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CARBON TAX, ENERGY TRANSITION AND CO2 EMISSIONS: A DYNAMIC PANEL DATA APPROACH FOR NORTHERN AFRICA AND EUROPE.

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Abstract:
This study aims to analyze the impact of the introduction of the carbon tax on CO_2 emissions per capita in a sample **of Northern African and European countries**. It also examines the influence of the energy transition on CO_2 emissions per capita.
We use an empirical approach based on dynamic panel data, a method that makes it possible to control unobserved heterogeneity between countries and to estimate the effects of fiscal and environmental policies. The model analyses countries that have implemented a carbon tax compared with those that have not, while incorporating variables such as GDP per capita, the transition to renewable energy and industrial added value.
The results show strong inertia in emissions, with the carbon tax having a negative and statistically significant effect on CO_2 emissions per capita, underlining its effectiveness in combating climate change. The use of renewable energy also has a strongly negative impact on emissions. On the other hand, GDP per capita and industrial added value have a positive and significant effect on carbon dioxide emissions.
The analysis shows that carbon taxes and transition towards renewable energies are effective levers for reducing CO_2 emissions. However, economic growth and industrialization present environmental challenges; the fact that requires a balance between development and sustainability.

Keywords: Carbon tax; CO2 emissions; Renewable energy; Mundlak's approach; system GMM method

1. Introduction

Concerns about global warming have become critically serious in recent decades due to the deterioration of climate indicators. Climate change refers to the alterations to the climate attributable, directly or indirectly, to human activities that modify the composition of the global atmosphere which are added to the natural variability of the climate observed over comparable periods. Climate change is the greatest challenge facing humanity today. The Secretary-General of the World Meteorological Organization (WMO) [1] has once again sounded the alarm, stating that 2024 was the hottest year on record and the first to exceed the critical threshold of 1.5°C warming compared with the pre-industrial period (1850- 1900). This rise in temperature generates serious economic consequences, ranging from the financial and the fiscal stability to the management of long-term economic prospects, and income distribution, which are being felt on a global scale [2]
The global atmospheric CO2 concentration averaged during 2023 reached 419.31 ± 0.1 ppm, increased by 2.87 ppm, reaching 422.45 ppm, 52 % above the pre-industrial level (around 278 ppm in 1750); a level has not been seen for 14 million years [3]. In addition, statistics from ref [4] show that greenhouse gas emissions have risen from 32,523.58 megatons' of carbon dioxide equivalent per year in 1990 to 49,758.23 in 2023.
Carbon emissions come mainly from the use of fossil fuels (for heating, transporting goods and

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people, and generating electricity) and from the manufacture of steel and cement. The level of carbon emissions, which follows that of economic development, varies greatly from one country to another. Highly developed economies emit the most carbon per capita, while less developed economies, particularly in Africa, emit less (Figure 1). However, there is no clear divide between advanced and emerging economies: because of their rapid economic development, many emerging economies tend to emit less carbon than advanced economies.

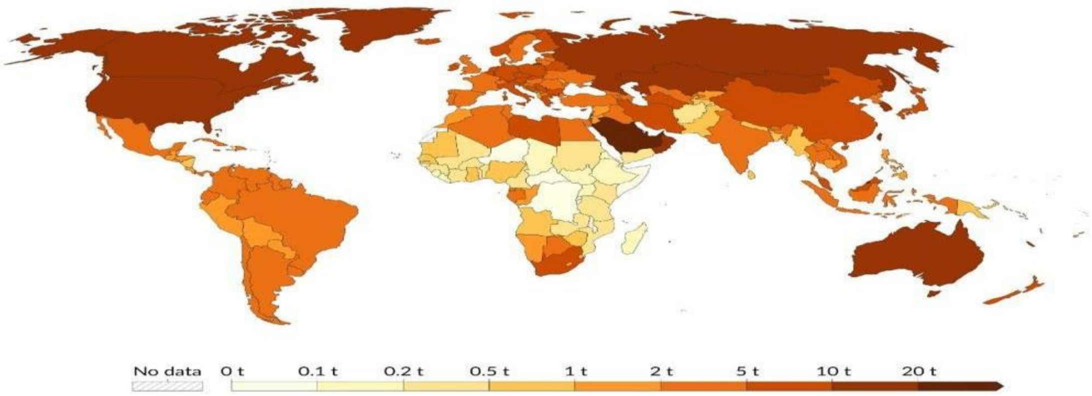

Fig.1. Per capita CO2 emissions from fossil fuels and industry, 2023 source: Global Carbon Budget (2023)

Faced with rapid global warming and the loss of biodiversity, the international community has recognized the need to establish an economic model capable of meeting human needs without damaging the planet. Researchers have always been focused on analyzing policies and measures to reduce environmental degradation and mitigate global warming. Some studies have focused on the role of the energy transition [5], [6], [7], Financial Development [8], [9], human capital [10], [11], economic openness and environmental innovations [12], [13], [14], [15], [16], [17].

Other studies have highlighted the role of implementing carbon pricing as an economic and environmental policy that imposes a monetary cost on emissions of carbon dioxide and other greenhouse gases (polluter pays theory) and its potential effect on mitigating these emissions to limit global warming and environmental degradation. It is designed to internalize the external (social) costs of these emissions, such as the damage caused by climate change, air pollution and associated health effects. As a climate policy tool, the carbon tax aims to incentivize businesses, industries and individuals to reduce their carbon emissions by making it financially worthwhile to switch to cleaner, more sustainable practices. This policy instrument can take a variety of forms, including taxes on energy, transport, resources, etc. Taxes on energy products, such as fossil fuels and electricity, are particularly important for reducing energy demand and greenhouse gas emissions.

Although the global energy crisis has hindered the development of carbon pricing and the transformation of energy taxation, or even led to a step backwards, a number of countries and territories are preparing to take carbon pricing policy further. Despite the importance of carbon pricing in reducing greenhouse gas emissions, only a few countries implemented environmental taxes unilaterally in the 1990s, as described in [18]. The situation has continued to evolve, with environmental taxes playing a more important role in climate change mitigation efforts. For example, total environmental tax revenues in the European Union represented 2.2% of gross domestic product (GDP) in 2020 [19].

