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"The interplay between carbon emissions and inequality: A complex networks approach"

José Alejandro Fernández Fernández [a,*], Miguel Ángel Casquet Cano [b], Sonia Quiroga [b]

[a] Department of Financial Management and Accounting, Complutense University of Madrid, Campus de Somosaguas, 28223, Pozuelo de Alarcón, Spain
[b] Department of Economic Analysis, Complutense University of Madrid, Campus de Somosaguas, 28223, Pozuelo de Alarcón, Spain

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ABSTRACT

The sustainable development process faces two key challenges: income inequality and carbon emissions, but their relationship remains unclear. This study analyzes interrelations between greenhouse gas emissions (GHG) and income inequality across European countries, using the Sustainable Development Goals (SDG) framework. First, the main determinants of greenhouse gas emissions are identified through Random Forest analysis, then two inequality groups are created via cluster analysis based on SDG1 and SDG10. Finally, two complex networks are constructed based on the inequality groups and main emission determinants to determine the most relevant factors influencing each group's impact on global emissions.

Our research reveals significant differences between countries with low and high levels of inequality. In the high-inequality group, productivity and emissions are negatively correlated, whereas, in the low-inequality group, the relationship is positive. This trade-off indicates that countries with lower inequality tend to have greater energy efficiency, but improvements in quality of life lead to higher consumption levels, influenced by the Marginal Propensity to Emit and consumer status levels. The negative relationship in the high-inequality group suggests a potential income threshold where productivity increases reduce emissions due to energy efficiency offsetting consumption increases. In agricultural activities, countries with higher inequality see a positive impact on emissions, whereas in countries with lower inequality, agriculture tends to be more productive with lower emissions. In countries with higher inequality, increased government investments correlate with higher emissions. Conversely, in countries with lower inequality, investments align with zero-carbon efforts, showing a negative correlation with emissions.

1. Introduction

The United Nations Conference on Sustainable Development, held in Rio de Janeiro in 2012, resulted in the approval by 193 countries of the Sustainable Development Goals (SDGs), which build upon the Millennium Development Goals (MDGs) to address pressing global challenges such as climate change, poverty and inequality. The onset of the SDGs by the United Nations in 2015 represents a crucial moment in the pursuit of sustainable development. Across 17 goals and 169 targets, the SDGs provide a comprehensive framework to address the environmental, social, and economic challenges facing our society. With a target set for 2030, these goals will be addressed collectively, and all objectives and targets are equally important, representing a commitment to advancing towards a sustainable future.

In the European Union, the European Green Deal establishes a minimum 55% reduction in net greenhouse gas emissions (GHG) by 2030 compared to 1990 and climate neutrality by 2050. However, according to the International Energy Agency (IEA) CO2 emissions from fossil fuel combustion and industrial processes reached a peak in 2022 of 36.8 Gt CO2 emissions accounting for almost 60% of the total in 2020 (Our World in Data, 2024).

Regarding inequality, the European Commission's Priorities address both within-country and across-country disparities, as reflected in the European Pillar of Social Rights. Nevertheless, according to Chancel et al. (2022), while global inequalities between countries have decreased over the last two decades mainly because of the strong growth of emerging countries (China and India), inequality within nations has increased significantly. The gap in average incomes between the wealthiest 10% and the poorest 50% within countries nearly doubled, underscoring persistent global inequality despite economic

* Corresponding author.
E-mail addresses: joseal16@ucm.es (J.A. Fernández Fernández), mcasqu01@ucm.es (M.Á. Casquet Cano), soniaq01@ucm.es (S. Quiroga).

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development (Ravallion, 2014).

Given the interconnection of the SDGs, conflicting interests among them may lead to varying outcomes, as improvements in one goal could negatively impact others (Bennich et al., 2020). About our work, the correlation between income inequality and carbon emissions remains a topic of ongoing debate in academic and policy circles, lacking a definitive consensus (Uddin et al., 2020; Dorn et al., 2024).

Thus, this article aims to contribute to this debate by exploring the interactions between net GHG emissions and inequality across Europe within the SDG framework. First, the key emission determinants are selected through a random forest method. Then, two inequality groups are created via cluster analysis one for the high inequality group and another for the low inequality group. Finally, two complex networks are constructed based on the two inequality groups and the main emission determinants to determine the most relevant factors influencing each group's impact on global emissions.

The main contributions of this analysis are i) moving beyond conventional analyzes, complex networks allow refraining from imposing a parametric structure, providing a nuanced perspective of how the main emission determinants are interrelated among groups exhibiting varying levels of inequality ii) to the best of our knowledge no article has proposed link this phenomenon with the SDG goals in the EU within complex network framework.

Our findings reveal significant disparities between countries characterized by low and high levels of inequality. In the low-inequality group, countries primarily engage in industrial activities, indicating advanced economic development and consequently higher emissions of greenhouse gases, despite significant government investments and high productivity levels. Conversely, the high-inequality group is characterized by a greater focus on the agricultural sector, reflecting less economic strength, productivity and emissions.

Our research highlights notable differences between countries with low and high levels of inequality. In the high-inequality group, there is a negative correlation between productivity and emissions, while in the low-inequality group, the relationship is positive. This trade-off suggests that countries with lower inequality often achieve greater energy efficiency; however, improvements in quality of life result in higher consumption levels, driven by the Marginal Propensity to Emit and consumer status. The negative correlation in the high-inequality group indicates a possible income threshold where productivity increases lead to reductions in emissions, as energy efficiency gains offset higher consumption. When examining agricultural activities, countries with higher inequality experience a positive impact on emissions, whereas those with lower inequality generally see more productive agricultural practices with lower emissions.

Regarding government investments, a positive correlation exists between investments and emissions in countries with higher inequality, suggesting that increased investments lead to greater emissions. Conversely, in countries with lower inequality, this correlation is negative, implying that investments are more likely to align with initiatives aimed at achieving a zero-carbon economy.

The rest of the paper is organized into four sections. The second section provides a review of existing literature concerning the association between inequality and carbon emissions. The third section discusses the data used, the selection of key emission determinants through a random forest method, and the two inequality groups created via cluster analysis. Section 4 presents the two complex networks, based on the inequality groups and the main emission determinants obtained in the previous section, and provides some results. Section 5 offers a conclusion and discussion and Section 6 some policy recommendations.

