Heliyon 9 (2023) e21443

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Review article

Taxing for a better life? The impact of environmental taxes on income distribution and inclusive education

Edmond Noubissi Domguia

Centre for Studies and Research in Management and Economics, Research Laboratory in Fundamental and Applied Economics, University of Dschang, Cameroon

ARTICLE INFO

Keywords:
Environmental tax
Income inequality
Inclusive education
PSM
Double differences
Randomisation
Heterogeneous treatment

ABSTRACT

This paper examines the impact of environmental taxes on economic and social inequalities using data from 38 OECD countries from 1994 to 2020. The results show that the introduction of an environmental tax can have unequal consequences on population groups due to differences in consumption behaviour and access to environmental alternatives. The results also indicate that environmental taxes with a progressive character (i.e. higher for higher income households) can reduce inequalities and improve environmental efficiency. The introduction of environmental taxes should therefore be done with care and with due regard to their impact on inequality. Tax policies must be designed to protect the most vulnerable households and promote equity while protecting the environment. Thus, environmental taxation should be accompanied by social and economic policies that reduce inequalities and support the most affected social groups. It is also important for governments to have better communication and awareness-raising on the impacts of environmental taxation on inequalities, in order to ensure a just transition towards sustainable lifestyles.

1. Introduction

The issue of environmental inequalities is not simply an extension of the concept of social justice, but an extension of environmental issues to new problems and populations. It leads us to update our questions and analyses of the impacts of human activities. These impacts go beyond the traditional understanding of natural elements and extend to the relationships between societies, populations and the environment. It is important to recognise that these impacts are not uniform and are experienced differently by different groups.

Environmental taxes have been implemented by many governments around the world to reduce the negative impact of human activities on the environment and environmental inequalities [1]. These taxes aim to reduce greenhouse gas emissions, promote energy efficiency, encourage the use of cleaner technologies and restore environmental justice. In general, environmental justice aims to correct the inequitable distribution of environmental burdens on the disadvantaged and economically disadvantaged.

Yet the impact of these taxes on socio-economic inequalities has been the subject of debate in recent years [2]. Environmental taxes are generally considered to be regressive. However, a review of the literature on the distributional effects of environmental taxes shows that heterogeneity within and between studies leads to different conclusions. While some argue that environmental taxes could exacerbate inequalities [3,4], others believe that they could help to reduce them [2,5]. Thus, the potential link between environmental taxes and income inequality needs to be carefully examined.

E-mail address: enoubissidomguia@yahoo.fr.

https://doi.org/10.1016/j.heliyon.2023.e21443
Received 12 June 2023; Received in revised form 20 October 2023; Accepted 20 October 2023
Available online 30 October 2023

While environmental taxes can help reduce pollution and promote sustainable development, they can also increase the cost of living for low-income households. This could lead to greater income disparities, as low-income households may not have the resources to adapt to the increased cost of living.

On the other hand, ecological taxation makes it possible to reduce other types of taxation: by taxing pollution, we can reduce taxes on labour, investment or innovation by the same amount. In this case, ecological taxation produces a “double dividend”: an ecological dividend, with a reduction in behaviour that is harmful to the environment, and an economic dividend, where the concomitant reduction in taxes on labour or capital helps to boost activity and make the economic system more efficient overall [6]. Environmental taxes have thus become a popular policy tool for reducing negative environmental externalities.

However, the impact of these taxes on inequality has not been widely studied. This research problem is important because environmental taxes have the potential to exacerbate existing inequalities or reduce them, depending on how they are implemented [1]. Therefore, it is essential to examine the impact of environmental taxes or environmental tax revenues on inequalities to ensure that they are implemented in a way that promotes social justice and thus achieves Goal 10 of the OECD SDGs. This goal aims to reduce inequalities, because development is only possible in a world with reduced inequalities.

For this study, we took the OECD countries as the treatment group and a set of non-OECD countries as the control group, because there is a basic difference between these two groups of countries, particularly where environmental policies are concerned. Indeed, OECD countries have more advanced and developed environmental policies, including taxes on greenhouse gas emissions and other types of pollution, whereas non-OECD countries tend to have less stringent or non-existent environmental policies. By comparing the impact of environmental taxes in these two groups of countries, we can therefore estimate the effectiveness of this policy in reducing greenhouse gas emissions and other pollutants, while at the same time examining the social impacts of these policies, particularly the impact on inequalities. Furthermore, by comparing these two groups, we can also identify certain factors that may mitigate or aggravate the impacts of environmental taxes, such as income levels, infrastructure and social policies in the countries concerned. These results can help guide policy decisions on the environment and economic development.

The importance of this study lies in its potential to inform policy decisions related to environmental taxes. By examining the effects of these taxes on inequalities, policymakers can make more informed decisions about how to implement them in a way that promotes social justice and reduces negative environmental externalities. Furthermore, by identifying these effects, this study can provide policymakers with more accurate information on how to implement environmental taxes in a way that promotes social justice and sustainable development. Indeed, previous studies have shown that the effects of environmental taxes on inequality are complex and depend on various factors, including income, race and geographical location [2,7,8]. Finally, this study can contribute to the broader literature on environmental justice and sustainable development.

The aim of this study is to analyse the effects of environmental taxes on inequality within the OECD. To achieve these objectives, this study will use econometric modelling techniques and will be structured as follows. Section 2 reviews the literature on the link between environmental taxation and inequality. Section 3 describes our data and methods for analysing the impact of carbon taxation policies on populations. Sections 4 and 5 present and discuss the results respectively. Section 6 concludes.

2. Literature review on environmental taxes and inequalities

Environmental taxes are defined as taxes levied on activities that have negative impacts on the environment, such as pollution or resource depletion [9]. Previous studies have examined the distributional impacts of environmental taxes, with some arguing that they can exacerbate inequalities while others suggest that they can be used to reduce other distortionary taxes or levies, ultimately leading to a fairer tax system [10]. [11] have sought to dispel misunderstandings about the distributional impacts of carbon taxes, which have been a disproportionate barrier to their implementation. These studies provide valuable information on the potential effects of environmental taxes on inequality and highlight the need for further research in this area.

The theoretical framework for studying the effects of environmental taxes on inequality is based on the consequences of air pollution and climate change, as well as on the redistributive effects of environmental policies. The implementation of an environmental tax can have both efficiency and equity implications, and it is important to analyse these consequences in order to design efficient and equitable policies [10]. In addition, the determinants at the heart of environmental justice issues, such as income and race, need to be taken into account in order to fully understand the potential impacts of environmental taxes on inequalities [12].

According to a 2013 study by the Organisation for Economic Co-operation and Development (OECD), an environmental tax can lead to higher prices for energy and polluting goods, which can have a negative impact on poorer households. However, the revenue generated by the environmental tax can be used to offset this price rise through income transfers and tax reductions, thereby reducing the gap between rich and poor.

[5] analysed the effects of environmental taxes on income inequality in the United States. The results show that environmental tax policy could reduce inequality, but this depends on the redistribution of tax revenues. The authors suggest that the government should use part of the tax revenue to develop social programmes targeting low-income households.

[13] assessed the impact of a carbon tax on social inequality in France. The results showed that this tax increased energy costs for the poorest households, but the tax revenue was then used to fund redistribution programmes. Ultimately, the environmental tax policy reduced income inequality.

The relationship between environmental taxes and inequality is the subject of ongoing research, with various studies examining the short- and long-term effects of these policies [14]. analysed the short-term effects of a climate policy of taxing polluting emissions, finding that it can lead to a reduction in emissions and an improvement in air quality. The CIRCLE project report of 2016 presented a detailed quantitative assessment of the consequences of climate change on growth and inequality in developing countries [15]. These studies provide important information on the potential impacts of environmental taxes on inequality and highlight the need for further research in this area.

In sum, the results of studies on the links between environmental taxes and inequality vary. Tax policies can increase energy costs for the poorest households, but they can also reduce inequalities by using tax revenues to finance social programmes targeting these households. It is therefore important to take account of the social effects of environmental taxes when implementing environmental policies.

This is the rationale behind this study. However, this study differs from its predecessors in several respects. It takes into account not only income inequality but also other forms of inequality (educational inequality). In addition, it uses a much wider study area (OECD and non-OECD countries) and compares them according to several indicators. Finally, it uses impact analysis techniques to assess the effectiveness of the tax in reducing inequality.

3. Methodology of the study

The methodology of the study is to collect data from various sources to create an econometric model that analyses the effects of environmental taxes on inequality. The data sources used in the study include data from the World Development Indicator [16] and information on environmental tax revenues from the OECD [9]. In addition, the study draws on previous research on the economics of climate change and related policies [2,17]. The study assumes that the impact of environmental taxes on inequality varies according to the specific policies implemented and the characteristics of the population concerned. It therefore aims to shed light on the determinants at the heart of environmental justice issues, such as socio-economic inequalities and the unequal distribution of environmental burdens.

The variables used in the study include income inequality, educational inequality, environmental tax, internet access, foreign direct investment, migrant remittances and financial development. Overall, the study's methodology aims to provide a comprehensive analysis of the effects of environmental taxes on inequality, drawing on a range of data sources and econometric modelling techniques.

3.1. *Descriptive statistics and data correlation matrix*

To conduct econometric modelling of the effects of environmental taxation on inequality, it is important to first analyse the descriptive statistics of the data. This includes calculating summary statistics for the variables, such as the mean, median, standard deviation and range, to obtain a better understanding of the data set (Table 1). Correlation analysis can also be performed to identify any relationships between variables and to determine which variables are most strongly associated with the outcome variable (Table 2).

Inequality is a major concern in environmental justice issues, and it is therefore important to consider the impact of the environmental tax on inequality, as shown in correlation Table 2. This table shows the Pearson correlation coefficients between the variables and their level of significance. Analysis of the determinants of inequality issues, such as access to the Internet (Internet), foreign direct investment (FDI), remittances and domestic credit to the private sector (findev), can shed light on the factors that contribute to inequality. The impact of environmental taxation on inequality can also be analysed in terms of its effects on businesses

Table 1
Descriptive statistics.

Treated Group						
Variables	Observations	Mean	Std. Dev.	Min	Max	Sources
Gini	2319	35.54671	7.099519	20.86	57.6	WDI
University	1526	1.020062	.2,769,761	.18,097	1.48931	WDI
Envtax	1003	2.322463	.8,894,769	−1.53	5.36	OCDE
Internet	1203	46.58844	35.17157	0	99.68702	WDI
FDI	1717	3.188107	8.682515	−57.53231	138.215	WDI
remitances	1523	.846,184	1.147067	0	9.338859	WDI
Findev	1163	80.81001	48.27531	.1,861,699	304.5751	WDI

OECD countries: Australia; Austria; Belgium; Canada; Chile; Colombia; Costa Rica; Czechia; Denmark; Estonia; Finland; France; Germany; Greece; Hungary; Iceland; Ireland; Israel; Italy; Japan; Korea, Rep. ; Latvia; Lithuania; Luxembourg; Mexico; Netherlands; New Zealand; Norway; Poland; Portugal; Slovak Republic; Slovenia; Spain; Sweden; Switzerland; Turkiye; United Kingdom; United States.

Control Group

Variables	Observations	Mean	Std. Dev.	Min	Max	Sources
Gini	2349	41.99135	8.667479	16.4	77.1	WDI
University	1122	.9,155,636	.371,216	.10,414	1.57157	WDI
Internet	1309	20.48505	25.17995	0	96.75143	OCDE
FDI	1,98	4.198037	20.76727	−117.4203	449.0809	WDI
remitances	1632	3.629919	4.877469	0	32.68594	WDI
Findev	1641	58.06093	532.0072	0	15675.28	WDI

No-OECD countries: Argentina; Bangladesh; Bolivia; Brazil; Bulgaria; China; Ivory Coast; Croatia; Cyprus; Dominican Republic; Ecuador; Egypt, Arab Rep. ; El Salvador; Guatemala; Honduras; India; Jamaica; Kazakhstan; Kenya; Kyrgyz Republic; Malawi; Malaysia; Mali; Malta; Nicaragua; Nigeria; Pakistan; Panama; Paraguay; Peru; Philippines; Romania; Serbia; Singapore; South Africa; Thailand; Tunisia; Uganda; Ukraine; Uruguay; Venezuela, RB; Vietnam.