Most panel data studies have focused on developed countries due to data availability. In addition, developed countries are the most likely to introduce environmental taxes. For example, Ref [20] examined the impact of environmental taxes on CO_2emissions in the Group of Seven (G7) between 1994 and 2014 using cointegration and causality techniques. However, little research has been conducted on the effectiveness of environmental taxes in limiting climate change and preserving

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ecology [21], [22].
The main objective of this article is to empirically examine the impact of carbon tax implementation on CO2 emissions in a sample of European and North African countries, taking into account economic and political factors. The empirical analysis also assesses the effect of the energy transition to renewable energies on CO2 emissions.
The remainder of this work is structured as follows. Section 2 summarizes the related literature, sections 3 and 4 present the methodology and data respectively, the empirical results examine in section 5, and finally section 6 concludes the research and provides both the economic policy recommendations and the limitations.

2- Review of the theoretical literature

It is generally accepted among economists and academics that a properly implemented carbon tax is the most economically efficient way to reduce a country's carbon emissions. It can also be an effective and efficient means of stimulating innovative economic activity [23], [24], [25].
The emergence of carbon taxes has its origins in the first half of the twentieth century, with the work of Arthur C. Pigou [26]. In his work, Pigou (1920) points out that certain economic activities, such as industrial production, create **negative externalities**, such as pollution, which generate **social costs that** are not taken into account in market prices. These externalities directly affect **social well-being** without the companies or individuals responsible bearing the costs. Pigou therefore proposes a tax measure aimed at taxing carbon dioxide emissions according to a principle of proportionality. The aim is to make the players responsible for pollution contribute directly and in proportion to their actions on society, thereby restoring a degree of market efficiency by aligning private costs with social costs
Pigou (1952) suggests that the public authorities can compensate for this market failure by introducing a tax on economic activity, the rate of which reflects the social damage caused by that activity. This tax, also known as the Pigouvian tax, aims to correct the negative externalities induced by economic activities. As illustrated in **Figure 1**, a Pigouvian tax is characterized by a decrease in the private marginal benefit of consuming goods as the quantity demanded increases, compared with the private marginal cost of the goods supplied, which increases along with the quantity supplied. In fact, the efficient market is characterized by the equality of marginal private benefits and costs, as illustrated in **Figure 1**. This equality is observed when the quantity demanded is equal to the market quantity and costs and benefits are equal to the price. This state of equilibrium within the market is referred to as market equilibrium.

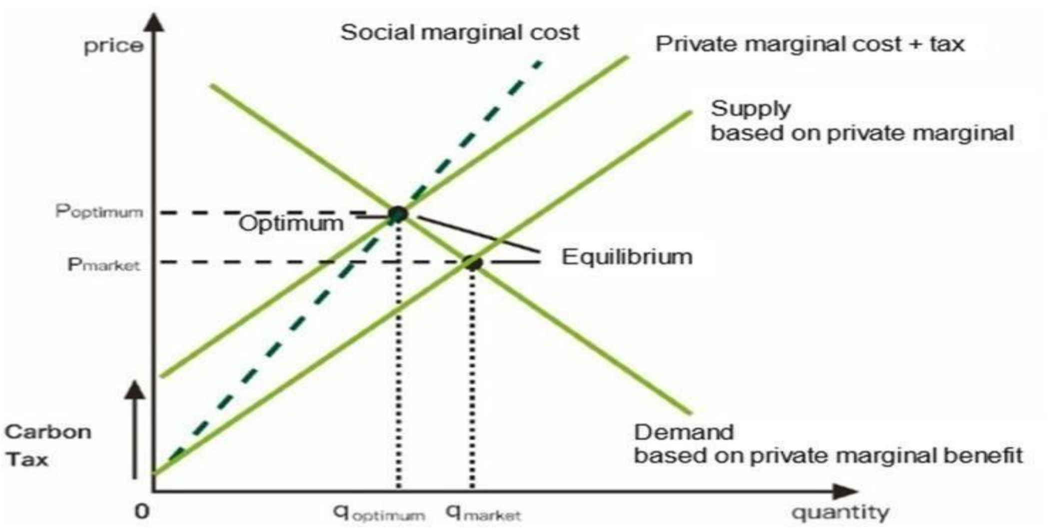

Figure 1: Pigouvian tax

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These taxes, based on behavioral taxation, aim to discourage the use of practices perceived as harmful. However, if the resources generated by the Pigouvian tax are allocated to public goods or redistributed, its implementation can generate a double dividend for the community. This is because, as well as reducing negative externalities through the price-signal effect, the use of the revenue generated by taxation can finance public policies aimed at reducing these externalities. In addition, unlike direct taxes, Pigouvian taxes are capable of adapting to economic fluctuations.

Conflicting to Pigou's approach, which advocates state intervention via taxation to internalize negative externalities, the Nobel Prize [27], proposes a solution based on liberal dogma via negotiation between the concerned parties. According to ***Coase***, under certain conditions, notably the clear definition of property rights and the absence of high transaction costs, the involved parties can reach an optimal solution through negotiation, without the need for state intervention.

This perspective has influenced thinking on carbon pricing policies by offering an alternative to the carbon tax whishes the emissions trading scheme [28]. This mechanism is based on the allocation of property rights on emissions, enabling companies to trade and exchange these rights in a market, thus seeking the most effective way of internalizing negative externalities linked to the environment. C***oasienne***, the allocation of these rights allows the market to determine the optimal solution, making regulation more flexible and economically viable. However, the Pigouvian tax, as the theoretical foundation of the carbon tax, offers a solid framework for integrating environmental costs into overall costs, with the aim of limiting CO2 emissions linked to the use of fossil fuels.

Another strand of the literature points out that environmental regulation, particularly taxes, can be counterproductive and have detrimental effects on ecology. Proponents of the so-called "*green paradox*" argue that environmental taxes lead to an increase in fossil fuel consumption and therefore targets the demand for fossil fuels [29]. As there is a time lag between environmental policy and implementation, fossil fuel suppliers will fear and accelerate their extraction activities, leading to increased energy demand and environmental degradation [22].