2. State of the art

Over the recent decades, several studies have addressed the issue of the relationship between carbon emissions and income inequality. However, there is no clear consensus in the literature (Che et al., 2023). See Berthe and Elie (2015) and Cushing et al. (2015) for a detailed survey.

The role of income inequality in the relationship between economic development and environmental degradation is founded on the Environmental Kuznets Curve (EKC) theory (Kaika and Zervas, 2013). This hypothesis describes that in the early stages of development, economic growth and environmental degradation are positively correlated, but beyond a threshold of per capita income this seems to be reversed so that economic growth leads to environmental improvements (Stern, 2018; Ali, 2023). This is associated with the "technological effect" where productivity increases led by technological improvements cause less input requirements and polluting materials (Ye et al., 2023).

Another complementary hypothesis proposes that the interrelation between income inequality and CO2 emissions is explained by the marginal propensity to emit (MPE). It states that the Marginal propensity to consume (MPC) for low-income households exceeds that of high-income households (Fisher et al., 2020). Consequently, reducing inequality by increasing the income of low-income individuals may result in higher emissions. This is supported by Guo (2014), who employed a VECM, Granger Causality, and a GIRF model, and showed that regional inequality in China causes a negative effect on CO2 emissions due to the MPE. Ravallion et al. (2000) using data for 42 countries for the period 1975–1992 observed that higher inequality, both within and among countries, is associated with lower carbon emissions, evidencing a trade-off between both dimensions. Also, Veblen (2009) considers that individuals may increase their consumption to display their status leading to an increase in carbon emissions (Griskevicius et al., 2010). Boyce (1994) argued that income inequality is negatively correlated with environmental quality, as wealthy individuals often own large, polluting firms engaged in carbon-intensive activities, which contribute to environmental degradation.

In contrast, another branch of the literature supports that reducing inequality leads to lower emissions. Scruggs (1998) suggests that the environment acts as a normal good, meaning that as individuals become wealthier, they prioritize a clean environment and are willing to spend more on environmental preservation. Baek and Gweisah (2013) using an autoregressive distributed lag (ARDL) approach stated that a more equitable income distribution in the U.S. will lead to lower emissions. Zhang and Zhao (2014) using data from 1995 to 2010 in China highlighted a stronger influence of income inequality on emissions in the Eastern region compared to the Western region, suggesting that promoting income equity could contribute to emission reduction. This argument is confirmed by Baloch et al. (2020) analyzing 40 sub-Saharan African countries.

Other authors consider country income per capita as a mediator between income inequality and emissions (Kusumawardani and Kartino-Dewi, 2020). Grunewald et al. (2017) showed that for low and middle-income economies, higher inequality is associated with lower carbon emissions while in upper-middle-income and high-income economies, there is a positive correlation. Dorn et al. (2021) found that reducing fossil energy use in middle-income countries achieves emission targets but may increase inequality. Conversely, in high-income countries, such reductions enhance income equality. Rojas-Vallejos and Lastuka (2020), using data from 68 countries spanning 1961 to 2010, found a negative relationship between income and environmental quality in low-to middle-income countries, which turned

Table 1
Variables used for each objective.

Goal 1 - No poverty (sdg_01)
People at risk of poverty or social exclusion (sdg_01_10) Total
Persons at risk of poverty or social exclusion by degree of urbanization (sdg_01_10)/C(Cities)/T(Towns and suburbs)/R(Rural Areas)
Persons at risk of monetary poverty after social transfers (sdg_01_20)
Persons at risk of monetary poverty after social transfers by citizenship (sdg_01_20a)
Severe material and social deprivation rate by age group and sex (sdg_01_31)
In work at-risk-of-poverty rate (sdg_01_41)
Goal 2 - Zero hunger (sdg_02)
Agricultural factor income per annual work unit (sdg_02_20)
Government support to agricultural research and development (sdg_02_30)
Area under organic farming (sdg_02_40)
Ammonia emissions from agriculture (sdg_02_60)
Goal 3 - Good health and well-being (sdg_03)
Healthy life years at birth by sex (sdg_03_11)
Share of people with good or very good perceived health by sex (sdg_03_20)
Self-reported unmet need for medical examination and care by sex (sdg_03_60)
Goal 4 - Quality education (sdg_04)
Early leavers from education and training by sex (sdg_04_10) T(Total)/A(By citizenship)
Tertiary educational attainment by sex (sdg_04_20)
Participation in early childhood education by sex (children aged 3 and over) (sdg_04_31)
Goal 5 - Gender equality (sdg_05)
Gender pays gap in unadjusted form (sdg_05_20)
Gender employment gap, by type of employment (sdg_05_30) E(Employed persons)/P(Employed persons working part-time)/T(Employed persons with temporary contract/U (Underemployed persons working part-time)
Persons outside the labour force due to caring responsibilities by sex (sdg_05_4) F
Seats held by women in national parliaments and governments (sdg_05_50) P(National parliament)/NG(National government)
Positions held by women in senior management positions (sdg_05_60) B
Goal 6 - Clean water and sanitation (sdg_06)
Population having neither a bath, nor a shower, nor indoor flushing toilet in their household by poverty status (sdg_06_10)
Goal 7 - Affordable and clean energy (sdg_07)
Primary energy consumption (sdg_07_10)
Final energy consumption (sdg_07_11)
Final energy consumption in households per capita (sdg_07_20)
Energy productivity (sdg_07_30) E(Euro per kilogram of oil equivalent)/P(Purchasing power standard (PPS) per kilogram of oil equivalent)
Share of renewable energy in gross final energy consumption by sector (sdg_07_40)
Energy import dependency by products (sdg_07_50) S(Solid fossil fuels)/N(Natural gas)/0(Oil and petroleum products (excluding biofuel portion)/T(Total)
Population unable to keep home adequately warm by poverty status (sdg_07_60) A(Above 60% of median equivalised income)/B(Below 60% of median equivalised income)/T(Total)
Goal 8 - Decent work and economic growth (sdg_08)
Real GDP per capita (sdg_08_10) P
Investment share of GDP by institutional sectors (sdg_08_11) T(Total Investment)/B(Business Investment)/G(Government Investment)/H(Households Investment)
Employment rate, by citizenship (sdg_08_30a)
Long-term unemployment rate by sex (sdg_08_40)
Fatal accidents at work per 100 000 workers, by sex (sdg_08_60)
Goal 9 - Industry, innovation and infrastructure (sdg_09)
R&D personnel by sector (sdg_09_30)
Patent applications to the European Patent Office by applicants'/inventors' country of residence (sdg_09_40)
Share of buses and trains in inland passenger transport (sdg_09_50)
Share of rail and inland waterways in inland freight transport (sdg_09_60)
Air emission intensity from industry (sdg_09_70)
Tertiary educational attainment by sex (sdg_04_20)[a]
Gross value added in environmental goods and services sector (sdg_12_61)
High-speed internet coverage, by type of area (sdg_17_60)
Goal 10 - Reduced inequalities (sdg_10)
Purchasing power adjusted GDP per capita (sdg_10_10)
Adjusted gross disposable income of households per capita (sdg_10_20)
Relative median at-risk-of-poverty gap (sdg_10_30)
Income distribution (sdg_10_41)
Income share of the bottom 40 % of the population (sdg_10_50)
Goal 11 - Sustainable cities and communities (sdg_11)
Population living in households considering that they suffer from noise, by poverty status (sdg_11_20)
Road traffic deaths, by type of roads (sdg_11_40)
Premature deaths due to exposure to fine particulate matter (PM2.5) (sdg_11_51)
Severe housing deprivation rate is defined as the percentage of population living in the dwelling, which is considered as overcrowded, while also exhibiting at least one of the housing deprivation measures (sdg 11_11)
Goal 12 - Responsible consumption and production (sdg_12)
Circular material use rate (sdg_12_41)
Gross value added in environmental goods and services sector (sdg_12_61)
Goal 13 - Climate action (sdg_13)
Net greenhouse gas emissions (sdg_13_10)
Net greenhouse gas emissions of the Land use, Land use change and Forestry (LULUCF) sector (sdg_13_21)
Goal 16 - Peace, justice and strong institutions (sdg_16)
General government total expenditure on law courts (sdg_16_30)
Corruption Perceptions Index (source: Transparency International) (sdg_16_50)
Population with confidence in EU institutions by institution (sdg_16_60) C(European Commission)/P(European Parliament)/B(European Central Bank)
Goal 17 - Partnerships for the goals (sdg_17)
Official development assistance as share of gross national income (sdg_17_10) D(Development assistance committee)/L(Least developed countries)

