig, 2019; Piketty *et al*., 2018). Our approach follows three steps: (i) ranking survey respondents by total income to match the tax data brackets; (ii) calculating a reweighting factor for each group based on the ratio of fiscal-to-survey total income; and (iii) scaling the survey income by these factors to achieve alignment with the tax data. This approach is similar to the one used by different studies, such as Piketty *et al*. (2018), Blanchet (2022) and Gobetti and Orair (2017).[7]

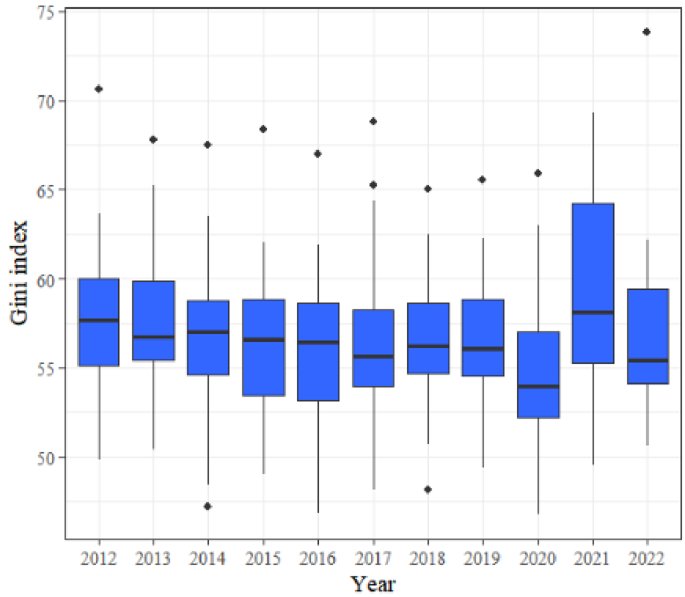
To ensure comparability and standardization across the estimated models, both series were multiplied by 100. Thus, the Gini coefficient ranges from 0 (perfect equality) to 100 (maximum inequality), while the income share of the top 10% is expressed as a percentage (e.g., 40 represents 40%).

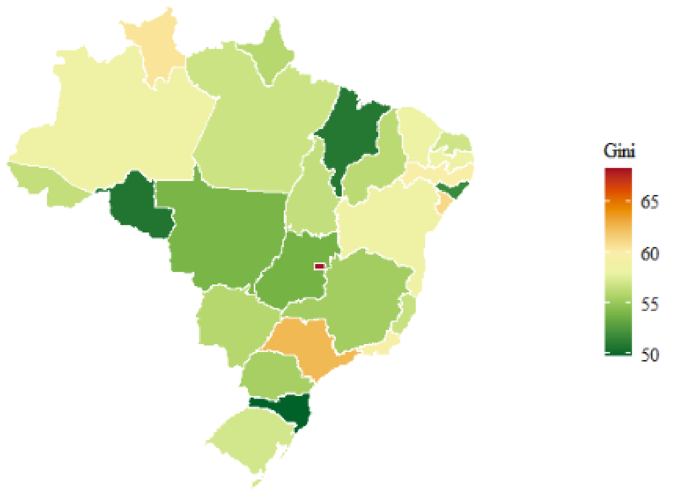
Both indicators reveal high-income concentration across Brazilian FUs during the study period (2012–2022). The Gini coefficient averaged above 55 in 21 out of 27 FUs, while the income share of the top 10% exceeded 50%, on average, in 12 FUs. The temporal and cross-state dispersion of these variables are illustrated in Figures 3 and 4.

It is noteworthy that, according to data from the World Bank's Poverty and Inequality Platform, Brazil ranks among the most unequal countries in the world, alongside South Africa, Namibia, Botswana, Colombia, and several other highly unequal African and Latin American nations (World Bank, 2026). This high level of inequality appears to be persistent across Brazilian federative units. The state-level Gini data for 2022 used in this study show an average of 56.8 with a standard deviation of only 4.7. Maranhão recorded the lowest Gini index in 2020 (46.8), while Federal District had the highest in 2022 (73.9).