Table 2
Correlation matrix.

	Gini	university	Envtax	Internet	FDI	remittances	findev
gini	1.0000						
university	−0.0873***	1.0000					
envtax	−0.3694***	0.1990***	1.0000				
Internet	−0.1318***	0.3693***	0.0343	1.0000			
FDI	−0.0341	0.1527***	0.0426	0.1031***	1.0000		
remittances	0.0739***	0.0533*	−0.0228	0.0165	0.0720***	1.0000	
findev	−0.0610**	0.1086**	−0.0763**	0.3835***	0.0097	−0.3911***	1.0000

Note: level of significance ***p < 0.01, **p < 0.05, *p < 0.1.

and development processes. However, the unequal distribution of the environmental burden can act as a brake on the development process. It is therefore important to consider the link between inequality and the environment when analysing the effects of environmental taxation.

3.2. Data

This document examines a panel of 38 OECD countries and 42 No-OECD countries over the period 1994–2020 with data from the OECD (OECD Statistics) and the World Bank's World Development Indicators (WDI). The periodicity and countries selected are carefully chosen according to the literature and data availability constraints. The full description of the data is as follows.

i. Dependent variables

In this particular study, economic and educational inequality are the two important dimensions of inequality that we take into account to understand how environmental taxes might affect population groups differentially. Certainly, these taxes can increase the cost of daily living, particularly by affecting the price of food and fuel, which account for a larger share of the budget of people on low incomes. The introduction of environmental taxes could therefore have a greater impact on people on low or average incomes and increase income inequalities. In addition, people with a higher level of education often have better-paid jobs and greater social benefits, which would probably enable them to cope better with the cost increases associated with environmental taxes. On the other hand, people with lower levels of education may find it more difficult to adapt to these new taxes, and may therefore be more affected by environmental inequalities. To measure income inequality and in accordance with the literature [18,19], we will use the Gini index. The Gini index provides a measure of the extent to which the distribution of income or consumption between individuals or households within an economy deviates from complete equality [16].

Disparity in educational opportunities is measured by the gender parity index of enrolment rates in tertiary education [20]. This index compares the number of women to the number of men enrolled in public and private higher education institutions [16].

Fig. 1 illustrates trends in income and education inequality. By analysing the Gini index, we can see a slight fall in income inequality over time within the OECD, with a peak between 2005 and 2010. However, when it comes to educational inequality, inclusive education has seen an upward trend from 1994 to 2020. These trends may also be exacerbated by the absence or poor implementation of environmental policies.

Fig. 1. Changes in income and education inequalities.

ii. Variable of interest

Our study focuses on environmental policy, and more specifically on the introduction of an environmental tax. Fig. 2 provides a visual representation of the evolution of this tax over time. From this figure, we can see that the environmental tax was at its lowest level in the OECD between 2005 and 2010. In recent years, a great deal of research has been carried out on this tax, which aims to discourage polluting businesses and industries by allocating a percentage of the funds collected to environmental initiatives. The data used for this research comes from the OECD. Furthermore, our main independent variable in the context of current environmental research is also the environmental tax, or ecotax, which is measured by the percentage of GDP generated by environmental tax revenues [2,17,21].

Fig. 3 shows that the environmental tax and income inequalities have tended to move in opposite directions. As far as inequalities in education are concerned, this tax has played a role in increasing educational inclusion. The figure shows that the Rio Earth Summit, the Kyoto Protocol and the Paris Conference in 1992, 1997 and 2015 respectively raised awareness of the effects of human activity on the environment. Governments have since taken steps to reduce emissions and encourage green innovation by introducing taxes on carbon dioxide and other pollutants. Because of the need to finance public policies linked to adaptation to climate change and green investment, governments have also sought new sources of revenue to justify the increase in environmental taxes between 1995, 1997 and 2015. In addition, globalisation during this period saw an increase in trade and labour migration, which had an impact on the bargaining power and wages of low-skilled workers. In developed countries, the automation of industry has led to an increase in productivity, while at the same time reducing the availability of low-skilled jobs. During these periods, there has been a growing awareness of the importance of a highly educated workforce for economic competitiveness and environmental preservation. Addressing the needs of students from disadvantaged backgrounds, marginalised ethnic and cultural minorities and disabled students has therefore become imperative in order to minimise disparities in access to education and quality of teaching, and to tackle environmental issues more effectively.

iii. Control variables

This article examines various factors that influence inequality, such as access to the Internet (called "Internet"), foreign direct investment (abbreviated to "FDI"), the level of financial development (called "findev"), and the flow of migration funds (called "remittances").

With regard to the internet, we have defined it as the proportion of individuals (% of the population) using the internet. According to Refs. [22–24], the internet is a determinant of long-term socio-economic inequality.

The proportion of foreign direct investment (FDI) in gross domestic product (GDP) indicates the net inflow of investment aimed at acquiring a lasting stake (10 % or more of voting shares) in a company operating in a country other than that of the investor. To obtain this measure, equity capital, reinvested earnings, other long-term capital and short-term capital as reported in the balance of payments are added together. According to several studies by Refs. [25–27], FDI explains inequalities in education and income. These authors found a link between FDI and inequalities in income and/or education in several developing countries.

The measure of financial development, often indicated by the credit granted to private companies, is expressed as a proportion of gross domestic product. The growth of this sector within the OECD can have a significant impact on disparities in education and income. In addition, studies by Refs. [28,29] have shown that socioeconomic inequality can be influenced by financial development.

Migrant remittances as a % of GDP. This variable describes the two types of personal transfers: personal transfers and compensation of employees. Personal transfers are defined as current transfers, which may be in cash or in kind, that are given or received by resident households from or to non-resident households. Several studies, including those by Ref. [30]; [31,32], have shown that remittances play an important role in determining income and education inequality. These studies illustrate the various ways in which migrant remittances can have both positive and negative effects on income and education inequality.

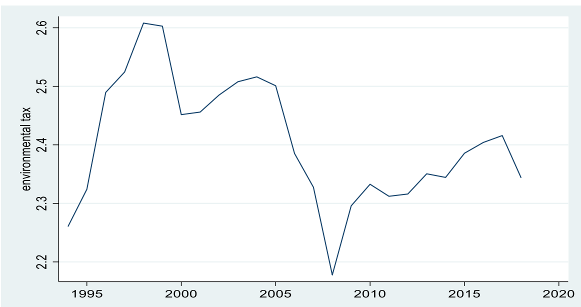

Fig. 2. Evolution of the environmental tax.

Fig. 3. Evolution of environmental taxes with inequality.

3.3. Methodology

a. Propensity score matching

The propensity score matching method is a data analysis technique used to assess the impact of an intervention or treatment on a group of people. It involves balancing the characteristics of an intervention group with those of a control group in order to obtain unbiased estimates of the effect of the intervention [33–35].

The standard evaluation analysis framework for formalising this problem is the potential outcomes approach or the Roy-Rubin model [33,36]. The main pillars of this model are individuals, treatment and potential outcomes. In the case of our study, the treatment is binary, with the treatment indicator equal to one if country i receives the environmental tax and zero otherwise. The potential results are then defined as Yi(treatment) for each country i, where i = 1, …, N and N represents the total number of countries in our panel and Yi the inequality. The treatment effect (Ti) for a country i can be written as follows (see equation (1)):

$$\mathrm{Ti} = \mathrm{Yi}(1) - \mathrm{Yi}(0) \tag{1}$$

The propensity score matching method is based on the creation of a probability score for each observation, usually calculated using a logistic regression algorithm [37]. This score measures the probability that an individual received the treatment, given a set of characteristics or covariates. These covariates can be factors that influence the probability of being treated. This probability is calculated using the formula presented in equation (2):

$$P(X=1) = \frac{1}{1+e^{-(\beta_0+\beta_1X_1+\ldots+\beta_kX_k)}} \tag{2}$$

Where.

- P is the propensity score, which represents the probability that an individual will receive the treatment (X = 1).
- X is a vector containing the explanatory variables (X_1, X_2, …, X_k) used to predict the propensity score.
- The β are the regression coefficients estimating the impact of each explanatory variable on the probability of receiving treatment.

The aim of the propensity score matching method is to create treatment and control groups that are comparable in terms of observed and unobserved subject characteristics. To do this, the method first calculates a probability score (propensity score) for each subject, which represents the probability that they will receive the treatment based on their observed characteristics. Subjects are then matched using these propensity scores so that each subject in the treatment group is matched to a subject in the control group with similar propensity scores. After calculating these propensity scores, individuals in the intervention group are matched with those in the control group with similar propensity scores [38]. The number of individuals matched may vary according to the method. Matching can be performed using several methods, including exact match, nearest neighbour, weighted matching or optimal subclass matching. In this study, we have chosen nearest neighbour matching. The aim of this matching is to ensure that the two groups are comparable in terms of observed and unobserved characteristics, thereby reducing the impact of any selection bias.

Once the groups have been matched, the results between the two groups can be compared to assess the impact of the treatment. This method is therefore an interesting alternative to the use of randomly assigned groups in experimental studies, allowing more robust conclusions to be drawn in observational studies. However, it should be remembered that the propensity score matching method cannot entirely eliminate all potential biases. It must be used in conjunction with other techniques to minimise the risk of bias.

b. The double differences

The difference-in-difference (DD) method is a data analysis technique that estimates the causal effect of an intervention by comparing outcomes before and after the intervention to a control group that did not receive the intervention. It is often used in economics, public policy evaluation and public health.

The difference-in-difference method is a statistical method for assessing the impact of an intervention or treatment on a group of people [39]. The method involves comparing the outcomes of a group that has been exposed to the intervention with a control group that has not been exposed to the intervention. This comparison is done by measuring changes in outcomes before and after the intervention for each group.

The difference in outcome changes between the intervention and control groups is a measure of the impact of the intervention. The difference-in-difference method therefore measures the effectiveness of an intervention by removing potential confounders, controlling for pre-existing differences between groups and measuring changes in these differences over time [38].

The advantages of the difference-in-difference method are its robustness to potential confounders, its ability to control for pre-existing differences between groups and its ability to measure impact over time. However, this method requires the existence of a control group, which may be difficult to implement in some circumstances.

c. Inference through randomisation

Randomisation inference is a statistical method used to estimate the causal effect of an intervention or treatment on a variable of interest. It is often used when the conditions for applying other causal inference methods, such as regression analysis or classical hypothesis testing, are not met. Equation (3) is used for randomisation.

$$\mathrm{Y} = \tau \mathrm{D} + \mathrm{X}\,\beta + \varepsilon \tag{3}$$

Where Y is a vector containing the observed outcome of interest for each observation, D is a vector indicating the treatment status for each observation, and X is a matrix of pre-treatment control variables.

The principle of randomisation is to randomly simulate the intervention and control groups that would have been observed if subjects had been randomly assigned to these groups. The difference between the result observed in the intervention group and that observed in the control group can then be compared with the differences obtained in a large number of random simulations.