(*continued on next page*)

Table 1 (*continued*)

EU financing to developing countries by financing source (sdg_17_20)
General government gross debt (sdg_17_40)
Share of environmental taxes in total tax revenues (sdg_17_50)
High-speed internet coverage, by type of area (sdg_17_60)

[a] Some SDG indicators belong to multiple groups because they address interconnected issues. For example, R&D personnel and patent applications impact not only industry and innovation (SDG 9) but also education (SDG 4) and global partnerships (SDG 17).
Source: Own elaboration based on Eurostat (2024).

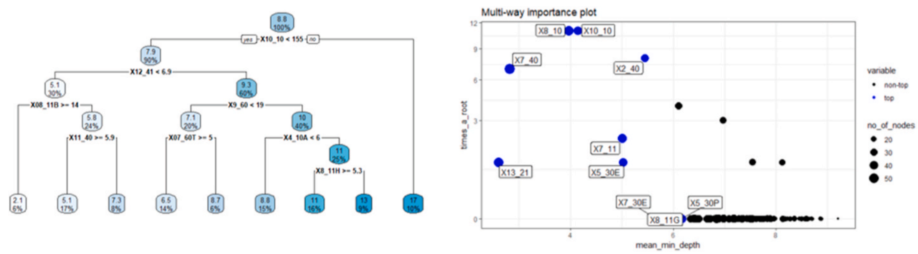

Fig. 1. Main drivers of net greenhouse gas emissions: A regression tree and the graph of the most important variables according to the random forest are presented. Source: Own elaboration

positive once a certain income threshold was reached. Coondoo and Dinda (2008) indicate that income redistribution can lead to higher average emissions levels in developed countries while having little to no significant impact on developing countries.

From a temporal perspective, authors have considered that the relationship between both dimensions is not constant. Uddin et al. (2020) for the period 1870 to 2014 in G7 countries revealed that income inequality had a positive effect on CO2 emissions from 1870 to 1880 and a negative impact from 1950 to 2000. Andersson (2023) studied the relationship between income inequality and carbon emissions in the United States between 1929 and 2019 showing that higher inequality was associated with lower emissions during the early part of the period and higher emissions towards the end.

Regarding methodological issues, most papers have focused on conventional methodologies imposing a parametric structure such as panel data estimations (Ravallion et al., 2000; Baloch et al., 2020; Hailemariam et al., 2020 or Che et al., 2023), ARDL models (Baek and Gweisah, 2013; Zhang, 2018; Kusumawardani and Kartino-Dewi, 2020) or survey data (Griskevicius, 2010). In our paper, complex networks are used to accommodating variability within the data more effectively than conventional models examining broader patterns that might be missed by traditional methods. Complex networks enable a non-parametric estimation, allowing for the exploration of the global properties of systems modeling them as graphs, with nodes representing dynamic units and links representing interactions between them (Boccaletti et al., 2006). Moreover, Wuchty and Stadler (2003) emphasize that central vertices in complex networks are of particular interest because they may function as organizational nodes.

In conclusion, the existing literature presents mixed evidence regarding the correlation between income inequality and CO2 emissions due to methodological differences, temporal dimension, and country selection. Thus, we propose to analyze the interrelations between GHG emissions and inequality through complex networks within the SDGs framework. The main contributions of this analysis are that to the best of our knowledge, no article has proposed to link this phenomenon with the SDG goals in the EU within a complex network framework facilitating an in-depth analysis without imposing a parametric structure. This methodology has already been applied to the analysis of conceptualization, communication, and achievement of SDGs (Bellantuono et al., 2022), the integration between the proposed SDG goals and their associated targets (Le Blanc, 2015) or the feasibility of accomplishment of the SDGs in the Mexican Federal Government but without considering the link between GHG emissions and inequality.

3. Data and variable selection

3.1. Variables and descriptive statistics

The data for this study covers annual data from 2015 to 2020 for 22 European countries,[1] using data from Eurostat. The countries used in the analysis are Austria (AT), Belgium (BE), Czech Republic (CZ), Germany (DE), Denmark (DK), Estonia (EE), Spain (ES), Finland (FI), France (FR), Croatia (HR), Ireland (IE), Italy (IT), Lithuania (LT), Latvia (LV), Luxembourg (LU), Netherlands (NL), Poland (PL), Portugal (PT), Sweden (SE) and Slovenia (SI). The variables used for this analysis are represented in Table 1, providing an overview of the SDGs and targets used for the analysis.[2] The utilization of Eurostat data ensures a reliable dataset for an examination of the SDGs and their dynamics during the specified timeframe. In Annex 1, the descriptive statistics of the variables used are presented.