[7] We follow the Distributional National Accounts (DINA)-style alignment despite the methodological caveats associated with merging disparate data sources. As Geloso and Toda (2025) argue, these hybrid approaches are subject to specific estimation risks; however, they currently remain the standard for correcting top-income underreporting in the absence of unified microdata.

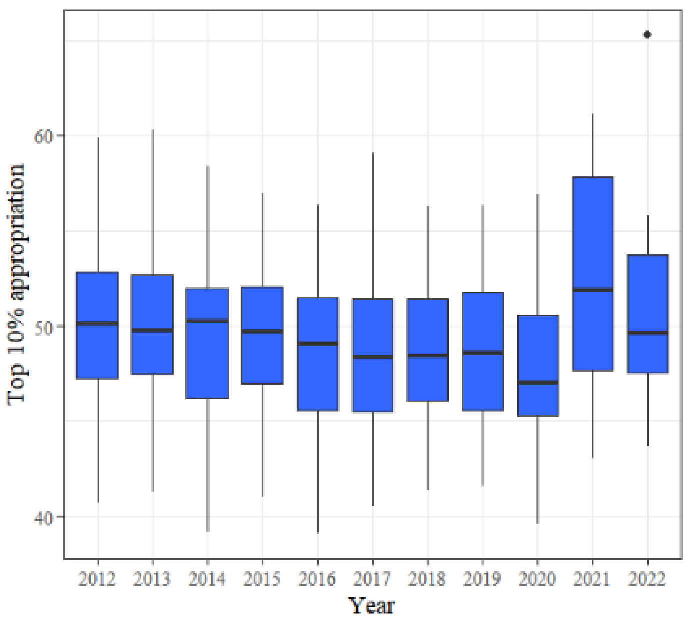
**Figure 3. Gini index (2012–2022)**

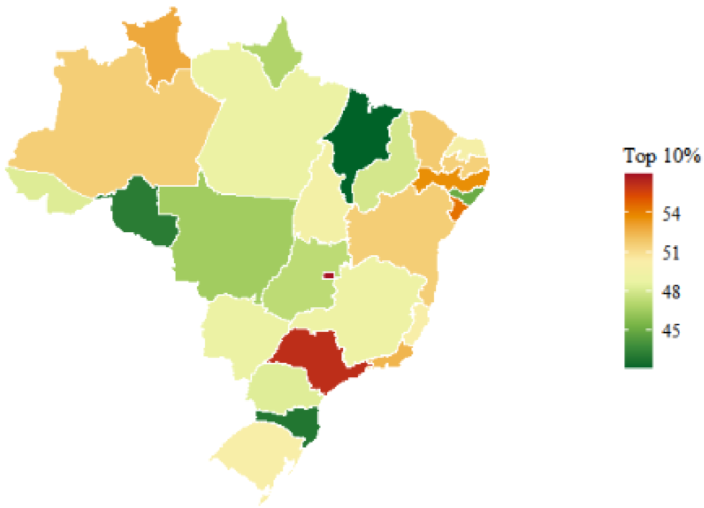



Note:
Left: Boxplots showing the distribution of data across all states by year. Each box represents the interquartile range (IQR), spanning from the 1st quartile to the 3rd quartile, with the horizontal line inside the box indicating the median. Whiskers extend to the minimum and maximum values within 1.5 times the IQR from the quartiles. Points beyond this range are plotted as outliers.
Right: Map displaying the average values by state over the 2012–2022 period.
Authors' own elaboration.

**Figure 4. Top 10% appropriation (2012–2022)**




Note:
Left: Boxplots showing the distribution of data across all states by year. Each box represents the interquartile range (IQR), spanning from the 1st quartile to the 3rd quartile, with the horizontal line inside the box indicating the median. Whiskers extend to the minimum and maximum values within 1.5 times the IQR from the quartiles. Points beyond this range are plotted as outliers.
Right: Map displaying the average values by state over the 2012–2022 period.
Authors' own elaboration.