One of the main arguments against the carbon tax is its regressive nature, as highlighted by economic theory: it imposes a disproportionate burden on consumers, particularly low-income households, who spend a larger proportion of their income on essential goods such as petrol, electricity and food, which are often associated with polluting emissions. What's more, these households have limited capacity to substitute these goods, which restricts their ability to reduce the loss of purchasing power caused by the tax. Thus, in the post-Covid-19 pandemic context, the geopolitical disturbances linked to the Russian- Ukrainian war and the inflationary environment explain the reluctance of many countries to introduce a carbon tax, which risks aggravating the economic burden at a time when economies are still in the recovery phase. In addition to its regressive nature, other arguments reinforce the negative perception of the carbon tax, such as the loss of economic competitiveness and the adverse effects on employment, which raise concerns about the overall impact of this measure on national economies.

In the contemporary economic literature, a small but significant number of researchers, including [30]for the United States, question the thesis of the regressivity of the carbon tax. These researchers argue that the tax affects not only the production system, but also the remuneration of production factors such as labor and capital. In addition, they argue that the tax influences the sources of household income (side effect), thereby it offsets the regressive effects, particularly if higher-income households are more exposed to falls in income from capital, which is more affected by taxation than labor in some sectors. According to [31], policies that target these industries affect capital more, proportionally penalizing richer households whose income comes more from capital. These conclusions are supported by empirical evidence, in particular general equilibrium model simulations, which corroborate a significant impact of environmental taxes on household income formation, in particular through changes in the prices of factors of production, such as relative wages and capital income. These studies show that, in certain contexts, progressivity on the income

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source side can sufficiently offset the regressivity observed on the income use side [32], [33], [34]. It is important to note that countries that integrate carbon tax revenues directly into the state budget limit their ability to achieve the so-called "double dividend"[35]. Recognition of the losses in purchasing power suffered by households, as well as their multidimensional heterogeneity, encourages the introduction of **social shock absorbers**, i.e. compensation mechanisms financed by the revenue generated by the carbon tax [36]. One of the simplest solutions for compensating those who suffer the greatest losses is to pay a lump sum that is the same for all households, regardless of their tax burden [37], [38], [39]. This approach, which particularly benefits low-income households, is progressive and can mitigate or even eliminate the regressive aspects of carbon taxation, as studies based on micro- simulation models have shown [37], [39], [40], [41], [42].

3- Review of Empirical Literature

The empirical literature on the carbon tax is abundant, with mixed results. Several studies have sought to assess the impact of this tax on global CO2 emissions. Researchers such as [43], [44], [45] and [46] have conducted in- depth analyses on this subject. Their work shows that, despite the variation in tax rates in their respective models, the carbon tax has a significant mitigating effect on CO2 emissions. This highlights the potential of this measure for reducing overall emissions, while taking into account the different assumptions and methodologies employed.
However, other studies point to a more limited impact of the carbon tax on reducing CO2 emissions. For example, [47] observed that the effectiveness of the carbon tax in Sweden varied according to economic sector. Some sectors knew a significant drop in emissions, while others showed less pronounced results, suggesting that the impact of this tax depends largely on the specific characteristics of each sector, such as their sensitivity to prices or their capacity for technological adaptation, studies in British Columbia have shown that the introduction of a carbon tax reduced per capita greenhouse gas emissions by between 5% and 15% [18], [29], [48]. While examining the case of Sweden, Andersson [49] found that the introduction of carbon and value-added taxes on transport fuels led to a reduction of around 11% in carbon dioxide emissions from the transport sector, compared with emissions in a similar group of Organization for Economic Co-operation and Development (OECD) countries. Further research has shown that the introduction of carbon taxes has led to significant reductions in carbon dioxide emissions, and also governments can create an economic incentive for individuals and businesses to reduce their carbon footprint and adopt low-emission technologies and practices. Indeed, studies in British Columbia, Canada, found that the imposition of a carbon tax led to an estimated 18.8% drop in oil sales and a 7-17% drop in gasoline sales [50], [51] and [52]. Moreover, a study by Martin et al. in the UK found that the carbon tax had a negative impact on energy intensity and electricity consumption [52]. For example, Bruvoll and Larsen, found that carbon taxes had led to more modest reductions in carbon dioxide emissions prior to 2008 [53], [54]. However, it should be stressed that this relatively modest result is mainly attributable to the existence of broad tax exemptions and less elastic demand in the sectors concerned by the tax. In parallel, a study by Wissema and Dellink found that Ireland was able to reduce its emissions more significantly by encouraging the adoption of renewable energy and reducing the use of coal and oil, compared with the imposition of a uniform and equivalent energy tax[55].

Although a carbon tax has not yet been implemented in the People's Republic of China, previous research has used various theoretical models to assess the potential impact of implementing such a policy. For example, Dong et al suggested that China could reduce its industrial carbon dioxide (CO2) emissions by between 7.0 and 12.2 billion tons by 2030, depending on different tax rates [56]. In addition, a study by Yang et al, suggested that the implementation of carbon tax at a rate of 50 yuan per ton would result in a reduction of CO2 emissions from 2010 levels by approximately 3% [57]. The results of this study also highlighted the geographical areas most exposed to the expected impacts of

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this measure, namely the eastern coastal regions, the municipalities, the south-west and the north-west of the country, compared to the central and northern regions.

4. Materials and Methods

4-1. Data

This study examines the responses of European and North African countries to the explosion in CO_2 emissions between 2015 and 2022, from the perspective of carbon pricing, the transition to renewable energy and economic development. We collect data from several sources. The data on carbon dioxide emissions per capita, measured in metric tons, comes from *Our World in data*. Demographic, economic and energy use data come from the World Bank (GDP per capita, urbanization rate, share of manufacturing industry in GDP and renewables in electricity production). Our database covers the period from Paris agreement in 2015 to 2022 and 35 countries. The selection of countries is motivated by several interdependent economic, geopolitical and environmental factors. Europe is the leading trading partner of several North African countries, particularly in the sectors targeted by the carbon adjustment scheme. As a result, European carbon taxes may encourage companies to relocate their activities to North African countries with less stringent tax regimes (tax havens). In addition, the choice of period is justified by Paris agreement and the availability of data for most of our variables.
It should be noted that the introduction of carbon taxes has followed two main waves. The first wave, which began in the early 1990s, saw the introduction of carbon taxes in countries such as Denmark, Finland, Norway and Sweden, to name but a few. Then, in the 2000s, seven countries adopted a carbon tax. From 2010 onwards, a second wave of carbon taxes was introduced in countries such as Switzerland, Iceland, Ireland, Japan, Mexico and Portugal. The experience gained so far with carbon taxes on a global scale now makes it possible to envisage an empirical assessment of their impact.