The advantage of this method is that it does not rely on assumptions about the distribution of the data or the existence of a linear relationship between the variable of interest and the explanatory variables. Nor does it depend on the model used to describe the data. It therefore allows a more robust and objective analysis of the data, based on minimal assumptions. However, the randomisation method requires a sufficiently large sample for the random simulations to be reliable.

d. The Kiviet method (2020)

The method of [40] is a Ridge-type regularisation method for linear regressions. It was developed to solve the problem of multi-colinearity in regression. Multi-linearity occurs when there are linear relationships between independent variables.

For this estimation, we use the following theoretical model (equation (4)):

$$Inequality_{it} = \alpha_0 + \alpha_1 Envtax_{it} + \alpha_2 Internet_{it} + \alpha_3 FDI_{it} + \alpha_4 remitances_{it} + \alpha_5 findev_{it} + \mu_i + \theta_t + \varepsilon_{it} \tag{4}$$

Where Inequality represents income and educational inequalities; μ_i, θ_t *et* ε_{it} represents an unobserved country-specific effect, a time-specific effect and the error term respectively.

The Kiviet method consists of penalising the regression coefficients by minimising the sum of the squares of the residuals weighted by an appropriate weighting matrix. This matrix is a function of the deviations of the main diagonal of the covariance matrix of the independent variables. The said method uses an initial estimate of the regression coefficients obtained from the Ordinary Least Squares (OLS) method.

This method also allows for the selection of the most important variables in the regression by eliminating those that do not have a significant impact on the dependent variable. It also provides more efficient estimates of the regression coefficients, as it takes into account the relationships between the independent variables.

The method of [40] is thus a robust regularisation method for linear regression that solves the problem of multi-colinearity and selects the most important variables in the regression.

4. Results of the econometric model

The notion of causal inference is central to many disciplines today, including econometrics. One of the most commonly used models for identifying causal effects is based on the notion of a counterfactual [41–43]. Thus, the causal effect will be measured by the contrast between the factual group and the counterfactual group. The fundamental problem with causality [44,45] is that, by definition, this counterfactual group is not directly observable. Thus, randomisation has been proposed as a solution to overcome this problem, while maintaining interchangeability and substitution between intervention and non-intervention groups, and ensuring that assumptions allowing causal inference are not violated, so that the intervention can only affect the health outcomes of the factual group, for example. One of the key issues that randomisation addresses is the issue of accounting for measured and unmeasured confounders [46]. Instead, we will focus on three types of quasi-experimental methods: propensity score matching, difference-in-differences (DD), and selection randomisation.

4.1. Propensity score matching (PSM) results

a. Matching

Matching methods attempt to pair each treated individual with one or more untreated individuals whose observable characteristics

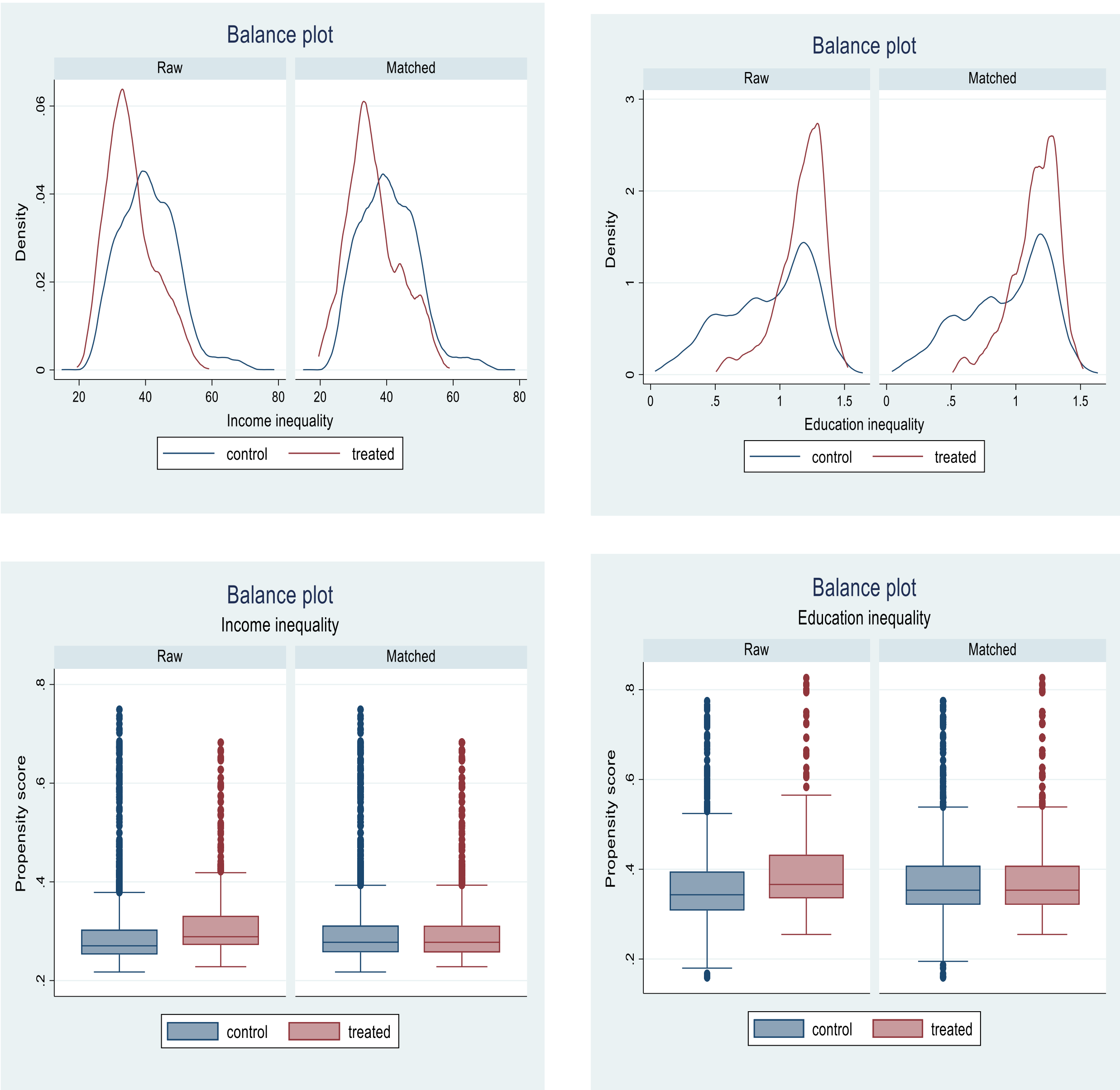

Fig. 4. Verification of overlap using the propensity score.

b. Estimated average treatment

Table 3
Estimation of the average treatment effect (ATT).

Probit regression			Number of obs	=	2116	
			LR chi2 (3)	=	679.51	
			Prob > chi2	=	0.0000	
Log likelihood=−1055.1667			Pseudo R2	=	0.2436	
Treatment	Coefficient	Std. Err.	z	P > z	[95 % conf.interval]	
Remittances	−.2,199,103	.0218,842	−10.05	0.000	−.2,628,025	−.177,018
Trade	.0038,969	.0005312	7.34	0.000	.0028,558	.004938
Findev	.0089,262	.0007049	12.66	0.000	.0075,446	.0103,078
_cons	−.892,115	.0732,603	−12.18	0.000	−1.035703	−.7,485,274
Effects of treatment income inequality						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Gini	Unmatched	35.3155995	41.4428003	−6.12720081	.380,707,743	−16.09
	ATT	35.3129246	43.4550575	−8.14213282	.863,595,322	−9.43
Common support						
			Psmatch2: Common support			
Psmatch2: Treatment assignment			Off support	On support	Total	
		Untreated	0	1332	1332	
		Treated	1	783	784	
		Total	1	2115	2116	

Probit regression			Number of obs	=	826	
			LR chi2 (3)	=	243.18	
			Prob > chi2	=	0.0000	
Log likelihood=−260.59431			Pseudo R2	=	0.3181	
Treatment	Coefficient	Std. Err.	z	P > z	[95 % conf.interval]	
Remittances	−.2,846,561	.0268,612	−10.60	0.000	−.3,373,032	−.2,320,091
Trade	.005205	.0006802	7.65	0.000	.0038,718	.0065,382
Findev	.0054,481	.0007933	6.87	0.000	.0038,933	.0070,029
_cons	−.4,902,021	.0856,992	−5.72	0.000	−.6,581,694	−.3,222,348
Effects of treatment educational inequality						
Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
University	Unmatched	1.1761144	.951,434,494	.224,679,906	.014,761,334	15.22
	ATT	1.1761144	1.00654763	.169,566,767	.025,496,682	6.65
common Support						
			Psmatch2: Common support			
Psmatch2: Treatment assignment			On support		Total	
		Untreated	853		853	
		Treated	682		682	
		Total	1535		1535	

are as close as possible. The objective of matching is to construct a control group comparable to the treated group in order to allow for an unbiased estimate of the effect of the treatment on the treated individuals, controlling for selection bias [47–51].

We plotted the distribution of SPs for treated and untreated units (Fig. 4). We observed that the overlap is good, as for any SP value we have sufficient frequencies of treated and untreated units. Thus, the box plots of the matched data indicate covariate balance as do the kernel density plots using the matched data. Therefore, the plots using the matched data appear to be in balance. This allows us to proceed with the evaluation, as the degree of overlap is sufficient to ensure reliable estimation results. If the overlap assumption is violated, it means that there are large portions of the income and education inequality support that we have treated without having untreated units, and vice versa. This situation does not allow us to find comparable units in both states for some values of income and education inequality, making matching impossible. Of course, one can restrict the analysis only to the available inequality intervals where both treated and untreated units are available. In this case, however, the estimate of the average treatment for the treated group (ATT) will refer to a sub-population, not to the whole population, making it impossible to generalise the results to the whole population.

In Table 3 we estimate the average treatment effect (ATT) on the outcome (income and education inequality) using a nearest neighbour in the common support of units which is the overlap set. The first part of the table shows the propensity score estimate, while the treatment effects compare matched outcomes with unmatched outcomes. The ATT value for income inequality is equal to −8.14 with a T-test significantly equal to −9.43, signalling a negative and significant effect at 1 % of the environmental tax. The result means that the application of an environmental tax has a significant impact on income inequality. More specifically, the ATT indicates that the environmental tax reduced the gap between the incomes of the richest and poorest households in the OECD by an average of 8.14 units. This can be seen as a significant reduction in income inequality. The *t*-test measures the statistical significance of the ATT estimate. With a t-value of −9.43, this means that the probability of obtaining a similarly extreme (or more extreme) ATT estimate if the real impact of the environmental tax were zero is very low. We can therefore conclude that the impact of the environmental tax on income inequality is statistically significant. This result is consistent with that of [5] who found that the environmental tax is an instrument for reducing inequality in the USA.

The ATT result of 0.17 which measures the impact of the environmental tax on inclusive education indicates a difference of 0.17 in the standard deviation of educational inequality between the treatment group and the control group. The T-test has a significantly high value of 6.65 indicating that the ATT result is statistically significant. In other words, the effect observed is different from that which could be observed by chance alone. This indicates that the result obtained is reliable and robust. Furthermore, this result suggests that an increase in the environmental tax is a factor in educational inclusion within the OECD. This result is contrary to those of [13], who found that the environmental tax accentuates social inequalities in France.

The environmental tax is therefore a tool that can stimulate the ecological transition while having a positive impact on income inequalities and inclusive education. Environmental taxes mobilise financial resources to fund public policies. If this revenue is redistributed fairly and progressively, it can reduce income inequalities. In addition, businesses have an economic incentive to develop more environmentally-friendly products and technologies to avoid the high costs of the environmental tax. This encourage investment in innovation and quality jobs. Similarly, environmental tax revenues can also be used to support environmental education. This enables a better understanding of environmental issues among the population and encourages the participation of all, including the poorest and most marginalised people. Finally, environmental taxes can be an effective way of raising people's awareness of the environmental impact of their consumption and encouraging them to adopt more sustainable lifestyles. It can also have positive effects on health, quality of life and social inclusion.