3.2. Determinants of emissions

In this section, we will focus on analyzing the key variables that determine the emissions levels of different countries. To do this, we use two machine-learning techniques. See Torgo (2017) for a more detailed explanation of both techniques. The first is a regression tree, that splits the dataset into smaller groups using a series of rules based on a feature of the data (shown in Table 1), and the tree selects the rules that best separate the data according to the target being predicted. As you move down the tree, the data gets divided into specific subsets, making predictions more accurate. The second technique is a random forest, a method that builds multiple decision trees during training and generates predictions as the average of the individual trees' predictions. Regression trees and random forests are utilized in this study due to their strong and flexible capabilities in predictive modelling. A regression tree is a machine learning technique used to build predictive models based on data, offering the benefits of ease of interpretation and robustness against outliers. This method can capture both linear and nonlinear

[1] Country and year selection was made based on data availability.
[2] The available targets were included for the years and countries present in our dataset.

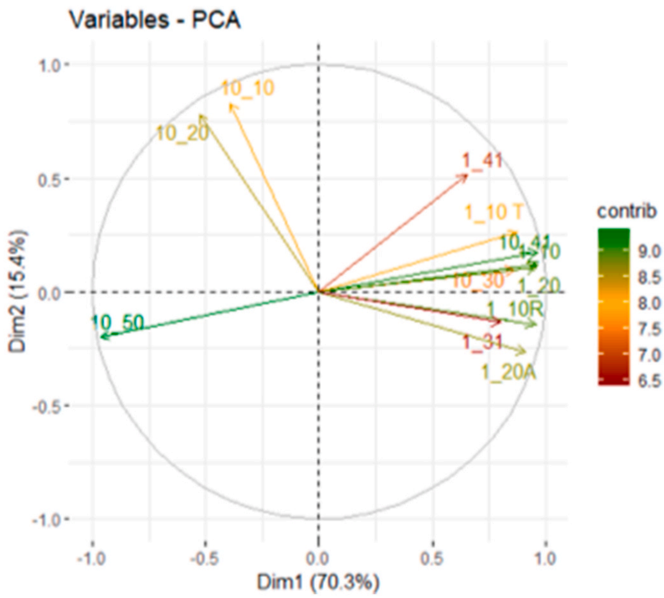

Fig. 2. Dimensions of SDGs 1 and 10 identified through PCA.
Source: Own elaboration

relationships, making it particularly effective for uncovering complex interactions between variables, which is crucial in the multifaceted context of SDG metrics.

However, one notable limitation of regression trees is their tendency to exhibit high variance, meaning that even small changes in the data can lead to significantly different splits, reducing the model's stability. This trade-off between simplicity and variability is discussed extensively in the works of Loh (2011), with the development of the regression tree algorithm initially attributed to Breiman et al. (1984).

To address the issue of high variance, ensemble methods like random forests are employed. As developed by Breiman (2001), random forests counteract the instability of regression trees by averaging the results from multiple trees, each constructed from different data subsets. This approach reduces variance and improves the predictive accuracy of the model, making it more reliable for complex datasets like those associated with SDG metrics.

In the regression tree (Fig. 1a), the terminal nodes, from left to right, show the increase in emissions based on the subdivisions of the most important variables, which are closer to the root of the tree, followed by the secondary variables that lead to the terminal nodes. The dependent variable in our regression tree is Net greenhouse gas emissions (sdg_13_10). The first split is made by the purchasing power variable (X10_10), dividing the tree to predict emissions, with index values above 155 (Volume indices of real expenditure per capita (in PPS_EU27_2020 = 100)) leading to the tree presenting 10% of observations with an average value of 17 (Tonnes per capita) in emissions. The next significant split in the regression tree occurs according to the variable representing the Circular Material Use Rate (X12_41), indicating how many materials within an economy are recycled and reintroduced into the economic cycle. It is observed that for values less than 6.9 (% of total material use), the emissions are lower, which may indicate that recycling processes are energy-intensive contributing to emission generation. In the next division, we encounter a variable of railway and inland waterways transportation (X9_60), indicating that for lower values, emissions are lower due to its lower emissions per ton-kilometer compared to road or air transport. Also, when the Investment share of GDP by business sectors (X8_11B) is greater than or equal to 14, the lowest levels of emissions are observed. In this context, a higher share of business investment in GDP seems to be associated with greater efforts toward sustainability and reducing emissions. Continuing with the nodes, where energy poverty (X7_60T) is greater than or equal to values of 5 (% of the population), emissions are lower leading to a trade-off between poverty and emissions. Finally, it is also noted that for the household sector (X8_11H), increased investments lead to a reduction in emissions.

In Fig. 1b, the most important variables from the random forest in determining net greenhouse gas emissions (variable sdg_13_10) are represented, on the X-axis (mean_min_depth), a low value indicates that a feature tends to appear near the top of the trees, suggesting it is relevant in data splitting. On the Y-axis (times_a_root), it is the number of times a feature has been used as the root of a tree in the Random Forest. A high frequency on the Y-axis suggests the high importance of that feature for performing the first split in the trees.

The sample is split into 80% for model training and 20% for making predictions for both techniques. Specifically, the regression tree achieves an accuracy of 85.4%, and the random forest improves accuracy to 90.5%. Consequently, the variables will be selected based on the random forest (Fig. 1b) owing to its higher accuracy. The variables selected to carry out the network analysis are Real GDP per capita (sdg_08_10), Purchasing power adjusted GDP per capita (sdg_10_10), Share of renewable energy in gross final energy consumption by sector (sdg_07_40), Area under organic farming (sdg_02_40), Net greenhouse gas emissions of the Land use, Land use change and Forestry (LULUCF) sector (sdg_13_21), Final energy consumption (sdg_07_11), Gender employment gap, by type of employment (sdg_05_30) E(Employed persons), Energy productivity (sdg_07_30) E(Euro per kilogram of oil equivalent) and Investment share of GDP by institutional sectors (sdg_08_11) G(Government Investment).