Table 2: Application of the carbon tax in our sample of countries in 2022.

Country		Country	2022
Albania	*No carbon tax*	*Norway*	*Has carbon tax*
Belarus	*No carbon tax*	*Poland*	*Has carbon tax*
Belgium	*No carbon tax*	*Portugal*	*Has carbon tax*
Bulgaria	*No carbon tax*	*Romania*	*No carbon tax*
Croatia	*No carbon tax*	*Serbia*	*No carbon tax*
Czechia	*No carbon tax*	*Slovakia*	*No carbon tax*
Denmark	*Has carbon tax*	*Slovenia*	*Has carbon tax*
Estonia	*Has carbon tax*	*Spain*	*No carbon tax*
Finland	*Has carbon tax*	*Sweden*	*Has carbon tax*
France	*Has carbon tax*	*Switzerland*	*Has carbon tax*
Germany	*No carbon tax*	*Ukraine*	*Has carbon tax*
Greece	*No carbon tax*	*United King*	*Has carbon tax*
Hungary	*No carbon tax*	*Algeria*	*No carbon tax*
Iceland	*Has carbon tax*	*Egypt*	*No carbon tax*
Ireland	*Has carbon tax*	*Libya*	*No carbon tax*
Lithuania	*No carbon tax*	*Morocco*	*No carbon tax*
Italy	*No carbon tax*	*Tunisia*	*No carbon tax*
Netherlands	*Has carbon tax*		

4-2. Theoretical Rationale and Model Construction

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We quantify the effects of climate policies on carbon emissions by using a dynamic panel model. The dynamic specification takes into account the high degree of persistence of CO2 emissions. Throughout the study, we control macroeconomic factors, such as economic development (GDP per capita, share of manufacturing in total output), as well as the energy mix used for electricity generation. Formally, we explore the effects of climate policies (denoted by the implementation of the carbon tax) on the logarithm of per capita carbon dioxide emissions (denoted by lnCO2).

In addition to the lagged dependent variable, we include climate policies as key explanatory variables. To address potential endogeneity issues, we use lagged climate policy variables, which minimize the risk of reverse causality. We also include a number of macroeconomic variables as control variables.

Throughout our models, we include country fixed effects to capture unobserved heterogeneities between countries that could affect the rate of carbon dioxide emissions. These include fixed institutional factors such as the enforcement of environmental laws, as well as natural factors such as average median temperatures, which tend to correlate with heating or cooling requirements. We also include all annual time variables to control for the effects of global factors. These include for example, technological advances that may reduce environmental impacts, besides to other global trends or shocks.

Throughout the study, we use dynamic panel estimates from $Mundlak$. As a robustness check, we re- estimate the model using the system GMM method.

4-3. Model specification

$Mundlak$ Model

An arsenal of methods are available for estimating panel data models with individual specificities, the common problem that arises in these methods is determining whether these specificities should be considered as 'fixed' or 'random'. In addition, many panel regressions include both time- invariant and individual variables. The well-known fixed-effects estimator eliminates these variables from the regression via the$within$ transformation and does not take into consideration their marginal effects on the dependent variable. In many empirical applications, these variables are very important for political decisions

$Mundlak$'s approach combines the strengths of fixed and random effects models, allowing a nuanced analysis of the complex relationships between energy policies, economic variables and CO2 emissions. These relationships often involve dynamics within and between countries, It also allows us to capture these dynamics more effectively [58]. Indeed, the$Mundlak$ estimator is particularly well suited to the analysis of our variable of interest, the application of the carbon tax (1 = apply the carbon tax, 0 = do not apply the carbon tax). This estimator makes it possible to introduce the individual mean of the explanatory variables (**Between Effects**) into a random- effects model, in order to better capture heterogeneity between observation units, which makes it possible to differentiate between individual-specific effects and general trends, and therefore to take account of unobserved heterogeneity that may be correlated with the implementation of the carbon tax and other variables [59]. Unlike fixed effects models, which can control unobserved heterogeneity but do not allow us to estimate time-invariant variables such as our binary variable (the implementation of the carbon tax), $Mundlak$'s approach allows us to estimate the impact of this variable on CO2 emissions; thus, it provides a more reliable analysis of the effects of the implementation of the carbon pricing policy. In addition, it corrects the random effects model by relaxing the assumption that individual specificities are not correlated with the explanatory variables, which reduces the potential bias [60].

4-3.1. The Starting Point: Standard Panel Data Models

We begin with a standard linear panel data model for individual i $(i = 1, \dots, N)$ at time t $(t = 1, \dots, T)$.

Model:

$$y_{it} = \mathbf{x}'_{it}\boldsymbol{\beta} + \alpha_i + \varepsilon_{it}$$

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where:

- y_{it} is the dependent variable (e.g., CO2 emissions).
- $\mathbf{x}_{it}$ is a $K \times 1$ vector of time-varying explanatory variables.
- $\boldsymbol{\beta}$ is a $K \times 1$ vector of coefficients to be estimated.
- α_i is the unobserved individual-specific effect (e.g., country-specific, firm-specific). This captures time-invariant heterogeneity.
- ε_{it} is the idiosyncratic error term, assumed to be independent and identically distributed (i.i.d.) with $E(\varepsilon_{it}) = 0$ and $Var(\varepsilon_{it}) = \sigma_\varepsilon^2$.

The central problem in panel data is the relationship between α_i and the regressors $\mathbf{x}_{it}$.

4-3.2. Fixed Effects (FE) Model

The FE model makes no assumption about the relationship between α_i and $\mathbf{x}_{it}$. It allows for arbitrary correlation: $Cov(\mathbf{x}_{it}, \alpha_i) \neq 0$.