However, it is important to bear in mind that PSM results are based on specific assumptions and that other factors that have not been controlled for may play a role in the results. It is therefore important to take a cautious approach when interpreting the results, and to consider other methods for confirming the results of the study.

The last part of Table 3 shows the "common support". The common support is the area of overlap of the two groups on the set of propensity score values [52]. The common support of the propensity score ensures that for each individual in the treatment group it is possible to find at least one participant in the control group with the same initial characteristics (propensity score) [53]. The use of the propensity score is only appropriate for individuals located in this zone. In this table we see that the 'non-support' units are only 1 out of 2116 units for income inequality, which indicates a strong overlap (as already shown in the graph of the distribution of SPs in the two groups). In contrast, for education inequality there are no 'non-supporting' units out of 1535 units, which also indicates a strong overlap within our data set.

c. Checking the balance before and after pairing

After checking the overlaps and estimating the ATT, we check whether our PSM managed to achieve a good balance between the PS (propensity score) and the covariates. The *t*-test columns of our table show the main results. For the balancing to hold, we would like the difference in the mean of each covariate "after matching" to be no longer significant (even if it was in the unmatched data). This happens in this case for each control variable considered in this analysis. Looking also at the last columns indicating the ratio of variance between treatment and non-treatment (V(T)/V(C)) before and after matching, we see that this ratio is equal to one (1), which indicates the existence of a good balance between the PS and the covariates. Furthermore, Table 4 of the balancing indices, shows a remarkable reduction of the mean and median bias, confirming that the matching procedure has succeeded in rebalancing the treated and untreated units. This result further confirms the reliability of our matching results. This result is further confirmed by Fig. 5, which shows the degree of PS or rebalancing achieved by the matching procedure we used. This graph confirms that a good balancing was achieved, although in some bins small differences still appear.

Table 4
Check for the pre- and post-matching balancing.

Income inequality

	Unmatched	Mean		%reduct		*t*-test		V(T)/
Variable	Matched	Treated	Control	%bias	Bias	t	p > t	V(C)
_pscore	U	.53,903	.26,178	133.3		28.86	0.000	0.66*
	M	.53,847	.53,845	0.0	100.0	0.00	0.998	1.00
Balancing indexes								
Sample	Ps R2	LR chi2	p > chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.235	656.36	0.000	133.3	133.3	133.3*	0.66	100
Matched	0.000	0.00	0.998	0.0	0.0	0.0	1.00	0

Educational inequality

	Unmatched	Mean		%reduct		*t*-test		V(T)/
Variable	Matched	Treated	Control	%bias	bias	t	p > t	V(C)
_pscore	U	.5859	.3226	125.4		23.84	0.000	0.40*
	M	.5859	.58,587	0.0	100.0	0.00	0.998	1.00
Balancing indexes								
Sample	Ps R2	LR chi2	p > chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.224	471.60	0.000	125.4	125.4	125.4*	0.40*	100
Matched	0.000	0.00	0.998	0.0	0.0	0.0	1.00	0

d. Testing the sensitivity of our results

To check the sensitivity of our results, we perform the Rosenbaum bounds test. The logic of this sensitivity test is as follows: we assume that we have obtained good matching results (as we did). If so, this means that we have succeeded in restoring near perfect randomisation ex-post [54]. defines Gamma as the ratio of the PS of the treated to the untreated groups that is equal to one under randomisation. We can therefore start by assuming that our matching has a Gamma equal to one. Next, we assume the existence of an unobservable confounding factor that generates an increase in the Gamma ratio. The larger this increase, the larger the deviation from randomisation. Consequently, the test simulates higher values of Gamma and explores to what extent the p-value of the ATE remains significant. It can be seen from the results in Table 5 that the p-value (see the "sig+" column) remains low even when Gamma increases significantly, which means that our matching results are robust. We therefore conclude that our matching results are robust to unobservable confounders.

Despite the robustness of our results, we believe it is worthwhile to further test our results with the difference-in-differences (DID) approach, which is robust to unobservable selection.

4.2. Double difference estimates

In this section, we provide the results of an ex-post programme evaluation analysis using as a reference example the procedure required by the application of the double-difference approach (or difference-in-difference method DID). This method is one of the most widely used methods in programme evaluation for dealing with "unobservable selection". The DID approach is easy to implement, as it essentially estimates a linear regression, but requires a detailed protocol to be correctly applied.

Nevertheless, it is more in the spirit of complementarity than opposition that this method is presented here. The propensity score is used to control selection bias on observable factors, while double differences are used to control selection bias on unobservable factors, provided that the influence of unobservable characteristics on the variable of interest is considered to be constant over time. In this way, the combined use of these two methods provides a better correction for selection bias, and the estimate obtained of the effect of the treatment will be an even more reliable measure of causality. The combination can be based on the different uses of the propensity score, i.e. matching and inverse weighting, depending on which method is best suited to the data. In the first case, the difference estimator is calculated on the matched data, while in the second it is calculated on observations weighted by the inverse of the probabilities of being treated.

The DID (Difference in Differences) method is used to assess the effect of a treatment on a group of people who have received it. To do this, the group is examined before and after the treatment to measure its effectiveness. In this particular study, an environmental policy was adopted by OECD countries in 1994. This policy consisted of imposing an environmental tax to make polluters responsible for the damage caused to the environment. The question to be resolved is whether or not this policy has had an effect. Fig. 6 shows a change in the outcomes of interest (inclusive education and income inequality) after the policy was introduced. However, this change is not necessarily due to the treatment, as other temporal factors can influence outcomes, such as climate or economic changes. To solve this problem, we need to identify a control group. This group did not receive the treatment but would have experienced the same unobserved effects. By comparing this group with the test group before and after the treatment, we can understand whether or not the treatment had an impact. Simply observing the test group before and after treatment is not enough to analyse the effectiveness of the treatment.

The ATET coefficient in Table 6 is equal to approximately −1.58 for the impact of the tax on income inequality, and this coefficient is also significant. This result shows that the average impact of the environmental tax on income inequality is −1.58. In concrete terms,

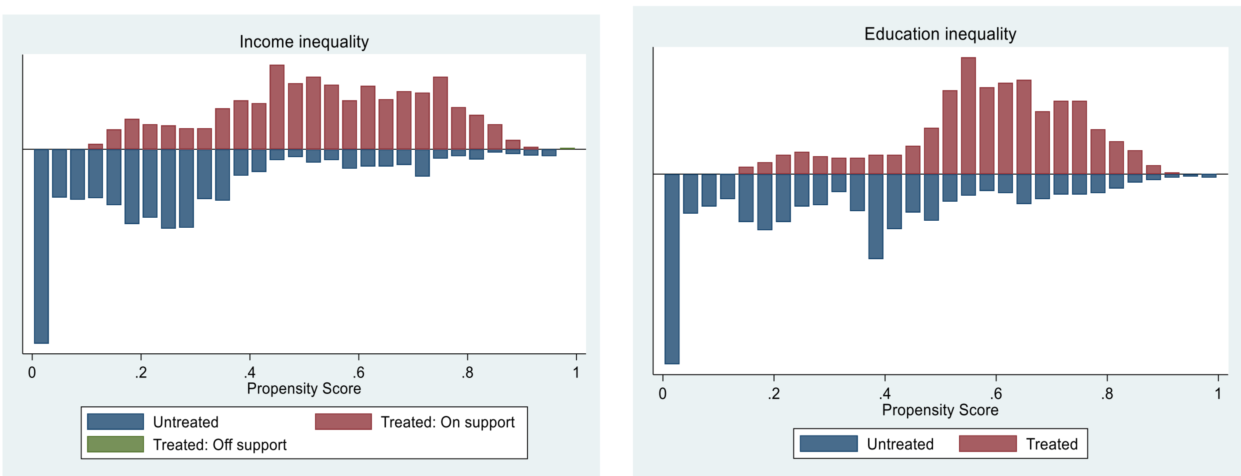

Fig. 5. Check for the ps post-matching balancing by a graph.

Table 5
Check the sensitivity of results to unobservable selection.

Rosenbaum bounds for delta (N = 783 matched pairs) income inequality							Rosenbaum bounds for delta (N = 682 matched pairs) educational inequality						
Gamma	sig+	sig-	t-hat+	t-hat-	CI+.	CI-	Gamma	sig+	sig-	t-hat+	t-hat-	CI+.	CI-
1	0	0	−7.665	−7.665	−8.635	−6.695	1	0	0	.145,135	.145,135	.119,655	.1727
1.05	0	0	−7.96	−7.37	−8.935	−6.4	1.05	0	0	.13,786	.15,281	.1126	.180,815
1.1	0	0	−8.24	−7.09	−9.22	−6.135	1.1	0	0	.13,106	.160,087	.105,924	.18,853
1.15	0	0	−8.505	−6.825	−9.495	−5.865	1.15	0	0	.12,453	.16,725	.09956	.195,955
1.2	0	0	−8.76	−6.57	−9.77	−5.62	1.2	0	0	.118,393	.174,145	.093,545	.203,155
1.25	0	0	−9.01	−6.335	−10.02	−5.385	1.25	0	0	.112,565	.18,085	.087,695	.21,017
1.3	0	0	−9.245	−6.11	−10.27	−5.15	1.3	0	0	.106,978	.18,724	.08246	.216,685
1.35	0	0	−9.475	−5.885	−10.505	−4.935	1.35	1.1e-16	0	.101,575	.193,395	.077,404	.223,105
1.4	0	0	−9.71	−5.675	−10.73	−4.72	1.4	1.8e-15	0	.096,486	.1995	.07271	.229,105
1.45	0	0	−9.92	−5.475	−10.955	−4.515	1.45	3.1e-14	0	.09151	.20,537	.068,071	.23,507
1.5	0	0	−10.13	−5.275	−11.165	−4.32	1.5	4.4e-13	0	.086,945	.211,135	.06365	.24,109
1.55	0	0	−10.335	−5.085	−11.365	−4.135	1.55	4.9e-12	0	.08265	.216,495	.059,625	.24,671
1.6	0	0	−10.53	−4.91	−11.575	−3.95	1.6	4.5e-11	0	.07852	.221,775	.055,587	.252,215
1.65	0	0	−10.715	−4.735	−11.775	−3.775	1.65	3.4e-10	0	.074,565	.22,678	.051,656	.25,758
1.7	0	0	−10.9	−4.565	−11.965	−3.605	1.7	2.2e-09	0	.070,776	.23,162	.047,903	.262,955
1.75	0	1.1e-16	−11.08	−4.4	−12.15	−3.44	1.75	1.3e-08	0	.066,965	.236,535	.044,095	.268,212
1.8	0	1.0e-15	−11.25	−4.245	−12.33	−3.275	1.8	6.2e-08	0	.063,415	.241,445	.04066	.27,285
1.85	0	9.7e-15	−11.42	−4.095	−12.5	−3.125	1.85	2.7e-07	0	.06016	.245,972	.03733	.27,756
1.9	0	8.1e-14	−11.59	−3.94	−12.67	−2.975	1.9	1.1e-06	0	.056,845	.25,046	.033,996	.28,222
1.95	0	5.9e-13	−11.75	−3.795	−12.84	−2.83	1.95	3.7e-06	0	.053,715	.254,816	.03077	.28,684
2	0	3.8e-12	−11.91	−3.655	−13.005	−2.685	2	.000012	0	.050,605	.25,916	.02769	.291,175

*gamma - log odds of differential assignment due to unobserved factors.
Sig + -upper bound significance level.
Sig–lower bound significance level.
t-hat-upper bound Hodges-Lehmann point estimate.
t-hat-lower bound Hodges-Lehmann point estimate.
CI+.-upper bound confidence interval (a = 0.95).
CI–lower bound confidence interval (a = 0.95).