3.3. *Cluster inequalities*

Once we have identified the main factors explaining net greenhouse gas emissions, we will analyze inequality. To do this, we will focus on the connection between SDG 1 and SDG 10. SDG 1 targets aimed at eradicating poverty worldwide, and SDG 10 seeks to reduce inequality both within and among countries. Both SDGs are included since there are synergies among them (Pradhan et al., 2017) and decreasing poverty holds the same level of significance as diminishing inequalities, particularly within countries (Kuc-Czarnecka et al., 2023).

First, we conduct a Principal Component Analysis (PCA) to reduce the dimensionality of SDGs 1 and 10, as their targets are correlated (see Fig. 2).[3] The first dimension accounts for 70.3% of the variance variation.

Once dimensionality is reduced, country position will be identified along these dimensions through a cluster analysis which is an unsupervised learning technique for organizing objects that are like each other and dissimilar to objects in other clusters based on their characteristics (Dubes and Jain, 1988).

Two clusters are identified (see Fig. 3a and a) (see Annex 2 for the

[3] The test statistic of Bartlett's K-squared is 116307 with 83 degrees of freedom, yielding a p-value $<2.2e\text{-}16$. This extremely low p-value suggests a rejection of the null hypothesis of equal variances, reinforcing the rationale for employing PCA. Furthermore, the Kaiser-Meyer-Olkin (KMO) measure, evaluating the sampling adequacy for the analysis, returns an Overall MSA (MSA = 0.8), signifying a satisfactory level of adequacy for the dataset. The KMO test assesses whether the variables are suitable for factor analysis, and a value of 0.7 is considered meritorious for this purpose.

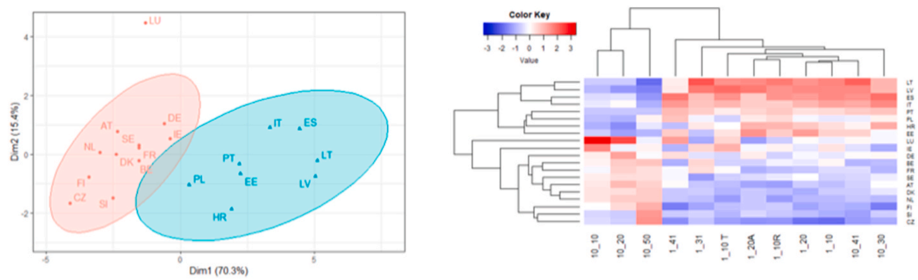

Fig. 3. Determining the number of clusters.
Source: Own elaboration

optimal number of clusters (Fig. 1a) and the Silhouette Score graph (Fig. 1b))[4]: In group one countries exhibit low levels of inequality and poverty such as Germany, Ireland, Finland, and the Netherlands. These countries possess robust social welfare systems, strong economies, more flexible labour markets, high employment rates, and effectiveness in government and governance structures (Iammarino et al., 2019; Amendola et al., 2006). Conversely, group two comprises countries characterized by high levels of inequality and poverty, elevated structural unemployment rates, and limited capital accumulation. These countries are predominantly situated in Southern and Eastern Europe (Amendola et al., 2006). This situation may be attributed to limited skills, insufficient technological investment, and weak governance structures, which contribute to their lag in comparison to countries with lower inequality and poverty levels (Iammarino et al., 2019; Balakrishnan et al., 2022). Notable examples include Spain, Portugal, Italy, and Latvia.

In Fig. 3b, the impact of each variable is assessed on the cluster by observing colour and intensity. In Group 1, we observe a correlation between positive indicators of GDP and negative indicators of low socioeconomic conditions suggesting a lower percentage of individuals at risk of poverty. Conversely, Group 2 exhibits contrasting characteristics, indicating adverse socioeconomic conditions.

4. Results

In this section, two complex networks are developed to explore the links and interactions between net greenhouse gas emissions and their main determinants obtained in the Random Forest (Fig. 1b) with the two inequality groups in Europe[5] obtained in the cluster analysis (Fig. 3a) to determine the most relevant factors of each inequality group on global emissions. The measures calculated in the complex networks are strength, closeness, betweenness and expected influence. The measures are explained as follows:

Strength centrality (1) is calculated as the sum of the absolute values of the correlations of all edges connected to a node, indicating how strongly a node is connected to other nodes. This helps us see how strongly a node is connected to others in the network. ρ_{ij} is the correlation coefficient between node i and node j, and $N(i)$ is the set of neighbour's nodes of i.

$$\text{Strength}(i) = \sum_{j \in N(i)} \left| \rho_{ij} \right| \tag{1}$$

Closeness centrality (2) in a correlation network measures how close a node is to all other nodes in terms of the length of the shortest paths. In correlation networks, distances can be defined inversely to the magnitude of the correlations.

$$\text{Closeness}(i) = \frac{1}{\sum_{j \neq i} \frac{1}{|\rho_{ij}|}} \tag{2}$$

Betweenness centrality quantifies the number of times a node acts as a bridge along the shortest paths between two other nodes, showing how often a node connects two other nodes in the network. For correlation networks, the shortest paths are based on the inverse distances of the correlations.

$$\text{Betweenness}(i) = \frac{\sigma_{st}(i)}{\sum_{s \neq j \neq i} \sigma_{st}} \tag{3}$$

Where:

σ_{st} is the total number of shortest paths between node s and node t, calculated using the correlation-based distances.

$\sigma_{st}(i)$ is the number of those shortest paths that pass-through node i.

Expected influence in a correlation network can be interpreted as the measure of how much a node impacts others directly and indirectly. This can be calculated by considering both direct correlations and those propagated through the network.

The results represented in Fig. 4a and b highlight graphically the different influences of each variable within the two inequality groups, while Fig. 4c displays the centrality measures in Z-scores. The two networks differ significantly in key aspects. Group 1 (low inequality) shows high integration, with strong interconnections among variables, while group 2 (high inequality) has lower integration and weaker connections. This suggests that in highly interconnected networks, a policy change in one area can indirectly affect other areas, whereas in less integrated networks, changes tend to have more localized impacts. In terms of centrality, group 1 variables are more central, allowing a faster spread of impacts and policy changes. In contrast, group 2 variables are less central, leading to slower policy response times. Additionally, group 1 has more variables with high betweenness, acting as key connectors in the network, unlike group 2, indicating a less cohesive network.

[4] In cluster analysis, the silhouette score is a measure used to evaluate the quality of the clusters created by a clustering algorithm. It helps determine how well each object lies within its cluster. The silhouette score combines two key factors: cohesion (how close each point in a cluster is to other points in the same cluster) and separation (how far a point in a cluster is from points in the nearest different cluster). The highest average silhouette width is observed at k = 2 clusters, which is around 0.45. This suggests that the best clustering solution, in terms of cohesion and separation, is achieved with 2 clusters.