Estimation: The "within" transformation is used. This involves demeaning the variables for each individual i.

Define the individual-specific means:

$$\bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it}, \bar{\mathbf{x}}_i = \frac{1}{T}\sum_{t=1}^{T} \mathbf{x}_{it}, \bar{\varepsilon}_i = \frac{1}{T}\sum_{t=1}^{T} \varepsilon_{it}$$

Subtracting the within-individual mean from the original equation:

$$y_{it} - \bar{y}_i = (\mathbf{x}_{it} - \bar{\mathbf{x}}_i)'\boldsymbol{\beta} + (\alpha_i - \alpha_i) + (\varepsilon_{it} - \bar{\varepsilon}_i)$$

This simplifies to the Fixed Effects (Within) Estimator equation:

$$(y_{it} - \bar{y}_i) = (\mathbf{x}_{it} - \bar{\mathbf{x}}_i)'\boldsymbol{\beta} + (\varepsilon_{it} - \bar{\varepsilon}_i)$$

By eliminating α_i, the FE estimator consistently estimates $\boldsymbol{\beta}$. However, it also eliminates any time-invariant variable (like the carbon tax application variable if it does not change over time for a country).

4-3.3. Random Effects (RE) Model

The RE model assumes that the individual effect α_i is uncorrelated with all explanatory variables: $Cov(\mathbf{x}_{it}, \alpha_i) = 0$.

The model is the same:

$$y_{it} = \mathbf{x}_{it}'\boldsymbol{\beta} + \alpha_i + \varepsilon_{it}$$

But now, α_i is treated as a random component of the error term. The composite error term is $u_{it} = \alpha_i + \varepsilon_{it}$.

Estimation: Generalized Least Squares (GLS) is used. The GLS transformation is a quasi-demeaning:

$$y_{it} - \theta\bar{y}_i = (\mathbf{x}_{it} - \theta\bar{\mathbf{x}}_i)'\boldsymbol{\beta} + (1-\theta)\alpha_i + (\varepsilon_{it} - \theta\bar{\varepsilon}_i)$$

where θ is a function of the variance components:

$$\theta = 1 - \sqrt{\frac{\sigma_\varepsilon^2}{T\sigma_\alpha^2 + \sigma_\varepsilon^2}}$$

If $\theta = 0$, RE reduces to Pooled OLS. If $\theta = 1$, RE becomes the FE estimator. The key advantage is that RE can estimate coefficients on time-invariant variables. However, if the key assumption $Cov(\mathbf{x}_{it}, \alpha_i) = 0$ is violated, the RE estimator is inconsistent.

4-3.4. The Mundlak (1978) Approach

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The Mundlak approach is a solution to the dilemma of choosing between FE and RE. It challenges the strict RE assumption by proposing that the correlation between α_i and $\mathbf{x}_{it}$ can be modeled through the individual means of the time-varying regressors.

4-3.5. The Key Mundlak Assumption

Mundlak proposed that the unobserved individual effect α_i is a linear function of the time-averages of the time-varying regressors, plus a random error term that is truly uncorrelated.

$$\alpha_i = \bar{\mathbf{x}}_i'\boldsymbol{\gamma} + \omega_i$$

where:

- $\bar{\mathbf{x}}_i$ is the $K \times 1$ vector of individual means for the time-varying variables.
- $\boldsymbol{\gamma}$ is a $K \times 1$ vector of coefficients.
- ω_i is a random error term, assumed to be i.i.d. with $E(\omega_i) = 0, Var(\omega_i) = \sigma_\omega^2$, and crucially, $Cov(\bar{\mathbf{x}}_i, \omega_i) = 0$ and $Cov(\varepsilon_{it}, \omega_i) = 0$.

4-3.6. The Mundlak Model Equation

Substitute the expression for α_i into the original model:

$$y_{it} = \mathbf{x}_{it}'\boldsymbol{\beta} + \alpha_i + \varepsilon_{it}$$
$$y_{it} = \mathbf{x}_{it}'\boldsymbol{\beta} + (\bar{\mathbf{x}}_i'\boldsymbol{\gamma} + \omega_i) + \varepsilon_{it}$$

This gives us the fundamental Mundlak model equation:

$$y_{it} = \mathbf{x}_{it}'\boldsymbol{\beta} + \bar{\mathbf{x}}_i'\boldsymbol{\gamma} + \omega_i + \varepsilon_{it}$$

Interpretation and Connection to FE and RE

- The $\boldsymbol{\beta}$ Coefficients: These represent the within-effect (or short-run effect) of a change in $\mathbf{x}_{it}$. It answers: "What is the effect of a change in x for a given individual i, relative to that individual's mean?"
- The $\boldsymbol{\gamma}$ Coefficients: These represent the between-effect. They capture how differences in the average levels of x across individuals are associated with differences in their average levels of y.

The Link to Fixed Effects:

If we apply the within transformation to the Mundlak equation:

$$y_{it} - \bar{y}_i = (\mathbf{x}_{it} - \bar{\mathbf{x}}_i)'\boldsymbol{\beta} + (\bar{\mathbf{x}}_i - \bar{\mathbf{x}}_i)'\boldsymbol{\gamma} + (\omega_i - \omega_i) + (\varepsilon_{it} - \bar{\varepsilon}_i)$$

This simplifies to:

$$(y_{it} - \bar{y}_i) = (\mathbf{x}_{it} - \bar{\mathbf{x}}_i)'\boldsymbol{\beta} + (\varepsilon_{it} - \bar{\varepsilon}_i)$$

This is identical to the FE within equation. Therefore, the estimate of $\boldsymbol{\beta}$ from the Mundlak model is numerically identical to the Fixed Effects (Within) estimator.

The Link to Random Effects:

The composite error term in the Mundlak model is $v_{it} = \omega_i + \varepsilon_{it}$. By construction, ω_i is uncorrelated with $\bar{\mathbf{x}}_i$. Mundlak's crucial insight is that by explicitly including $\bar{\mathbf{x}}_i$, we have purged the individual effect α_i of its correlation with the regressors. The remaining individual heterogeneity ω_i now satisfies the RE assumption of no correlation.