### 3.2.3 Control variables

In this paper, we use several control variables in the econometric estimations to account for additional factors that may influence GHG emissions at the state level in Brazil. These controls seek to capture the effects of economic scale, sectoral structure, energy intensity, and land use changes on emissions outcomes. Below, we describe each variable, its source, and the theoretical channels through which it may affect GHG emissions.

We obtained the state-level GDP per capita series by dividing the GDP series from the Brazilian Institute of Geography and Statistics (IBGE) by the corresponding population estimates, also from IBGE. We adjusted the GDP values to 2015 prices (in thousands of reais) using the Consumer Price Index (IPCA). Income levels can affect GHG emissions through opposing channels: economic growth can raise emissions by expanding carbon-intensive production and consumption, while higher per capita income may foster structural shifts toward cleaner sectors, technological adoption, and stricter environmental regulation, thereby reducing emissions (Hao *et al*., 2016).

We extracted the share of agriculture in total value added from an IBGE database, developed in collaboration with state planning secretariats and the Superintendence of the Manaus Free Trade Zone (SUFRAMA). This data represents the sectoral share of agriculture and livestock in GDP. We converted these values into percentages by multiplying them by 100. Agricultural activities, especially those associated with cattle ranching and mechanized crop production, are major drivers of land-use change and deforestation (Hailemariam *et al*., 2020). By controlling for the agricultural share in state economies, we account for the emissions generated by these land-intensive and high-emission production activities.

To capture the effect of energy use intensity on GHG emissions, we include in the model the total final electricity consumption in megawatt-hours (MWh) per million reais at 2015 prices, extracted from the Ministry of Mines and Energy (MME) and IBGE. Energy consumption is a direct driver of emissions, particularly when electricity generation relies on fossil fuels (Sarkodie and Strezov, 2019; Salari *et al*., 2021; McCurdy and Rhodes, 2023). Higher energy intensity, i.e., greater energy use per unit of output, typically correlates with increased GHG emissions. Including this variable helps isolate the effect of inequality on emissions from the effect of varying energy use patterns across states.

Finally, we control for deforestation data from the Satellite-Based Deforestation Monitoring Program in the Brazilian Legal Amazon (PRODES), using the TerraBrasilis platform. This data accounts for accumulated deforestation by biomes (Amazon, Cerrado, Caatinga, Atlantic Forest, Pampa, and Pantanal), aggregated by Brazilian states for this study and expressed in thousands of square kilometers ($km^2$). Deforestation is one of the most significant sources of GHG emissions in Brazil. In addition to direct emissions, land-use changes from deforestation alter carbon sinks, reduce forest cover, and contribute to changes in local and regional climate patterns. A previous study estimated that deforestation fires in Brazil and Indonesia contributed to 7% of global GHG emissions in 2019 (Datta and Krishnamoorti, 2022).

## 3.3 Estimation method

A panel data methodology is employed to examine the relationship between income inequality and greenhouse gas (GHG) emissions across Brazilian states from 2012 to 2022. This approach offers advantages over techniques that separately analyze time-series or cross-sectional data, as it allows for assessing heterogeneity among sample units. Additionally, panel data increases the amount of information and degrees of freedom, reduces collinearity among independent variables, and enhances data variability.

Equation (1) highlights potential issues related to unobserved effects stemming from specific characteristics of Brazilian states. Typically, Fixed Effects (FE) or First-Difference estimators can address these issues by correcting problems arising from heterogeneities between cross-sectional units. However, these methods do not rectify potential bias that may occur when the lagged dependent variable is included as a regressor in the equation to be estimated (Pesaran, 2015). Furthermore, coefficients of interest may suffer from omitted-variable bias if the model does not account for all relevant control variables in the baseline equation. To overcome these challenges and robustly estimate the model parameters, the Generalized Method of Moments (GMM) estimator is utilized (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998). This method is more appropriate as it considers the potential endogeneity of one or more regressors and controls for specific unobserved effects of the cross-sectional units. The GMM estimation techniques for panel data include the GMM-Difference and GMM-System methods.