[5] Both graphs in Annex 3 illustrate the robustness of the network's edge clustering. The strong alignment between the original sample and bootstrap mean, coupled with narrow confidence intervals, demonstrates stable and reliable clustering results. These insights confirm the network's robustness. The Network Invariance Test results, with a test statistic (M) of 0.6291692 and a p-value of 0.03225806, indicate significant differences between the two networks being compared. The p-value, which is less than the commonly used significance threshold of 0.05, suggests that the structures of the two networks are statistically different from each other. This finding implies that there are underlying differences in how nodes are interconnected or in the overall network configurations between the two groups.

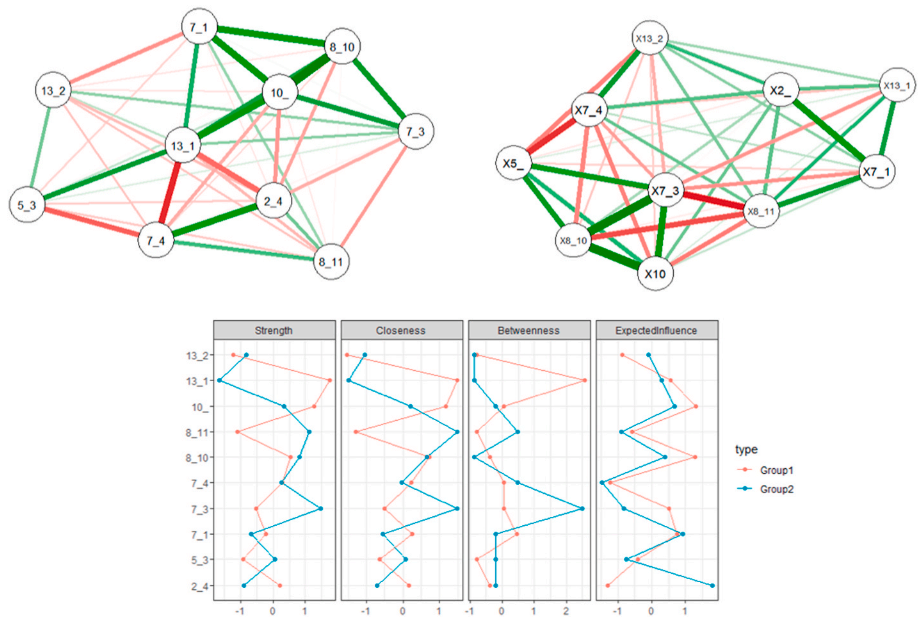

Fig. 4. Complex Networks: The topology of the two networks and the differences in the statistical measures of these networks are presented.
Source: Own elaboration

Furthermore, the potential impact is greater in group 1 than in group 2, suggesting significant potential for widespread positive impacts from targeted policies.

In group 1, greater influence within the network is observed in net greenhouse gas emissions, purchasing power-adjusted GDP per capita, and real GDP per capita. Additionally, greenhouse gas emissions display higher betweenness centrality. Conversely, in group 2 net greenhouse gas emissions have a low strength and centrality in the network, whereas variables such as energy productivity, Investment share of GDP by institutional sectors and Real GDP per capita possess higher relevance. Likewise, energy productivity in this group plays a central role in connecting targets within this network.

In group 1 (lower inequality), the relationship between energy productivity and emissions is positive. While countries with lower inequality often have more resources to invest in energy efficiency and clean technologies (Green and Healy, 2022), improvements in quality of life and increased purchasing power from higher productivity can lead to greater consumption of goods and services. This, in turn, can result in higher overall carbon emissions (Veblen, 2009; Guo, 2014). In contrast, in group 2 (high inequality), the relationship is negative. This suggests that in high-inequality countries, productivity increases reduce emissions because energy efficiency gains outweigh the rise in consumption. In low-inequality countries, however, the opposite occurs.

This result is further supported by the relationship with income per capita. In the high-inequality group, the link between emissions and income is minimal, so higher income does not lead to more emissions. However, in the low-inequality group, higher purchasing power results in increased emissions.

In countries with higher inequality, agricultural activities have a positive impact on emissions, likely because agriculture is less productive and more emissions-intensive (Abd El-Aal, 2024). In contrast, in countries with lower inequality, agriculture tends to be more productive, benefiting from higher levels of technological development and capital accumulation (Bustos et al., 2020). Another key difference between the two networks is related to government investments. In countries with greater inequality, there is a positive correlation between investments and emissions, whereas in countries with lower inequality, the correlation is negative. This suggests that investments in the latter group may be more aligned with efforts to achieve a zero-carbon economy. The disparity may arise because not all investments are green. Countries that invest heavily, particularly those with a strong focus on industrial activities, high productivity, and higher GDP, are likely to experience higher emissions (Onofrei et al., 2022; Iammarino et al., 2019). This is supported by the relationship between net greenhouse gas emissions and the share of renewable energy in final energy consumption. In the low inequality group, there is a strong negative relationship, indicating that higher use of renewable energy leads to a significant reduction in greenhouse gas emissions suggesting that in these countries a more equitable distribution of resources may enable greater investments in renewable technologies, enhancing environmental outcomes. In contrast, in the second group, while the relationship between renewable energy and emissions is still negative, it is much weaker. This weaker link may imply that other factors, such as economic constraints or less effective policy frameworks, limit the impact of renewable energy on emissions reduction (Simionescu and Cifuentes-Faura, 2024).

5. Conclusions and discussion

The correlation between carbon emissions and inequality poses significant attention in academic literature since both issues intersect in the realm of combating climate change. Nevertheless, there is not a clear consensus among both dimensions. A new framework employing the SDG dimensions is proposed to analyze the relationship between emissions and inequality. First, the main determinants of greenhouse gas emissions are obtained in a Random Forest, then two inequality groups are created through a cluster analysis. Lastly, two complex networks are constructed based on the GHG drivers and the two inequality groups to determine the most relevant factors influencing each group's impact on global emissions.

Our research reveals significant differences between nations characterized by low and high levels of inequality. In terms of integration and centrality, Group 1 (countries with lower inequality) exhibits greater integration and centrality among its dimensions which leads to a broader widespread of policy changes across different dimensions. In contrast, in Group 2 (countries with higher inequality), the impact of policy changes tends to be more localized (Bai et al., 2023).