Therefore, the Mundlak model can be estimated consistently using Random Effects GLS on the equation:

$$y_{it} = \mathbf{x}_{it}'\boldsymbol{\beta} + \bar{\mathbf{x}}_i'\boldsymbol{\gamma} + v_{it}, \text{where } v_{it} = \omega_i + \varepsilon_{it}$$

The Hausman Test as a Test on $\boldsymbol{\gamma}$

The standard Hausman test compares FE and RE estimates. In the Mundlak framework, this translates to a simple test of a joint hypothesis:

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$$H_0: \boldsymbol{\gamma} = \mathbf{0}$$
$$H_1: \boldsymbol{\gamma} \neq \mathbf{0}$$

- If H_0 is true, the individual effects are uncorrelated with the regressors ($\alpha_i = \omega_i$), and the standard RE model is correct and efficient.
- If H_0 is rejected, the correlation is significant, and the Mundlak model (which gives the FE estimate for $\boldsymbol{\beta}$) is the consistent specification.

This is an F-test (or Wald test) on the coefficients of the group means $\bar{\mathbf{x}}_i$.

4-3.6. **Incorporating Time-Invariant Variables**

The paragraph emphasizes that the carbon tax variable is a key, likely time-invariant, binary variable. Let's denote it as z_i. The Mundlak framework elegantly incorporates it.

The extended model becomes:

$$y_{it} = \mathbf{x}'_{it}\boldsymbol{\beta} + \delta z_i + \alpha_i + \varepsilon_{it}$$

Applying the Mundlak assumption $\alpha_i = \bar{\mathbf{x}}'_i\boldsymbol{\gamma} + \omega_i$:

$$y_{it} = \mathbf{x}'_{it}\boldsymbol{\beta} + \delta z_i + \bar{\mathbf{x}}'_i\boldsymbol{\gamma} + \omega_i + \varepsilon_{it}$$

This is the full empirical model for estimation. We can now estimate the coefficient δ for the time-invariant carbon tax variable.

- In a pure FE model, z_i would be collinear with α_i and drop out.
- In a standard RE model, the estimate of δ would be biased if z_i is correlated with the omitted part of α_i.
- In the Mundlak model, by including $\bar{\mathbf{x}}_i$, we control for the part of α_i that is correlated with the time-varying regressors. This reduces the potential for omitted variable bias in the estimate of δ, making it "more reliable" as stated in the paragraph.

The$Mundlak$ model is implemented in R software with the following code:

$Mundlak < -plm(log(Carb\_emiss) \sim lag(log(Carb\_emiss)) + Between(Carb\_emiss)$
$+ Carbon\_Tax + Renewable\_EC + Between(Renewable\_EC)$
$+ log(GDP\_per\_capitaPPP) + Between(GDP\_per\_capitaPPP)$
$+ log(IndusVA\%) + Between(\log(IndusVA\%)), pdata, model = "random")$

Results and discussion

Table 3 shows the results of the estimation of the Mundlak model.

Table 3: Estimation results $\boldsymbol{Mundlak\ method}$

Dependant variable	$log(CO2\_Emission)$
$\boldsymbol{Mundlak}$ **Model**	
$lag(log(CO2\_Emission))$	0.769***(0.045)
$Dummy\ carbon\ tax$	-0.022*(0.012)
$GDP\_per\_capitaPPP$	0.508***(0.115)
$Renewable\_EC$	-0.188***(0.051)
$IndusVA$	0.548(0.560)
$Adjusted\ R2$	0.974
$F\ Statistic$	6,145.267***
Notes: $***\ Significant\ at\ the 1 percent\ level.$ $**\ Significant\ at\ the\ 5\ percent\ level.$ $*\ Significant\ at\ the\ 10\ percent\ level.$	

Our estimation shows a modest inertia of emissions (modest temporal persistence). Similarly, the average carbon emissions per country have a **strong positive** effect on current emissions. This means that countries with historically high emissions continue to emit more.
A **negative and statistically significant** impact (*$p < 0.1$*) of the carbon tax, clearly shows that the implementation of a carbon tax **reduces CO_2 emissions**, although the effect is moderate. This validates the effectiveness of carbon pricing. These findings align with the research conducted by [50], [51], [52], [54], [55], [56], [61], [62].
Similarly, renewable energy has a strongly **negative and statistically significant** effect (*$p < 0.01$*) on CO2 emissions, which mean that **increasing consumption of renewable energy reduces carbon emissions**. This is an empirical proof of the energy transition.
A **positive and statistically significant effect** (*$p < 0.01$*) of GDP per capita suggests that richer countries tend to have **more carbon emissions**. This follows the hypothesis that initial economic growth leads to an increase in emissions (the environmental Kuznets curve hypothesis).
Although the coefficient associated with the share of industry in the production process is positive, it is not statistically significant, which means that the impact of the industrial sector on carbon emissions is uncertain in this model.

Robust results:
To test the robustness of the results obtained by using Mundlak's approach, we re- estimated the model by using the GMM method in Blundell and Bond's system.
The GMM system estimation is chosen because it ought to give more robust results.
1. The Context: Why System GMM?
The paragraph states that System GMM is used to test the robustness of the Mundlak model. The primary reasons for this are:

1. **Endogeneity:** The Mundlak model controls for correlation between the *level* of regressors and the individual effect, but it does not solve endogeneity arising from:
   - **Simultaneity:** CO2 emissions might simultaneously affect explanatory variables (e.g., economic growth, policy intensity).
   - **Dynamic Endogeneity:** Past values of the dependent variable (CO2 emissions) might influence current values, a relationship not captured in a static Mundlak model.
2. **Dynamic Panel Bias:** If the true data-generating process is dynamic, including a lagged dependent variable $y_{i,t-1}$ as a regressor creates a correlation between the regressor and the error term, rendering standard estimators like FE and RE inconsistent, especially in panels with a short time dimension (small T).

System GMM is specifically designed to handle these issues.