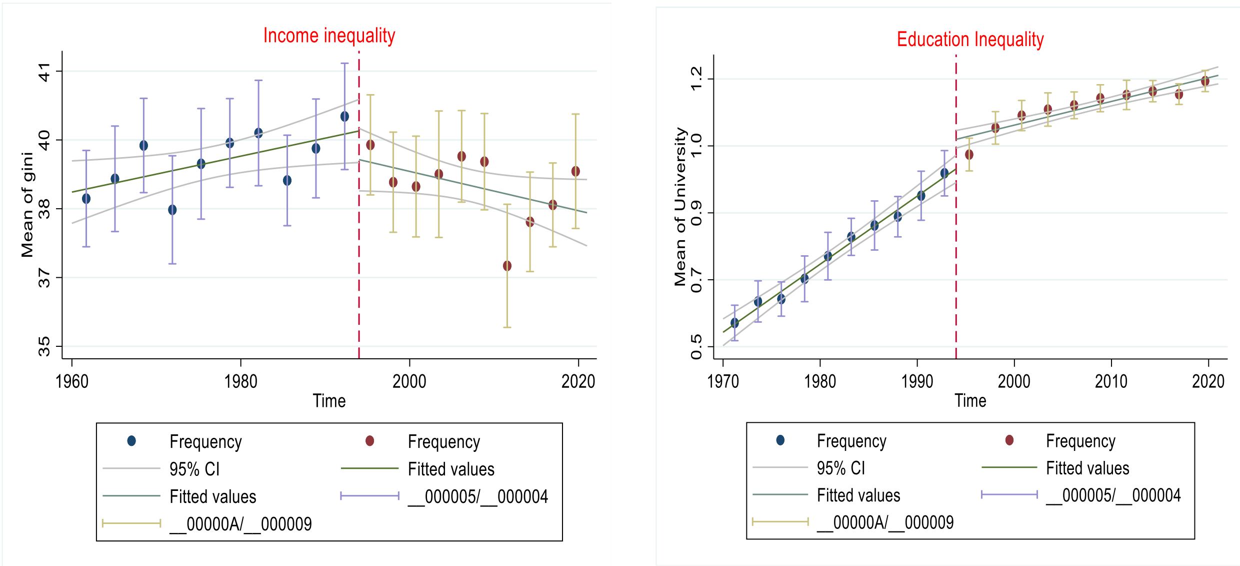

Fig. 6. Evolution of income and educational inequalities.

this means that every time an environmental tax is implemented, income inequality between socio-economic groups is reduced. Environmental tax policy has therefore been beneficial in reducing income inequality. It is important to note that this result is based on ‘double differences’, which is a statistical method for comparing the average effect of the environmental tax on two different groups (for example, the rich and the poor) and which also controls for differences in these groups over time (for example, if the rich experience faster income growth than the poor).

Regarding the impact of this tax on inclusive education (educational inequality), our results show that environmental taxes have a beneficial effect on inclusive education. A coefficient of 0.0711 means that for each unit increase in environmental taxes, there is a corresponding increase of 0.0711 units in inclusive education outcomes. This suggests that environmental taxes have a positive effect on inclusive education. In other words, when environmental taxes increase, the level of inclusive education will increase. Taken together, these results support those found by Refs. [12,15].

However, it is also important to consider that ‘double differences’ do not control for all factors that could influence both the tax and income and educational inequality, which could limit the causality of the effect found. In addition, it is important to take into account the different aspects of environmental tax policy and discuss them with the finance and environment departments to find a solution.

While the combination of the propensity score with the double-difference method seems at first sight to provide a clearer estimate of the causal impact, it comes at the cost of increasing the assumptions to be met. The DID approach relies on an important assumption called ‘common trend’ (sometimes also called ‘parallel trend’). This implies that prior to treatment, the pattern of results of treated and untreated units must be the same. This ensures that prior to treatment, both groups experienced the same pattern, which is a fundamental “all else being equal” condition for interpreting the post-intervention pattern as “causal”. The central hypothesis of a common trend in double differences cannot be tested directly, but its respect can be approximated when several pre-period measurement times (at least two) are available. A simple graphical representation or descriptive statistics of the variable of interest before the treatment can be used to visualise the likelihood of the common trend between the two groups. In general, some “balancing” between the two groups is also required, so that the difference between the results of the two groups fluctuates around zero in the pre-treatment period.

This Fig. 7 shows that the pre-processing pattern (with processing occurring at *t*) fluctuates erratically around zero. This is a possible common trend signal. The second results panel shows the appropriate test and directly suggests that the common (or parallel) trend has passed. We can then interpret the post-processing pattern causally. The results show a mixed effect of environmental taxes on income and educational inequality throughout the post-treatment period, with the largest effect displayed at *t,* the time when the intervention took place.

These results highlight the importance of environmental taxes as a policy tool for promoting sustainable development and restoring social and environmental justice. The results of these analyses provide policy makers with valuable information for designing and implementing effective environmental tax policies that promote sustainable development while minimising inequalities. By integrating environmental justice considerations into policy design, it is possible to create a more equitable and sustainable future for all.

4.3. The study of the impact of the environmental tax on inequalities using the selection randomisation method

A good experiment or trial minimises variability in assessment and provides an unbiased assessment of the intervention by avoiding confounding by other factors, which are known and unknown. Randomisation ensures that each patient has an equal chance of

Table 6
Estimation of the average treatment effect.

Time variable:	Time													
Control:	treatment	0												
Treatment:	treatment	1												
	Income inequality							Educational inequality						
	Control	Treatment						Control	Treatment					
Group							Group							
Id	42	38					Id	41	38					
Time							Time							
Minimum	1960	1994					Minimum	1960	1994					
Maximum	1993	2020					Maximum	1993	2020					
Difference-in-differences regression Number of obs = 4668							Difference-in-differences	regression		Number of obs =	1652			
Data type: Longitudinal							Data type: Longitudinal							
(Std. Err. Adjusted for 80 clusters in id)									(Std. Err. Adjusted for 79 clusters in id)					
Income	Coefficient	Robust std. Err.	T	P > t	[95 % conf.	interval]		Education	Coefficient	Robust std. Err.	t	P > t	[95 % conf.	interval]
ATET treatment (1 vs 0)	−1.585517	.4,467,494	−3.55	0.001	−1.6962846	1.474749		ATET treatment (1 vs 0)	.0711,077	.0350,658	2.03	0.046	−.0012,971	.1,409,183

Note: ATET estimate adjusted for panel effects and time effects.

Fig. 7. Parallel trends.

receiving one of the treatments under study, generates comparable intervention groups, which are similar in all important respects except for the intervention each group receives. It also provides a basis for the statistical methods used in data analysis. The fundamental advantages of randomisation are that it eliminates selection bias, balances the groups with respect to many known and unknown confounding or prognostic variables, and provides the basis for statistical tests, a basis for a free statistical test hypothesis of equality of treatment.

Note: The vertical line indicates the location of the estimate under the implemented treatment assignment.

The results (Table 7 and Fig. 8) suggest that the environmental tax had a significant effect on income and education inequality in the OECD. In other words, it is highly likely that the observed difference in income and education inequality between the control and experimental groups is due to the environmental tax. The results do not reject the null hypothesis that the environmental tax did not have a significant effect on income and education inequality. For income inequality, we obtained the value of "_pm_1″ equal to −1.656997, which is significant at the 10 % level on the effects of the environmental tax and income inequality. This value of "_pm_1″ corresponds to the measure of the "Quantile Treatment Effect on the Treated" (QTE on the Treated) which is a measure of the impact of the environmental tax on individuals who have actually been affected by the environmental tax. This value is significant at the 10 % level. Significance at the 10 % level corresponds to the probability of obtaining such a value of "_pm_1″ or a more extreme value if the null hypothesis were true (i.e. if the environmental tax had no effect on income inequality). Our results suggest that the environmental tax has a significant effect on income inequality among affected individuals, with a probability of about 10 % that this result is due to chance if the null hypothesis were true. This indicates the need to take this measure into account if governments wish to implement policies or interventions to compensate for the effects of the tax on affected populations.

On the other hand, with regard to educational inequality, the results obtained indicate that the environmental tax variable also has a statistically significant impact on educational inequality. Indeed, the value of _pm_1 = 0.0435099 is less than 0.05, which means that the estimated effect of the environmental tax on inclusive education is different from zero at the 95 % confidence level. In other words, there is a high probability that the environmental tax variable has a real and positive impact on inclusive education in the population of interest. In sum, the result suggests that the introduction of an environmental tax could help to significantly finance inclusive

Table 7
Estimation of the average treatment effect.
Note: Confidence interval is with respect to p = c/n; c = # {|T| ≥ |T (obs)|}.

_pm_1: _b[treatment]
res. Var(s) : treatment
Resampling: Permuting treatment
Clust. Var(s) : __000000
Clusters: 4960
Strata var(s) : id
Strata: 80

Income inequality								Education inequality							
T	T(obs)	C	n	p=c/n	SE(p)	[95% Conf.	Interval]	T	T(obs)	c	N	p=c/n	SE(p)	[95% Conf.	Interval]
_pm_1	-1.656997	35	500	0.0700	0.0114	.0492386	.0960111	_pm_1	.0435099	2	500	0.0040	0.0028	.0004848	.0143741

Note: Confidence interval is with respect to p=c/n ; c = # {|T| >= |T(obs)|}

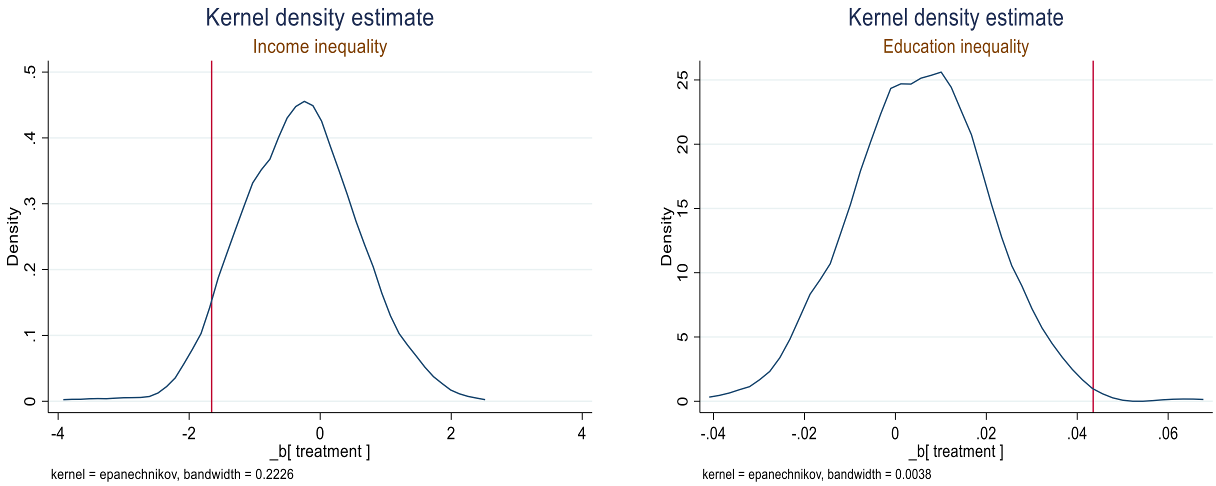

Fig. 8. Densities of estimates under the null hypothesis obtained by resampling.

education.