The GMM-Difference method represents a significant improvement over standard fixed-effects and first-difference estimators. The first-difference GMM estimator by Arellano and Bond (1991) aims to eliminate specific effects associated with cross-sectional units and uses lagged observations of endogenous explanatory variables as instruments. However, the first-difference GMM method has a disadvantage when dealing with variables that exhibit low variability over time within a country, such as income distribution. This implies that taking the first difference eliminates most of the variation in the variable(s). Consequently, lagged observations of endogenous regressors tend to be weak instruments for the endogenous variables in difference.

The system GMM method by Arellano and Bover (1995) and Blundell and Bond (1998) is employed to address this issue. This method creates a system of regressions in difference and in level. The instruments for the regressions in first difference remain the same as in the GMM-Difference method. The instruments used in the regressions in level are the lagged differences of the explanatory variables. Although endogenous variables can still be correlated with country-specific effects in this estimation technique, the lagged differences of these variables used as instruments do not correlate with these unit-specific effects.

The validity of the GMM estimators heavily depends on the exogeneity of the instruments used in the baseline model. The exogeneity of the instruments can be tested using the J-statistics of the commonly employed Hansen test. The null hypothesis implies the joint validity of the instruments; thus, rejection of the null hypothesis indicates that the instruments are not exogenous, rendering the GMM estimator inconsistent. Roodman (2009) advises researchers to be cautious of Hansen test p-values below 0.1. Regarding the instruments, a large number of instruments may overfit the endogenous variables. The literature does not provide specific guidelines on the maximum number of instruments to be used in each case. Roodman (2009) suggests, as a relatively arbitrary rule of thumb, that the number of instruments should not exceed the number of individual units in the panel (or states, in this case). The Arellano and Bond test for AR (2) in the first difference should also be tested. The null hypothesis of this test examines whether the residuals of the baseline equation are serially correlated in the second order.

## 4. Testing the impact of changes in income inequality on greenhouse gas emissions at the state level in Brazil

### 4.1 Model setup

It is important to emphasize that the primary objective of this study is not to deliver an exhaustive empirical account of all potential determinants of GHG emissions, but rather to specifically assess how emissions respond to changes in income distribution. In this context, the inclusion of a large number of control variables presents considerable challenges, particularly when working with panel data. The limited availability of consistent and comparable state-level data for all Brazilian Federative Units over time imposes a trade-off between the number of explanatory variables and the sample size, as adding more controls would reduce the number of cross-sectional units, potentially undermining the consistency and reliability of the estimates.

While a conventional Ordinary Least Squares (OLS) estimator with a restricted set of controls would be vulnerable to omitted-variable bias, even when incorporating state- and time-fixed effects, we address these concerns through the use of a System Generalized Method of Moments (GMM-System) estimator. This approach helps mitigate risks associated with omitted-variable bias and reverse causality by employing internal instruments based on lagged values of the inequality measures and the autoregressive component of the dependent variable. We deliberately limit the set of instrumented variables to the income distribution parameters and the autoregressive term, in line with the central focus of the analysis. This choice is intended to avoid potential problems of overidentification and weak instruments that could result from an excessively large instrument matrix, which would jeopardize the validity and precision of the estimates.

Furthermore, since providing a comprehensive analysis of the control variables falls outside the scope of this investigation, we treat them as exogenous regressors. This decision contributes to maintaining a parsimonious specification and preserving the strength of the instrument set. To further address possible omitted-variable bias, we conducted a robustness analysis in which, for each inequality measure, three alternative GMM-System models were estimated (see Tables 6). In these estimations, the instrument matrix, comprising the second lag of the inequality parameters and the autoregressive term in the GMM-System collapsed style, remained fixed, while the set of control variables varied. The selection of the instrument matrix was guided by its capacity to satisfy the Hansen test for overidentification and the Arellano-Bond test for second-order serial correlation.