The Foundation: The Dynamic Panel Data Model
We start by specifying a model that includes a lag of the dependent variable.
Model:

$$y_{it} = \delta y_{i,t-1} + \mathbf{x}'_{it}\boldsymbol{\beta} + \alpha_i + \varepsilon_{it}$$

where:

- y_{it} is the dependent variable.
- $y_{i,t-1}$ is its first lag.
- δ is the coefficient on the lagged dependent variable, capturing persistence.
- $\mathbf{x}_{it}$ is a vector of other explanatory variables (which may include the carbon tax variable).
- α_i is the unobserved individual-specific effect.
- ε_{it} is the idiosyncratic error term, assumed to be i.i.d.

The composite error term is $\alpha_i + \varepsilon_{it}$.
The Problem: Bias in Standard Estimators

If we apply the Fixed Effects (within) transformation to this dynamic model:

$$(y_{it} - \bar{y}_i) = \delta(y_{i,t-1} - \bar{y}_{i,-1}) + (\mathbf{x}_{it} - \bar{\mathbf{x}}_i)'\boldsymbol{\beta} + (\varepsilon_{it} - \bar{\varepsilon}_i)$$

The term $(y_{i,t-1} - \bar{y}_{i,-1})$ is correlated with $(\varepsilon_{it} - \bar{\varepsilon}_i)$ because $y_{i,t-1}$ is a function of α_i, and $\bar{\varepsilon}_i$ contains $\varepsilon_{i,t-1}$. This correlation induces **Nickell Bias**, which is non-negligible for small T.

The Solution: Difference GMM (Arellano & Bond, 1991)

The first step towards System GMM is the Difference GMM estimator. It addresses the problem by first-differencing the model to eliminate the individual effect α_i.

First-Differenced Equation:

$$\Delta y_{it} = \delta \Delta y_{i,t-1} + \Delta \mathbf{x}'_{it}\boldsymbol{\beta} + \Delta\varepsilon_{it}$$

where $\Delta y_{it} = y_{it} - y_{i,t-1}$, etc.

This removes α_i. However, the new regressor $\Delta y_{i,t-1}$ is now correlated with the new error term $\Delta\varepsilon_{it} = \varepsilon_{it} - \varepsilon_{i,t-1}$ because $y_{i,t-1}$ in $\Delta y_{i,t-1}$ is correlated with $\varepsilon_{i,t-1}$ in $\Delta\varepsilon_{it}$.

The Instrumental Variables (IV) Solution

Arellano and Bond proposed using **internal instruments**: deeper lags of the variables themselves. Under the assumption of no serial correlation in ε_{it}, the following moment conditions hold:

Moment Conditions for the Lagged Dependent Variable:

For the equation in first differences at time t, valid instruments for $\Delta y_{i,t-1}$ are $y_{i,t-2}, y_{i,t-3}, \ldots$. The logic is that these earlier lags are correlated with the change in the lagged dependent variable but are uncorrelated with the error term in differences (since ε_{it} is not serially correlated).

The general moment condition is:

$$E[y_{i,t-s} \cdot \Delta\varepsilon_{it}] = 0 \text{for } s \geq 2;\ t = 3, \ldots, T$$

Moment Conditions for Other Explanatory Variables ($\mathbf{x}_{it}$):

The choice of instruments depends on the exogeneity assumption of the variable x_{it}.

- If x_{it} is **strictly exogenous**: $E[x_{is}\varepsilon_{it}] = 0$ for all s, t. Then all past, present, and future values are valid instruments. The moment conditions are $E[\Delta x_{is} \cdot \Delta\varepsilon_{it}] = 0$.
- If x_{it} is **predetermined (weakly exogenous)**: $E[x_{is}\varepsilon_{it}] = 0$ for $s \leq t$, but not for $s > t$. This allows for feedback from past shocks to future regressors. Then, lags of x_{it} are valid instruments. The moment conditions are $E[x_{i,t-s} \cdot \Delta\varepsilon_{it}] = 0$ for $s \geq 1$.
- If x_{it} is **endogenous**: $E[x_{is}\varepsilon_{it}] = 0$ for $s < t$, but not for $s \geq t$. Then, deeper lags are needed: $E[x_{i,t-s} \cdot \Delta\varepsilon_{it}] = 0$ for $s \geq 2$.

The GMM Estimation Framework

The GMM estimator works by minimizing the distance between the sample moments and their population value of zero. Let $\mathbf{Z}_i^D$ be a matrix containing all the selected instruments for individual i. The moment conditions can be written compactly as:

$$E[(\mathbf{Z}_i^D)'\Delta\boldsymbol{\varepsilon}_i] = \mathbf{0}$$

where $\Delta\boldsymbol{\varepsilon}_i$ is the vector of first-differenced errors for individual i.

The GMM objective function is:

$$J^D(\boldsymbol{\theta}) = \left(\frac{1}{N}\sum_{i=1}^{N} \Delta\boldsymbol{\varepsilon}'_i\mathbf{Z}_i^D\right)\mathbf{W}_N^D\left(\frac{1}{N}\sum_{i=1}^{N}(\mathbf{Z}_i^D)'\Delta\boldsymbol{\varepsilon}_i\right)$$

where:

- $\boldsymbol{\theta} = (\delta, \boldsymbol{\beta}')'$ is the vector of parameters to be estimated.
- $\mathbf{W}_N^D$ is a **weighting matrix**. The efficient GMM estimator uses $\mathbf{W}_N^D = (\frac{1}{N}\sum_{i=1}^{N}(\mathbf{Z}_i^D)'\mathbf{H}\mathbf{Z}_i^D)^{-1}$, where $\mathbf{H}$ is a matrix with 2's on the diagonal, -1's on the off-diagonals, and 0's elsewhere, which arises from the variance structure of $\Delta\varepsilon_{it}$ under homoscedasticity.

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The estimator that minimizes $J^D(\boldsymbol{\theta})$ is the **Difference GMM estimator**.

The Advancement: System GMM (Blundell & Bond, 1998)

Difference GMM can suffer from **weak instrument problems** when the series are highly persistent (e.g., CO2 emissions, GDP). In this case, lagged levels are weak instruments for first differences. Blundell and Bond's System GMM augments the Difference GMM with an additional set of equations in **levels**.

The System is composed of two sets of equations:

1. The **first-differenced equation** (from above), instrumented by lagged levels.
2. The **original level equation**, instrumented by lagged first differences.