4.4. Analysis of heterogeneous treatment effects

Analysis of the heterogeneity of treatment effects is useful for going beyond PSMs, DIDs and randomises. The experience of [55] vividly illustrates how the same treatment can have a different effect on different types of people. In most previous techniques, they have focused on the average effects of the treatment. In this different and important data environment, continuing to estimate only mean treatment effects will surely lead us to miss the ways in which estimates of heterogeneity of treatment effects can provide clues about how treatment works, how it can be improved and how it can be targeted to those most likely to benefit. The heterogeneous treatment effect is a statistical phenomenon that refers to the fact that the effect of a treatment varies from one person to another depending on individual characteristics. In other words, the environmental tax will have different effects in different countries. Heterogeneity may be the result of an interaction between a covariate and the effect of the environmental tax. It may also be the result of a high degree of random variability in the effect, without it being possible to link these fluctuations to one or more specific factors. It is therefore vital to understand the mechanisms of the heterogeneous treatment effect in the populations concerned in order to develop personalised and more effective treatments.

The results (Table 8) for income inequality (Gini) indicate the effect of different predictors on the effectiveness of a heterogeneous treatment. More specifically, the results show that: The predictor "FDI" has a positive effect on the effectiveness of the environmental tax. The p-value is 0.046, which is below most significance levels. This indicates that the probability of this effect being real is fairly high. The predictors "findev", "Internet" and "primary" also have significant effects on the effectiveness of the environmental tax. The

Table 8
Estimated conditional effect of average treatment.

Gini						
	point_estimate	**stderr**	**zstat**	**pvalue**	**ci_lower**	**ci_upper**
findev	0.006	0.006	2.981	0.032	−0.006	0.018
FDI	0.326	0.163	2.0	0.046	0.006	0.646
Internet	0.087	0.365	1.239	0.081	−0.628	0.802
primary	−152.188	162.074	3.939	0.003	−469.847	165.471
CATE Intercept Results						
	point_estimate	**stderr**	**zstat**	**pvalue**	**ci_lower**	**ci_upper**
cate_intercept	101.176	153.351	1.66	0.050	−199.387	401.739
University						
	point_estimate	**stderr**	**zstat**	**pvalue**	**ci_lower**	**ci_upper**
findev	0.0	0.0	1.756	0.079	−0.0	0.001
FDI	0.009	0.005	1.881	0.06	−0.0	0.019
gini	−0.053	0.042	2.266	0.002	−0.134	0.029
Internet	−0.034	0.011	−3.18	0.001	−0.055	−0.013
primary	−9.106	4.394	−2.072	0.038	−17.718	−0.494
CATE Intercept Results						
	point_estimate	**stderr**	**zstat**	**pvalue**	**ci_lower**	**ci_upper**
cate_intercept	11.755	4.817	2.44	0.015	2.314	21.196

p-values are 0.032, 0.081 and 0.003 respectively, suggesting that this effect is not due to chance. For the CATE intercept, the point_estimate value is 101.176, indicating that there is an average treatment effect on the sample. However, given that the p-value is 0.050, it can be stated that this effect is not due to chance and there is significant evidence of a real effect of the environmental tax on income inequality. The confidence intervals (ci_lower and ci_upper) provide a range of plausible values for these effects, based on the data and the model used for the analysis. In summary, these results provide indications of the predictors that may influence the effectiveness of the environmental tax, as well as an average estimate of the effect of the treatment on the sample. For this reason, the decision tree in Fig. 9 summarises the various possibilities. A decision tree is a graphical representation of a decision-making process that breaks down a problem into a series of possible choices and outcomes. Each node in the tree represents a decision point and the branches represent the possible choices or outcomes. CATE (conditional average treatment effect) is a concept in statistics and causal inference that helps us understand how the effect of a treatment or intervention varies according to different conditions or groups.

The initial decision point or starting condition in Fig. 9 is inclusive primary education, which serves as the top node of the decision tree. According to the graph, if the level of school inclusion in primary education falls below 80.6 %, the environmental tax has the potential to reduce income inequality by 77.379 points. However, the decision tree indicates that this impact could be even greater in particular circumstances. The decision tree then divides into various paths based on distinct conditions or attributes. Each branch point represents a decision based on a specific attribute or condition. Therefore, these divisions represent different subgroups or conditions under which the effect of the environmental tax varies for each of the CATEs. Income inequality is represented by the terminal nodes at the end of each path. The figure presented here provides valuable information on the average treatment effect for specific subgroups or conditions, as indicated by the different CATEs at the terminal nodes.

For example, at the terminal node where the CATE value is −135.0, we can deduce that the estimated difference in income inequality between the application of the environmental tax and its absence is −135.0. The sample size for this node is 4252, which means that 4252 observations were used to form this particular end node. The cost-value = [−135.0] indicates that the value of the treatment, or the difference in outcome between the treated and untreated groups, is estimated to be −135.0. In addition, the T [0] treatment was applied to this node. In summary, these results provide us with valuable information on the estimated impact of the implementation of the environmental tax in our panel. According to this model, the negative CATE indicates that the implementation of the T [0] treatment is associated with a reduction in income inequality as opposed to the scenario where the treatment is not used.

For educational inequality, the regression coefficients indicate the relationship between the variables in the model. The independent variables include Findev (financial development), FDI (Foreign Direct Investment), gini (the Gini index measuring income inequality), internet (internet penetration rate) and primary (primary school enrolment rate). The dependent variable in this case is inclusive education. The results indicate that Findev and FDI have a positive relationship with inclusive education, but with low statistical significance. The Gini variable has a negative relationship with inclusive education with statistical significance. This means that the greater the income inequality, the lower the access to inclusive education. The Internet variable also has a negative relationship with inclusive education, but with greater significance. Finally, the Primary variable shows a significant negative relationship with inclusive education. This means that the lower the primary school enrolment rate, the more restricted access to inclusive

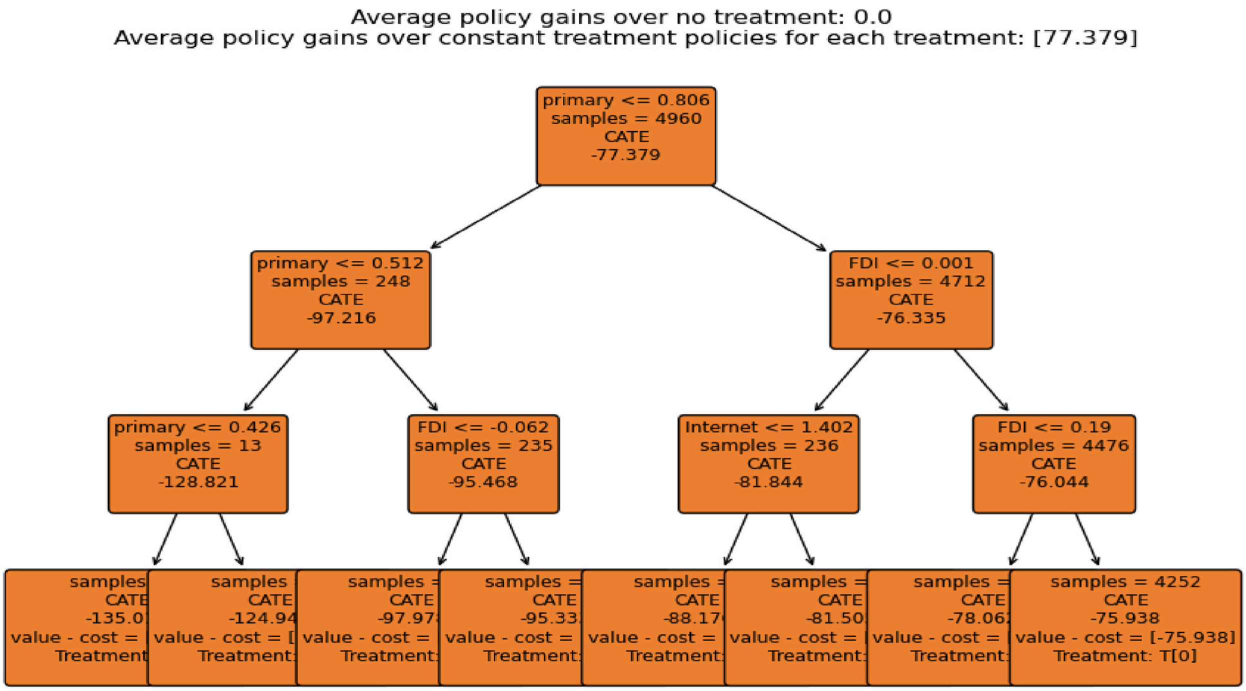

Fig. 9. Decision tree for income inequality.

education is. The CATE Intercept model shows that the effect of the heterogeneous treatment of environmental taxes on inclusive education has an estimated point of 11.755. This means that the application of heterogeneous environmental taxes can have a positive effect on inclusive education.

Fig. 10 shows a predictive decision tree that is constructed from our data after applying heterogeneous treatments to measure the effects of the environmental tax on inclusive education at university. The main node of this tree is income inequality. This node informs us that a level of income inequality below 26.75 units, based on a sample of 4960 observations from our panel, leads to a decrease in inclusive education of 2.309 units due to the application of the environmental tax. We can also see that the result varies according to several criteria at the terminal nodes of the predictive decision tree. At these end nodes, we can see that the tax can help improve inclusive education. Thus, the result "Samples = 212; CATE = −2.475; value-cost = [−2.475]; Treatment: T [0]" obtained at a terminal node indicates that for treatment T [0], there are a total of 212 samples with an expected difference of −2.475 in inclusive education for observations that received treatment T [0], compared to those that did not. Therefore, the group of non-OECD countries has a 2.475 lower rate of inclusive education than the group of OECD countries due to the application of the environmental tax by the latter. The cost value of −2.475 corresponds to the cost saving associated with the use of this treatment compared to its absence. Similarly, the result "Samples = 37; CATE = 0.15; cost-value = [0.15]; Treatment: T [1]" obtained at another end node means that there are 37 samples associated with treatment T [1] with an expected difference of 0.15 in the target outcome for observations that applied the environmental tax compared to those that did not. The cost value of 0.15 represents the cost saving associated with using the environmental tax to reduce inequality in educational outcomes compared to not using the tax.

By using the decision tree with CATE, as illustrated in Figs. 9 and 10, we are able to drill down and convey the variable impact of the environmental tax on income and educational inequality in different circumstances. This facilitates the identification of the most effective applications of the environmental tax and the specific conditions under which it proves most effective. As such, it serves as a powerful tool for understanding the complex ramifications of environmental taxation on income inequality and for making informed choices based on distinct scenarios or demographics.