### 4.2 Results

This section presents the findings of the empirical analysis conducted in this study. To investigate the relationship between income inequality and greenhouse gas (GHG) emissions, five distinct specifications were estimated for each of the inequality measures: the Gini index and the income share of the top 10%. These specifications progressively incorporate additional control variables to test the robustness of the results.

The main finding indicates that, by and large, higher levels of the Gini index are associated with greater GHG emission intensity (in tonnes) per million units of GDP.

Table 6 reports the estimated coefficients using the income share of the top 10% for models (1) – (3) and the Gini index for models (4) – (6) and as the explanatory variable, respectively. In all specifications, the number of instruments remains below the number of cross-sectional units, satisfying the identification condition (Roodman, 2009). Both the Hansen/Sargan and the Arellano-Bond AR(2) tests did not reject the null hypothesis, thus suggesting the validity of the instruments of no second-order serial correlation in all specifications.

**Table 6. GHG emission and income distribution by states, GMM-Sys models**

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Log of GHG emission/GDP$_t$ | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Log of GHG emission/GDP$_{t-1}$ | 0.829*** | 0.916*** | 0.905*** | 0.851*** | 0.869*** | 0.877*** |
| | (0.159) | (0.109) | (0.106) | (0.133) | (0.074) | (0.091) |
| Top 10% appropriation$_t$ | 0.066*** | 0.066** | 0.063*** | | | |
| | (0.024) | (0.026) | (0.018) | | | |
| Gini index$_t$ | | | | 0.062** | 0.003 | 0.069*** |
| | | | | (0.025) | (0.006) | (0.016) |
| GDP per capita (thsd. Reais)$_t$ | -0.011*** | -0.007* | -0.007* | -0.011*** | -0.005** | -0.009*** |
| | (0.003) | (0.003) | (0.004) | (0.003) | (0.002) | (0.003) |
| Deforestation (thsd. Km$^2$)$_t$ | 0.001 | 0.0002 | 0.0003 | 0.001 | 0.0002 | 0.0004 |
| | (0.011) | (0.001) | (0.0005) | (0.001) | (0.001) | (0.0004) |
| Agriculture/GDP$_t$ | | 0.026** | 0.026** | | 0.010* | 0.030*** |
| | | (0.011) | (0.010) | | (0.005) | (0.009) |
| Energy/GDP$_t$ | | | 0.001 | | | 0.001 |
| | | | (0.001) | | | (0.001) |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 297 | 297 | 297 | 297 | 297 | 297 |
| N. of states | 27 | 27 | 27 | 27 | 27 | 27 |
| Instruments | 18 | 20 | 22 | 18 | 22 | 22 |
| Hansen test of overidentification (p-value) | 0.323 | 0.261 | 0.284 | 0.275 | 0.219 | 0.374 |
| Arellano-Bond test for AR(2) (p-value) | 0.702 | 0.656 | 0.679 | 0.302 | 0.652 | 0.481 |

Note:
1. Below the coefficients we report the standard errors. The Windmeijer (2005) heteroscedasticity correction is applied to the standard errors.
2. Only the autoregressive term and the distribution variable (top 10% appropriation and Gini index) are considered endogenous variables.
3. The second lag of the endogenous variables were used as instruments for the endogenous variables across all models.
4. We have collapsed the instruments to restrict the number of instruments (Roodman, 2009).
5. The Hansen test: the null hypothesis is that the instruments are not correlated with the residuals.
6. The AR(2) serial correlation test: the null hypothesis is that the residuals of order 2 are not serially correlated; the test is performed with the standard covariance matrix of coefficients.
7. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Model (3) reveals that a 1 p.p. increase in the income share of the top 10% is associated with an increase of 6.3% of GHG emissions per million units of GDP, while model (6) shows that a 1 p.p. increase in the Gini index yields an increase of 6.9% of GHG emissions per million units of GDP. Both estimates are statistically significant at the 1% level.