In the high-inequality group, productivity and emissions are negatively correlated, while in the low-inequality, the relationship is positive. In this relationship, there is a trade-off, as noted by Ravallion et al.

(2000), where countries with lower inequality tend to have greater energy efficiency due to capital accumulation. However, improvements in quality of life and productivity typically lead to increased consumption, resulting in higher carbon emissions. This phenomenon is supported by Veblen (2009) and Guo (2014), who argue that rising income levels drive higher consumption, influenced by the marginal propensity to emit and consumer status. Furthermore, Rojas-Vallejos and Lastuka (2020) and Coondoo and Dinda (2008) suggest that there is an income threshold at which the effect of inequality on emissions shifts. This perspective contrasts with findings by Scruggs (1998), who proposed that wealthier individuals tend to prioritize a clean environment, and Baek and Gweisah (2013), who argued that a more equitable income distribution in the U.S. would lead to reduced carbon emissions.

In countries with higher inequality, agricultural activities have a positive impact on emissions. In contrast, in countries with lower inequality, agriculture tends to be more productive and less polluting, benefiting from higher levels of technological development and capital accumulation (Bustos et al., 2020; Abd El-Aal, 2024).

About government investments. In countries with higher inequality, there is a positive correlation between investments and emissions, indicating that increased investments lead to higher emissions. In contrast, in countries with lower inequality, this correlation is negative, suggesting that investments in these countries are more likely aligned with efforts to achieve a zero-carbon economy. This is consistent with the findings of Wang and Feng (2022), which indicate that in wealthier countries, emissions have decreased, while in developing countries, emissions have remained stable. This suggests that investments in wealthier nations are focused on achieving "green growth," whereas developing countries tend to prioritize growth to catch up with wealthy nations (Onofrei et al., 2022; Iammarino et al., 2019).

Future research could broaden its scope by increasing sample sizes to include countries from other continents. This would help identify additional inequality groups and allow for a regional perspective to analyze interregional differences. Additionally, researchers could examine the impact of shocks within a complex network framework. Furthermore, employing a temporal scale in future studies to assess the evolution of these complex networks could provide valuable insights into how the interrelations among variables change over time.

6. Policy recommendations

From a policy perspective, our findings suggest that policies in the low-inequality group can be broader and multidimensional because there are more connections between different targets. Therefore, policymakers should be cautious when setting policies, as increasing productivity due to technological improvements could have the unintended effect of increasing emissions owing to demand increases. On the other hand, in the low-emissions group, these policies should be more focused, targeting specific areas to address problems.

On the other hand, it is relevant to consider the emissions perspective. According to data from Chancel (2022), the bottom 50% of the world's population accounted for 12% of global emissions in 2019, while the top 10% was responsible for 48% of total emissions. This highlights the need for wealthier countries to promote growth while ensuring sustainable resource consumption, avoiding consumption patterns that are dependent on income. Meanwhile, in countries with high inequality and lower incomes, growth is the main objective to catch up with low-inequality countries, but this must follow three main patterns: promoting green growth, supported by wealthier and more equal countries that have the resources and technology to invest in sustainable growth activities, rather than the carbon-intensive growth these low-inequality countries have followed in the past; ensuring that consumption is not solely dependent on income, or only up to a certain threshold, to secure adequate well-being; and supporting vulnerable groups (given the high inequality and, consequently, high poverty rates) to ensure inclusive growth.

CRediT authorship contribution statement

José Alejandro Fernández Fernández: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Miguel Ángel Casquet Cano:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Methodology, Investigation, Conceptualization. **Sonia Quiroga Gómez:** Writing – review & editing, Visualization, Supervision, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization.

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The authors declare that there are no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Annex 1.

	Min	1st Quartile	Median	Mean	3rd Quartile	Max
1_10	11.50	17.18	19.95	20.53	23.70	30.00
1_10C	10.40	17.00	19.90	20.45	23.70	31.80
1_10 T	11.50	15.28	18.20	19.68	23.15	32.50
1_10R	10.50	15.65	19.60	21.43	27.02	38.20
1_20	9.10	13.38	16.05	16.35	20.00	23.30
1_20A	7.80	11.70	13.40	14.76	17.82	23.60
1_31	0.70	2.60	4.50	5.34	7.20	15.40
1_41	2.70	5.30	7.80	7.70	9.70	13.10
2_20	4734.00	8800.00	20180.00	20547.00	28717.00	52163.00
2_30	0.20	3.20	4.90	6.47	8.60	22.70
2_40	1.63	5.98	8.20	9.99	14.00	25.69
2_60	6.90	14.55	20.35	24.02	28.68	62.60
3_11	51.40	57.67	60.95	61.49	64.30	73.30
3_20	42.80	59.73	68.15	65.62	73.38	84.10
3_60	0.10	0.48	1.60	2.58	2.90	16.40
4_10 T	2.20	6.15	8.00	8.41	10.03	20.00
4_31	69.50	88.30	91.90	91.46	95.50	100.00
4_20	25.20	38.58	43.15	42.70	47.33	60.60
4_10A	2.10	5.30	7.35	7.64	8.73	17.80
5_20	0.70	9.20	14.05	13.42	17.20	26.70
5_30E	1.00	5.90	8.00	8.67	11.25	19.90
5_30P	-47.80	-24.10	-17.60	-18.08	-6.28	-2.20
5_30T	-6.80	-3.50	-2.00	-2.16	-0.70	0.90
05_30U	-8.00	-2.90	-2.20	-2.43	-1.00	-0.20
5_4F	6.90	21.65	31.50	31.18	4.88	68.40
5_50P	16.00	25.65	31.25	31.76	38.38	49.60
5_50NG	11.80	24.02	29.40	32.31	40.90	57.60
5_60B	7.40	18.18	26.05	25.14	31.93	45.20
6_10	0.00	0.10	0.30	1.48	0.83	12.30
7_10	1.89	2.46	3.19	3.42	3.80	7.34
7_11	1.45	1.92	2.31	2.64	2.92	7.16
7_20	266.00	539.20	617.50	625.80	720.50	1046.00
7_30E	2.85	5.29	7.61	8.04	9.35	22.41
7_30P	4.55	7.17	8.51	8.97	10.04	22.06
7_40	4.99	14.92	21.30	23.75	31.69	60.12
7_50S	-11.70	71.12	94.23	81.17	100.91	391.79
7_50N	-56.07	81.37	98.66	81.24	100.00	122.85
7_50O	-5.31	95.10	98.48	94.42	100.74	129.96
07_50T	1.21	43.81	52.92	55.82	73.49	96.28
07_60A	0.20	1.50	3.10	5.77	6.32	:29.10
07_60B	2.30	7.65	12.70	14.98	19.45	43.30