4.5. Robustness checks on the results

In order to ensure the robustness of the results of the econometric modelling of the effects of the environmental tax on inequalities, different sensitivity analyses can be conducted. Sensitivity analysis involves testing the response of the model to changes in assumptions or data inputs. This can help to determine the extent to which results depend on certain assumptions or data points and can provide insight into the reliability of the model. By conducting sensitivity analyses, we ensure that the results are robust and not overly

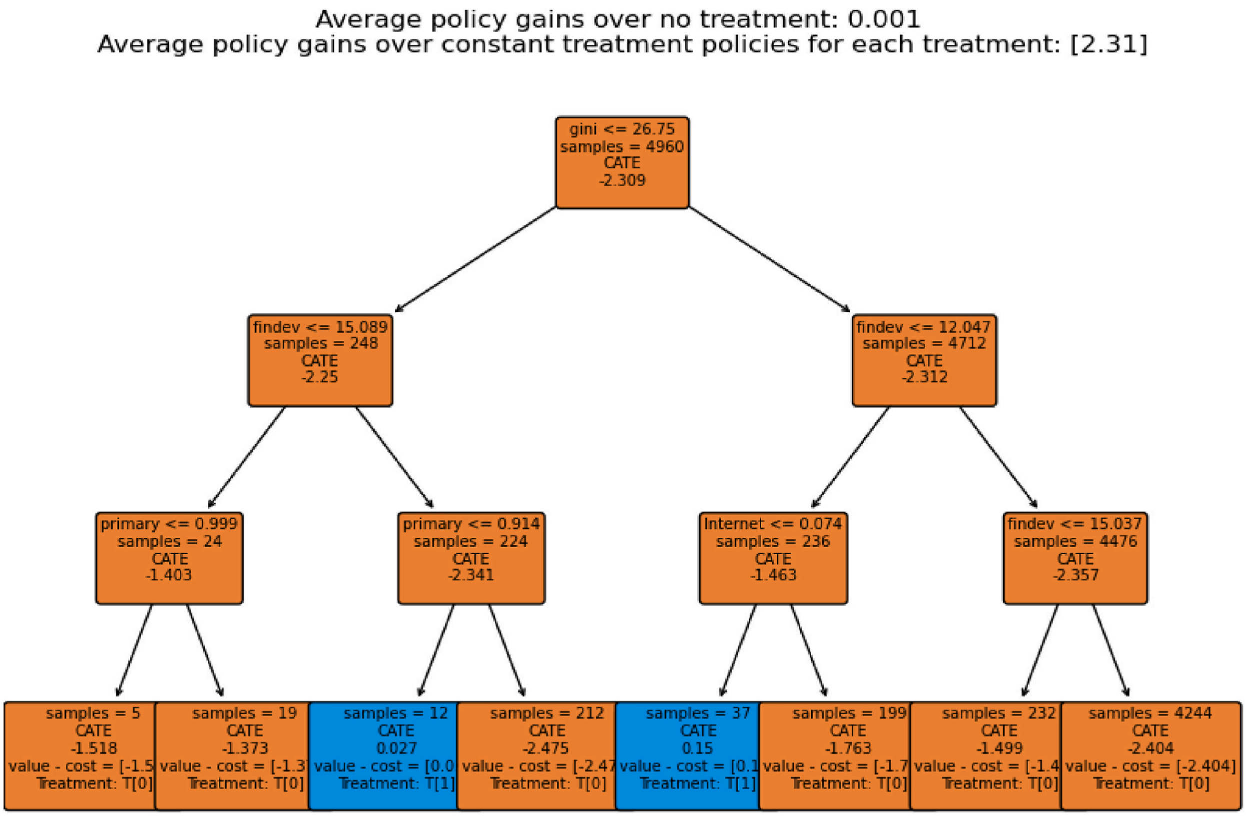

Fig. 10. Decision tree for educational inequality.

Table 9
Estimated marginal impact of the environmental tax on inequality.

VARIABLES	Income inequality						Education inequality					
	1	2	3	4	5	6	7	8	9	10	11	12
envtax	−2.925***	−2.655***	−1.421**	−1.896***	−1.535**	−1.426**	0.0578***	0.0453***	0.0687**	0.0603**	0.0830***	0.0947***
	(0.777)	(0.776)	(0.566)	(0.615)	(0.685)	(0.616)	(0.0192)	(0.0173)	(0.0321)	(0.0241)	(0.0244)	(0.0257)
Internet		0.0623*	0.0507*	0.0551*	0.0705**	0.0804***		0.00191**	0.000593	0.000297	0.000984	0.00175*
		(0.0366)	(0.0299)	(0.0293)	(0.0353)	(0.0307)		(0.000789)	(0.00106)	(0.000886)	(0.000943)	(0.000994)
FDI			0.146**	0.157**	0.141**	0.114*			−5.65e-05	−0.000901	−0.000383	−0.00151
			(0.0685)	(0.0672)	(0.0702)	(0.0604)			(0.00233)	(0.00195)	(0.00183)	(0.00185)
Trade			−0.126***	−0.131***	−0.136***	−0.152***			0.000790	0.00136***	0.000940**	0.00238***
			(0.0162)	(0.0160)	(0.0174)	(0.0164)			(0.000602)	(0.000469)	(0.000465)	(0.000719)
remittances				−1.285*	−1.322	−1.599*				0.0833***	0.0899***	0.100***
				(0.728)	(0.899)	(0.847)				(0.0239)	(0.0262)	(0.0266)
findev					−0.0109	0.00704					0.000831	0.000694
					(0.0279)	(0.0250)					(0.000755)	(0.000742)
Education						9.645*						
						(5.268)						
gini												−0.0102**
												(0.00418)
Constant	46.84***	48.88***	52.16***	54.65***	54.60***	45.05***	0.947***	0.891***	0.830***	0.720***	0.738***	0.195
	(1.712)	(2.060)	(1.519)	(2.045)	(2.561)	(5.000)	(0.0416)	(0.0469)	(0.0575)	(0.0674)	(0.0727)	(0.241)
Comments	65	65	65	65	57	52	57	60	57	57	52	52
xkurtosis	3.366	3.366	8.865	8.865	8.547	7.789	3.179	3.100	7.753	7.753	7.789	7.789

Standard errors in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

dependent on specific assumptions or data inputs. Another way to ensure the robustness of the results is to test alternative model specifications. This involves testing different model specifications to see if the results are consistent between the different specifications. By testing alternative model specifications, researchers can ensure that the results are not too dependent on a specific model specification and are robust to different modelling choices. It is for the latter purpose that we have opted to use two additional estimation techniques, namely the instrumental variable estimation technique of [40]. The results are presented in Table 9. The environmental tax, trade and migrant funds have the potential to reduce income inequality depending on their implementation and appropriate use. This is the meaning of the negative sign associated with their parameter values in Table 9. Indeed, the implementation of the environmental tax in the OECD provides an incentive for companies to adopt more sustainable practices and to reduce their environmental footprint. The tax revenues from these taxes are then used to fund projects aimed at reducing income inequality, such as vocational training programmes for low-skilled workers or social assistance programmes for disadvantaged groups.

Financial development does not have a significant influence on income inequality. Trade helps to reduce income inequality by promoting economic growth and creating jobs. However, it is important to note that free trade can have complex effects on income inequality and that tax and redistribution measures may be needed to compensate for losses due to international competition. Migrant remittances also play a role in reducing income inequality by allowing migrant workers to send money back to their families in their home countries. These remittances can help families cover living expenses and invest in education, health and community development. These findings are in line with those of [30] which show the importance of migrant remittances in reducing income inequality. However, these results are contrary to those of [31] who explores how remittances between migrants and their families in their country of origin contribute to creating a socio-economic hierarchy between migrant communities according to their socio-economic status.

Overall, the proper implementation and responsible use of these mechanisms can potentially contribute to reducing income inequality. However, their effectiveness will depend on various factors such as policy design and implementation, the economic, social and cultural context of the countries concerned, among others. Furthermore, our results suggest that people with limited access to the internet or who are not digitally literate may be at a disadvantage in the labour market. Jobs that involve the use of technology may be better paid and offer additional benefits such as working from home or flexible hours. People with no access to or low proficiency in technology may be denied these jobs or forced to take lower paid jobs. This result is in line with those of [22–24], who found that ICT in general is useful for reducing socio-economic inequalities.

Similarly, foreign investment tends to be concentrated in regions or industries that are more profitable. This can lead to higher wages and profits for workers and companies in these regions or industries, but it can also widen the gap between less profitable regions and industries. Foreign companies also tend to repatriate their profits rather than reinvest them locally, which can contribute to the concentration of wealth. Foreign investment can also lead to job losses in certain industries or regions, which can exacerbate income inequality. Laid-off workers may have difficulty finding new, well-paid jobs, especially if they do not have transferable skills or if they are in regions where employment is scarce. Companies may outsource jobs or business processes abroad because of the lower costs. This can lead to the loss of local jobs and contribute to the concentration of wealth in favour of the outsourcing company. These results are similar to those of [25,26] who suggest that there is a negative relationship between FDI and income or wage inequality in Indonesia and Egypt.

Inclusive education enables all students, including those with special educational needs, to access quality education. This reduces the initial inequalities between students who often have access to different education, depending on their social background, ethnicity or religion. A quality education also enables students to be more successful in their schooling, and therefore more successful at all stages of their lives. In addition, a good education enables them to be better prepared for their future working life, by acquiring skills and knowledge that will give them access to better paid jobs. A good education thus reduces economic dependency in the long term, as people with access to quality education are more likely to find stable, well-paid employment. This can help to reduce income inequality in the long term. Students from the poorest or most marginalised families often have limited access to education. By ensuring equal access to quality education, inclusive education provides opportunities for this vulnerable population. It can break the cycle of poverty that pushes them into precarious and low-paid jobs. This result is in line with that of [13].

In sum, internet use and foreign investment can exacerbate income inequalities by giving an advantage to the technologically literate, concentrating wealth in certain regions and industries, causing the loss of local jobs and outsourcing jobs abroad. Furthermore, inclusive education supports educational equity in access to knowledge. In this way, individuals have the opportunity to achieve their full potential, increase their income, and improve their quality of life in the long term.

As regards the second part of our Table 9, which highlights the effects of the environmental tax and other covariates on inclusive education, we can see that the variables selected in this study are beneficial to inclusive education.

The argument in favour of the environmental tax for inclusive education is that tax revenues can be used to fund education in areas where resources are limited or for social groups that have limited access to education [13]. Indeed, revenues from an environmental tax can be used to fund inclusive education projects. This can include building schools that are accessible to disabled children, hiring specialist teachers for children with special educational needs and funding scholarship programmes for disadvantaged children. In addition, the implementation of the environmental tax can be accompanied by an environmental awareness campaign for local communities. This can include educational programmes for children and adults on ecological practices and climate change, which can help to raise awareness and interest in education in general. In addition, a well-designed environmental tax can reduce social and economic inequalities, which can help to make education more inclusive. Reducing greenhouse gas emissions, for example, can improve air and water quality, which in turn can reduce environmentally-related illnesses and improve the overall health of communities. This in turn can simplify access to education for marginalised communities who might otherwise have significant health problems. In sum, the environmental tax can be an important tool in promoting inclusive education by enabling the funding of inclusive education projects, raising environmental awareness for local communities, and reducing the social and economic inequalities that can hinder access to education.

Financial development does not significantly affect inclusive education. The use of the internet can contribute to inclusive education in a number of ways. Firstly, the use of technology can make education more accessible to people who cannot physically travel to a school or university, such as people living in rural or remote areas. In addition, the use of technology can facilitate access to educational resources and information for people who do not have access to a library or other sources of knowledge. Finally, the Internet can also facilitate collaboration and the exchange of knowledge between students and teachers in different parts of the world. These results are similar to those of [22], who stresses the importance of access to technology in promoting education and the involvement of students in their own learning.

Commerce can contribute to inclusive education by generating revenue that can be used to fund education in areas where resources are limited. There is also a case for using Fair Trade to ensure that educated workers receive a fair wage for their work, which can help break the cycle of poverty and improve access to education for disadvantaged families. Migrants' remittances are money sent home by migrants to their families in their country of origin. Migrants' remittances can contribute to inclusive education by providing financial resources that can be used to fund the education of children in families that would otherwise have few resources to do so. In addition, migrant funds can also be used to finance community education projects, to improve access to education in areas where resources are limited. Our results are thus comparable to those of [30,32] who showed that remittances have a positive impact on improving access to education.

Income inequality can have negative effects on inclusive education, as families with fewer financial resources often have less access to education. However, by adopting redistributive policies such as progressive taxation or financial support programmes for low-income families, it is possible to mitigate the negative effects of income inequality on inclusive education. Furthermore, by investing in education in regions where resources are limited, it is possible to reduce income inequality in the long term by creating a more qualified and competitive workforce on the labour market.

5. Discussion of the results

The results of the econometric modelling of the effects of environmental taxation on inequality have important implications for policy makers. Importantly, the estimation results suggest that environmental taxation can help reduce income inequality and increase inclusive university education, which can be seen as a positive impact for OECD member countries.