As for the controls, it is worth mentioning that the GDP per capita is inversely related to GHG emissions in all models, while agriculture as a share of GDP exhibits a positive coefficient. Both are statistically significant at the 10% level at least. Lastly, deforestation in thousand $Km^2$ and energy consumption relative to GDP did not display statistical significance at the 10% level in any of the models.

However, as these control variables are not the primary focus of our analysis, we did not develop a specific identification strategy for it. We recommend, therefore, that future research investigate this relationship more rigorously, accounting for possible endogeneity.

#### 4.3 Discussion

These findings can be interpreted in light of the hypotheses discussed in Section 2 and the Brazilian data presented in Section 3. The aggregation hypothesis posits that reducing income inequality would increase emissions, as lower-income households tend to exhibit higher marginal propensities to consume and, consequently, to emit more than middle- and high-income households. However, the Brazilian evidence presented here contradicts this prediction. Reductions in income inequality, whether measured by the Gini index or by the income share of the top 10%, are consistently associated with lower carbon intensity, measured by GHG emissions per million units of GDP.

Our results indicate that the consumption composition and the political economy hypothesis are better suited to explain the Brazilian case. First, as shown in Section 3, the composition of consumption among Brazil's wealthy reveals that the carbon footprint of the top 1% is approximately five times larger than that of the poorest 10%. Crucially, the drivers of these footprints differ fundamentally. For lower-income groups, emissions are dominated by essential goods like food and residential energy, which tend to have lower income elasticities. In contrast, for the top income deciles, the footprint is increasingly driven by transport and aviation, sectors with high carbon intensity. Consequently, when income is more concentrated, consumption becomes more skewed towards carbon-intensive luxury goods.

Lastly, the political economy approach provides further theoretical contributions to the inequality-emissions nexus. Recalling that the Brazilian emissions profile is driven by land-use change and deforestation, sectors historically influenced by land ownership concentration, and if high inequality correlates with the political strength of the agribusiness elite, this political leverage may hinder the implementation of stricter environmental regulations, resulting in higher emissions per unit of GDP beyond deforestation.

From the empirical literature reviewed in Section 2, our findings are in line with results for single-country models. While cross-country panel data studies tend to find non-linear relationships between income inequality and per capita emissions (Grunewald *et al*., 2017; Mittmann and Mattos, 2020; Cappelli, 2025; Lamperti *et al*., 2025), the results of single-country research find that the impact of income inequality on GHG emissions tends to be positive (Jorgenson *et al*., 2017; Hao *et al*., 2016). The difference probably stems from the fact that single-country analyses better account for national structural and institutional dynamics that are smoothed out in a cross-country data set. Moreover, our results emerge within a context of exceptionally high-income inequality and are consistent with evidence from cross-country studies showing how income inequality tends to increase emissions beyond a certain threshold, suggesting that the magnitude of income inequality is a critical determinant of this relationship. Brazil's high level of inequality probably places the country above this threshold, where inequality becomes a structural barrier to emission reductions. Future research could examine these transmission channels more directly, assessing their individual contributions and interactions with income levels. Additionally, it could consider how the interaction between the sectoral composition of production and income inequality influences greenhouse gas emissions, further elucidating the mechanisms through which inequality affects environmental outcomes.

## 5. Final remarks

This study sought to address a central question: What is the relationship between income inequality and greenhouse gas (GHG) emissions in Brazil, considering the theoretical mechanisms underlying this link? The analysis focused on the effects of income inequality on emissions while controlling for variables such as GDP per capita, sectoral composition, deforestation, and energy intensity, using subnational data from Brazil's 27 states between 2012 and 2022.

The results indicate that both the Gini coefficient and the income share of the top 10% exhibit a positive and statistically significant relationship with state-level GHG emissions per GDP. This effect persists even after accounting for potential indirect channels. The findings suggest that, in Brazil, income inequality is associated with higher emissions, aligning with the consumption composition and political economy hypotheses. In contrast, the aggregation hypothesis, which predicts a negative inequality-emissions relationship, appears less relevant in explaining Brazil's outcomes.