Fig. 1. Variables Statistics Table

07_60T	0.90	2.60	4.15	6.84	7.78	31.10
8_10	10760.00	16070.00	28890.00	30628.00	38360.00	84750.00
8_10P	-11.80	0.70	1.85	1.55	3.30	23.20
8_11T	15.49	19.25	21.31	22.03	23.88	54.30
08_11B	7.88	11.50	12.91	14.03	15.14	50.44
8_11G	1.54	2.59	3.41	3.47	4.29	5.70
8_11H	1.42	3.59	4.48	4.51	5.44	7.15
8_30a	60.30	70.08	74.80	74.00	78.22	84.70
8_40	0.60	1.58	2.20	2.87	3.25	11.40
8_60	0.30	1.34	2.01	2.07	2.74	6.32
09_70	0.02	0.07	0.10	0.21	0.20	1.12
9_30	0.21	0.97	1.46	1.36	1.73	2.21
9_40	9.00	147.80	1249.00	3203.80	2703.20	26762.00
9_50	5.80	13.78	16.70	16.30	18.60	25.30
9_60	0.60	13.97	26.40	28.10	34.70	79.80
9_71	0.01	0.05	0.07	0.16	0.14	0.92
10_10	61.00	80.50	101.50	111.40	125.20	282.00
10_20	12015.00	16946.00	21024.00	21235.00	24622.00	35274.00
10_30	13.20	17.80	21.05	21.74	25.35	33.80
10_41	3.32	4.04	4.40	4.74	5.36	7.46
10_50	17.20	20.05	22.30	21.70	23.20	25.10
11_11	0.70	1.80	2.80	4.00	5.00	15.50
11_20	7.70	12.83	15.10	15.95	18.30	27.80
11_40	2.00	3.70	4.90	5.02	6.20	9.50
11_51	12.0	277.80	459.00	528.00	775.80	1537.00
12_41	1.60	5.68	9.45	10.50	12.40	30.00
12_61	0.72	1.81	2.30	2.64	2.97	6.92
13_10	0.70	5.90	8.80	8.81	10.90	20.20
13_21	-241.10	-85.48	-48.50	-35.96	-8.52	161.90
16_20	2.20	7.00	9.25	9.65	12.73	19.40
16_30	35.80	64.65	90.45	95.78	119.45	239.90
16_50	44.00	59.00	70.00	69.29	81.00	91.00
16_60C	26.00	39.75	49.00	48.00	57.00	76.00
16_60P	27.00	43.00	52.00	51.52	60.00	79.00
16_60B	22.00	36.75	45.00	46.86	55.25	71.00
17_10D	0.07	0.15	0.29	0.38	0.54	1.40
17_10L	0.01	0.03	0.06	0.11	0.14	0.48
17_40	8.20	39.42	64.75	66.81	89.15	154.90
17_50	3.61	5.38	6.71	6.94	8.18	11.75
17_60	0.40	22.98	49.05	46.12	64.85	95.10

Fig. 1. (*continued*).

Annex 2.

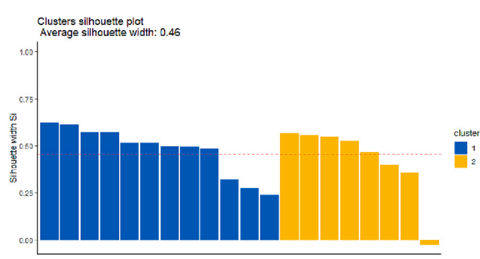

Fig. 2a. Optimal number of clusters

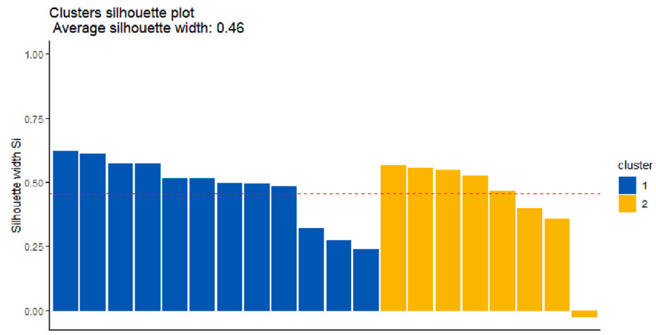

Fig. 2b. Silhouette graph

Annex 3.

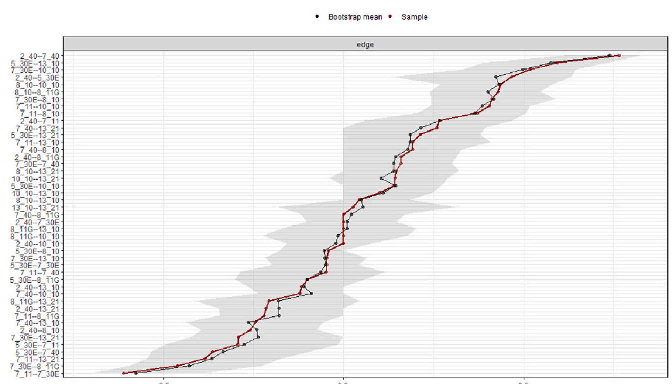

Fig. 3a. Low inequality group

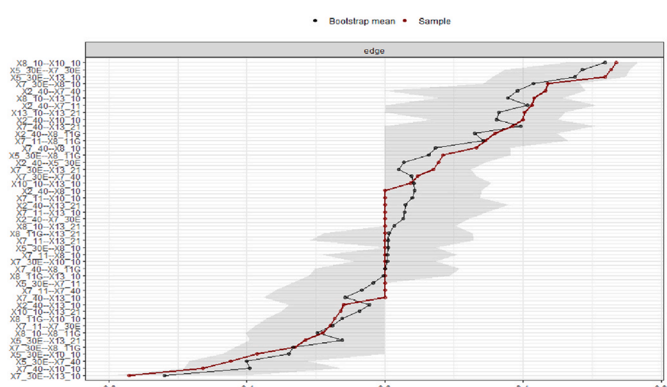

Fig. 3b. High inequality group

Data availability

Data will be made available on request.

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