To take full advantage of these results, we recommend taking steps to educate the general public about the importance of environmental taxes and the benefits they can bring. This could be done through information campaigns, environmental education programmes for children and young people, and training programmes for adults.

In addition, it may be beneficial to review existing tax policies to ensure that they effectively support the implementation of the environmental tax. This could involve reviewing tax rates on environmental products, identifying ways to provide tax credits for environmentally friendly products, and introducing tax schemes on waste production.

Finally, it is essential to ensure that environmental taxes are properly targeted and do not create an excessive burden on low-income households. Measures such as tax compensation for low-income households could be put in place to reduce the negative impact on people who may find it more difficult to bear the burden of such taxes.

In sum, the results of this assessment suggest that the environmental tax can make a significant contribution to reducing income inequality and increasing the level of inclusive university education. However, to get the most out of it, it is important to implement effective policies and measures in terms of information, taxation and protection of low-income households.

Despite the important implications and policy recommendations of the study, some limitations must be recognised. For example, the study relies on impact models (PSM, DID, Randomized selection methods, Kiviet), which have their own limitations and assumptions. Furthermore, the study focuses on the effects of environmental policies on a heterogeneous group of countries which may hide disparities in the actual impact of environmental taxes on inequalities. Therefore, policy makers should take these limitations into account when interpreting the results of the study and making policy decisions. Nevertheless, the study provides valuable information on the potential impact of environmental policies on inequality and sustainable development.

6. Conclusion of the study

In conclusion, this study aimed to investigate the effects of environmental taxation on inequality, with a focus on social justice. The research problem and objectives were clearly defined, and the study contributed to the literature by providing new insights into the relationship between environmental taxation and inequality. The study also highlighted the determinants of environmental justice issues, such as income, education and access to employment.

The contribution of this study to the literature lies in its econometric modelling approach, which allowed a quantitative analysis of the effects of environmental taxation on inequality. This approach has been used in previous studies that have demonstrated the significant impact of environmental policies on economic outcomes. The findings of this study provide policy makers with valuable information on the potential impact of environmental tax policies on different segments of the population.

Future research directions could include expanding the scope of the study to other environmental policies, such as cap-and-trade systems or renewable energy subsidies. Overall, this study contributes to the growing body of literature on the intersection of environmental policy and social justice, and provides valuable information for policymakers seeking to address environmental inequalities.

Ethical approval

"not applicable".

Data availability statement

Data will be made available on request.

Additional information

No additional information is available for this paper.

CRediT authorship contribution statement

Edmond Noubissi Domguia: Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

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.

References

[1] X. Yang, W. Tang, Additional social welfare of environmental regulation: the effect of environmental taxes on income inequality, J. Environ. Manag. 330 (2023), 117095.
[2] E.N. Domguia, T.M. Pondie, B.A. Ngounou, H. Nkengfack, Does environmental tax kill employment? Evidence from OECD and non-OECD countries, J. Clean. Prod. (2022), 134873.
[3] J. Agyeman, Sustainable Communities and the Challenge of Environmental Justice, NYU Press, 2005.
[4] A. Prakash, M. Potoski, Racing to the bottom? Trade, environmental governance, and ISO 14001, Am. J. Polit. Sci. 50 (2) (2006) 350–364.
[5] J. Andersson, G. Atkinson, The Distributional Effects of a Carbon Tax: the Role of Income Inequality, Grantham Research Institute on Climate Change and the Environment, 2020.
[6] W. Oueslati, V. Zipperer, D. Rousselière, A. Dimitropoulos, Exploring the Relationship between Environmentally Related Taxes and Inequality in Income Sources: an Empirical Cross-Country Analysis, 2016.
[7] A. Fremstad, M. Paul, The impact of a carbon tax on inequality, Ecol. Econ. 163 (2019) 88–97.
[8] D.C. Klenert, G. Schwerhoff, O. Edenhofer, L. Mattauch, Environmental Taxation, Inequality and Engel's Law. *1014279/depositonce-5567*, 2016.
[9] OCDE, Taxes liées à l'environnement (indicateur) (Consulté le 27 juillet 2023), 2023.
[10] M. Chiroleu-Assouline, M. Fodha, Verdissement de la fiscalité: à qui profite le double dividende? Rev. OFCE (1) (2011) 409–431.
[11] E. Combet, F. Ghersi, J.C. Hourcade, Taxe carbone, une mesure socialement régressive? Vrais problèmes et faux débats (2009).
[12] A. Berthe, Analyse économique des inégalités environnementales: Fondements normatifs, mesures et application au contexte brésilien, Université de Bordeaux, 2015.
[13] F. Caillavet, A. Fadhuile, V. Nichèle, Assessing the distributional effects of carbon taxes on food: inequalities and nutritional insights in France, Ecol. Econ. 163 (2019) 20–31.
[14] N. Piluso, E. Le Heron, La taxe carbone dans une économie d'inspiration keynésienne, Dév. Durable et territoires Écon., Géogr., Politique, Droit, Sociol. 8 (3) (2017).
[15] R. Dellink, The OECD ENV-Linkages Modeling Framework, OECD, Paris, 2012.
[16] WDI. https://databankworldbankorg/source/world-development-indicators, 2023.
[17] E. Noubissi, B. Poumie, H. Nkengfack, Effect of environmental policies on exports from sub-Saharan African countries, Afr. Dev. Rev. 33 (4) (2021) 688–702.
[18] A. Sen, Poverty, inequality and unemployment: some conceptual issues in measurement, Econ. Polit. Wkly. (1973) 1457–1464.
[19] A. Deaton, D. Lubotsky, Mortality, inequality and race in American cities and states, Soc. Sci. Med. 56 (6) (2003) 1139–1153.
[20] G. Lindsay, Inclusive education: a critical perspective, Br. J. Spec. Educ. 30 (1) (2003) 3–12.
[21] C. Brunel, A. Levinson, Measuring the stringency of environmental regulations, Rev. Environ. Econ. Pol. (2016).
[22] R.W. Fairlie, The effects of home computers on school enrollment, Econ. Educ. Rev. 24 (5) (2005) 533–547.
[23] M.G. Quibria, S.N. Ahmed, T. Tschang, M.-L. Reyes-Macasaquit, Digital divide: determinants and policies with special reference to Asia, J. Asian Econ. 13 (6) (2003) 811–825.
[24] P. DiMaggio, E. Hargittai, C. Celeste, S. Shafer, From unequal access to differentiated use: a literature review and agenda for research on digital inequality, Soc. Inequality 1 (2004) 355–400.
[25] Z. Drabek, W. Payne, The impact of foreign direct investment on inequality: the case of Indonesia, J. Dev. Sustain. Agric. 14 (4) (2002) 571–581.
[26] Y. Makhlouf, N.M. Kellard, Foreign direct investment and wage inequality in developing countries: evidence from Egypt, World Dev. 33 (10) (2005) 1645–1663.
[27] D. Nayyar, Globalization and inequality: real or imagined ?, in: Working Paper University of Oxford, Oxford, UK, 2006.
[28] M. Ncube, J.C. Anyanwu, K. Hausken, Inequality, economic growth and poverty in the Middle East and North Africa (MENA), Afr. Dev. Rev. 26 (3) (2014) 435–453.
[29] J. Ma, G. Tian, Risks, financing constraints, and high savings ratio in the rural economy of China: a model incorporating precautionary savings and liquidity constraints, Front. Econ. China 1 (2006) 112–125.
[30] S. Chelly, V.D.V. Dirk, Human development impact of remittances on receiving countries, Ann. Am. Acad. Polit. Soc. Sci. 677 (1) (2018) 102–115.
[31] Y. Lu, Unequal remittance and social inequality: transnationalism and localized stratification among Mexican immigrants, Soc. Sci. Res. 52 (2015) 1–16.
[32] B. Xiang, Remittances, schooling, and child labor in Nepal, World Dev. 80 (2016) 48–61.
[33] D.B. Rubin, Estimating causal effects of treatments in randomized and nonrandomized studies, J. Educ. Psychol. 66 (5) (1974) 688.
[34] R. Tibshirani, Regression shrinkage and selection via the lasso, J. Roy. Stat. Soc. B Stat. Methodol. 58 (1) (1996) 267–288.
[35] E.D. Noubissi, H. Nkengfack, T. Messie Pondie, B.A. Ngounou, Economic impact of the carbon tax: evaluation of the reduction in CO2 emissions, Nat. Resour. Forum (2023) 1–28.
[36] A.D. Roy, Some thoughts on the distribution of earnings, Oxf. Econ. Pap. 3 (2) (1951) 135–146.

[37] S. Wager, S. Athey, Estimation and inference of heterogeneous treatment effects using random forests, J. Am. Stat. Assoc. 113 (523) (2018) 1228–1242.
[38] J. Peters, D. Janzing, B. Schölkopf, Elements of Causal Inference: Foundations and Learning Algorithms, The MIT Press, 2017.
[39] M-j Lee, Matching, Regression Discontinuity, Difference in Differences, and beyond, Oxford University Press, 2016.
[40] J.F. Kiviet, Testing the impossible: identifying exclusion restrictions, J. Econom. 218 (2) (2020) 294–316.
[41] A.I. Naimi, J.S. Kaufman, Counterfactual theory in social epidemiology: reconciling analysis and action for the social determinants of health, Curr. Epidemiol. Rep. 2 (2015) 52–60.
[42] J. Pearl, Causal inference, Causality: object. Assess. (2010) 39–58.
[43] M. Susser, Glossary: causality in public health science, J. Epidemiol. Community Health 55 (6) (2001) 376–378.
[44] P.W. Holland, Statistics and causal inference, J. Am. Stat. Assoc. 81 (396) (1986) 945–960.
[45] J.S. Kaufman, Commentary: causal inference for social exposures, Annu. Rev. Publ. Health 40 (2019) 7–21.
[46] C.P. Bonell, J. Hargreaves, S. Cousens, D. Ross, R. Hayes, M. Petticrew, B. Kirkwood, Alternatives to randomisation in the evaluation of public health interventions: design challenges and solutions, J. Epidemiol. Community 65 (7) (2011) 582–587.
[47] A. Abadie, G.W. Imbens, Large sample properties of matching estimators for average treatment effects, Econometrica 74 (1) (2006) 235–267.
[48] M. Caliendo, S. Kopeinig, Some practical guidance for the implementation of propensity score matching, J. Econ. Surv. 22 (1) (2008) 31–72.
[49] R. Dehejia, Practical propensity score matching: a reply to Smith and Todd, J. Econom. 125 (1–2) (2005) 355–364.
[50] R.H. Dehejia, S. Wahba, Propensity score-matching methods for nonexperimental causal studies, Rev. Econ. Stat. 84 (1) (2002) 151–161.
[51] J.A. Smith, P.E. Todd, Reconciling conflicting evidence on the performance of propensity-score matching methods, Am. Econ. Rev. 91 (2) (2001) 112–118.
[52] J.J. Heckman, R.J. LaLonde, J.A. Smith, The economics and econometrics of active labor market programs, in: Handbook of Labor Economics, vol. 3, Elsevier, 1999, pp. 1865–2097.
[53] A. Bryson, R. Dorsett, S. Purdon, The Use of Propensity Score Matching in the Evaluation of Active Labour Market Policies, 2002.
[54] P.R. Rosenbaum, P.R. Rosenbaum, Sensitivity to hidden bias, Observ. Stud. (2002) 105–170.
[55] P.W. Schultz, J.M. Nolan, R.B. Cialdini, N.J. Goldstein, V. Griskevicius, The constructive, destructive, and reconstructive power of social norms, Psychol. Sci. 18 (5) (2007) 429–434.