These results carry important implications for the literature. First, they corroborate earlier single-country studies finding a positive inequality-emissions link (Jorgenson *et al*., 2017; Hao *et al*., 2016). Second, they underscore the role of national contexts: Brazil's extreme income concentration and the carbon-intensive production structure (e.g., agribusiness and deforestation) amplify the inequality-emissions nexus. Third, they reinforce the idea that inequality is not solely a distributive issue but also an environmental one, as higher inequality appears to exacerbate consumption and governance patterns that intensify climate pressures.

The study's primary contribution lies in its subnational approach, which captures the average effect of inequality across Brazil's federative units, a granularity unattainable in cross-country analyses. By explicitly testing competing theoretical hypotheses, the paper advances understanding of the mechanisms linking inequality and emissions, particularly in peripheral economies with high income concentration and atypical sectoral emissions, like Brazil. The use of dynamic panel methods (system-GMM) further strengthens the results by mitigating endogeneity concerns.

Nevertheless, the study has limitations. First, while the 2012–2022 period captures recent trends, longer time series could enable structural change analysis. Second, the focus on direct emissions overlooks carbon footprint perspectives, which might offer additional insights into how income-driven consumption patterns affect global emissions.

Future research could address the identified limitations and investigate these transmission channels more directly, evaluating their individual and interactive effects with income levels. Further examination of how sectoral production structures interact with inequality to shape emissions could also clarify the mechanisms through which inequality influences environmental outcomes.

In summary, the results suggest that reducing income inequality may yield not only socioeconomic benefits but also contribute to environmental sustainability. In Brazil, redistributive policies could thus serve a dual purpose: mitigating emissions while promoting greater social equity.

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## Appendix

**Table A1. GHG emissions per GDP, Gini index, and Top 10% appropriation – average per Federative Unit for the period 2012–2022**

| Federative Unit | GHG | Gini | Top 10% |
|---|---|---|---|
| Rondônia | 2638.1 | 50.7 | 43.1 |
| Acre | 2398.2 | 56.4 | 48.3 |
| Roraima | 2098.7 | 60.4 | 52.8 |
| Pará | 2028.4 | 56.8 | 48.9 |
| Mato Grosso | 1842.0 | 53.9 | 46.5 |
| Tocantins | 1768.2 | 56.4 | 49.5 |
| Maranhão | 1222.5 | 50.8 | 42.1 |
| Amazonas | 872.3 | 58.5 | 51.5 |
| Mato Grosso do Sul | 743.5 | 56.0 | 48.9 |
| Piauí | 635.2 | 56.2 | 48.0 |
| Goiás | 437.3 | 53.8 | 47.3 |
| Bahia | 352.8 | 58.6 | 51.5 |
| Amapá | 281.9 | 56.0 | 46.9 |
| Minas Gerais | 276.1 | 55.3 | 49.1 |
| Rio Grande do Sul | 245.5 | 57.0 | 50.1 |
| Espírito Santo | 240.6 | 56.6 | 50.1 |
| Ceará | 208.1 | 58.2 | 51.7 |
| Paraíba | 207.6 | 58.3 | 51.4 |
| Sergipe | 206.7 | 61.0 | 54.3 |
| Rio Grande do Norte | 193.5 | 56.9 | 49.8 |
| Paraná | 181.1 | 55.5 | 48.3 |
| Alagoas | 177.9 | 51.7 | 45.0 |
| Santa Catarina | 168.0 | 49.7 | 42.9 |
| Pernambuco | 135.7 | 59.7 | 53.6 |
| Rio de Janeiro | 98.7 | 59.4 | 52.4 |
| São Paulo | 73.2 | 62.4 | 56.2 |
| Distrito Federal | 33.3 | 68.1 | 56.9 |

Authors' own elaboration.