The Level Equation and its Instruments

The level equation is:

$$y_{it} = \delta y_{i,t-1} + \mathbf{x}'_{it}\boldsymbol{\beta} + \alpha_i + \varepsilon_{it}$$

The problem is that $y_{i,t-1}$ is correlated with α_i. Blundell and Bond proposed that if the process is mean-stationary, then lagged *differences* are valid instruments for the equation in *levels*.

The key assumption for mean-stationarity is:

$$E[\Delta y_{it}\alpha_i] = 0$$

This implies that the process has converged, and deviations from long-run means are not correlated with the individual effect.

Moment Conditions for the Level Equation:

Under this assumption, the following moment conditions are valid:

$$E[\Delta y_{i,t-1} \cdot (\alpha_i + \varepsilon_{it})] = 0$$
$$E[\Delta \mathbf{x}_{i,t-1} \cdot (\alpha_i + \varepsilon_{it})] = 0$$

These state that lagged first differences of the variables are uncorrelated with the composite error term in the level equation.

The Combined System GMM Estimator

System GMM stacks the moment conditions from both the difference and level equations.
Let $\boldsymbol{\varepsilon}_i^L = \alpha_i + \varepsilon_{it}$ be the error term for the level equation. The full set of moment conditions is:

$$E[\mathbf{Z}_i^{S'}\mathbf{u}_i] = \mathbf{0}$$

where:

- $\mathbf{u}_i = \begin{bmatrix} \Delta\boldsymbol{\varepsilon}_i \\ \boldsymbol{\varepsilon}_i^L \end{bmatrix}$ is the stacked vector of errors from both equations.
- $\mathbf{Z}_i^S = \begin{bmatrix} \mathbf{Z}_i^D & \mathbf{0} \\ \mathbf{0} & \mathbf{Z}_i^L \end{bmatrix}$ is the block-diagonal matrix of instruments for the system. $\mathbf{Z}_i^D$ contains instruments for the differenced equation (lagged levels), and $\mathbf{Z}_i^L$ contains instruments for the level equation (lagged differences).

The **System GMM objective function** is:

$$J^S(\boldsymbol{\theta}) = (\frac{1}{N}\sum_{i=1}^{N}\mathbf{u}_i'\mathbf{Z}_i^S)\mathbf{W}_N^S(\frac{1}{N}\sum_{i=1}^{N}(\mathbf{Z}_i^S)'\mathbf{u}_i)$$

The estimator that minimizes $J^S(\boldsymbol{\theta})$ is the **System GMM estimator**. It is more efficient and less biased than the Difference GMM estimator when the instruments for the level equation are valid.

Key Specification Tests for Robustness

When using System GMM for robustness, researchers must report several critical tests, as implied by the paragraph's goal.

Test for Serial Correlation

- **Null Hypothesis:** No serial correlation in the idiosyncratic errors ε_{it}.
- **Test:** Applied to the residuals $\Delta\hat{\varepsilon}_{it}$ from the first-differenced equation.

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- **Interpretation:**
  - **AR(1):** We expect to reject the null because $\Delta\varepsilon_{it}$ is mechanically correlated with $\Delta\varepsilon_{i,t-1}$ through $\varepsilon_{i,t-1}$.
  - **AR(2):** This is the crucial test. **Failure to reject the null** for AR(2) supports the model's validity, as it indicates no second-order serial correlation, which validates the moment conditions.

Hansen Test of Over-Identifying Restrictions

- **Null Hypothesis:** All instruments are valid (i.e., uncorrelated with the error term).
- **Interpretation:** A **failure to reject the null** is desired. A p-value > 0.05 or 0.10 indicates that the instrument set is valid. (Note: The Hansen test is preferred over the Sargan test as it is robust to heteroscedasticity).

Difference-in-Hansen Test for Subsets of Instruments

- **Purpose:** To test the validity of a subset of instruments, most importantly, the **additional moment conditions for the level equation**.
- **Null Hypothesis:** The instruments used in the level equation are valid.
- **Interpretation:** A **failure to reject the null** provides confidence that the key assumption of mean-stationarity holds and that System GMM is appropriate.

$$Blund\_Bond < -\, pgmm(formula = log(Carb\_emiss) \sim lag(log(Carb\_emiss)) + Carbon\_Tax + lag(log(GDP\_per\_capitaPPP)) + lag(log(Renewable\_EC)) + lag(log(IndusVA\%)) \,|\, lag(log(IndusVA\%)), 2{:}\,99) + lag(log(Renewable\_EC)) + lag(log(GDP\_per\_capitaPPP), 2{:}\,99), data = pdata, effect = "twoways", model = "onestep", transformation = "ld")$$

Researchers often use contemporaneous values of explanatory variables in econometric models when they want to address a research problem. Given that the dependent variable and the explanatory variables, over a given period, are likely to be determined jointly and the possibility of an endogeneity bias in these regressions is quite obvious.

The system GMM method [63] is adapted to **dynamic panel models** (where the dependent variable depends on its past values) and can be used to solve a number of econometric problems.

This suggests that there will be a significant reduction in finite sample bias and significant gains in accuracy due to the additional moment conditions. In this sense, the system GMM estimator can be seen as an extension of a difference GMM estimator that extracts more information from the equations. In addition, system GMM estimators are more likely to have more satisfactory finite sample properties than difference GMM estimators because time series information is used more efficiently in the system GMM methodology.

Validity of instruments

In his influential article "**A Note on the Theme of Too Many Instruments**", David $Roodman$ addresses the issue of instrument proliferation in GMM estimation, particularly in the context of dynamic panel data models. He indicates out that having too many instruments can lead to an over-fitting of endogenous variables and weaken the Hansen (or $Sargan$) test, which can give rise to high and misleading p-values. When the number of instruments is too high in relation to the number of observations, the Hansen test (or$Sargan$) can become unreliable. This can result in p-values that are too high, wrongly suggesting that the instruments are valid. Roodman suggests a cautious approach to interpreting the p-values of the$Sargan$ test when there are many instruments. According to $Roodman$, p-values between 0.1 and 0.3 may be more reliable indicators of the validity of the instruments, provided that the number of instruments is not excessively high. This interval is more of a guideline than a strict rule, and reflects a balance between too few and too

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many instruments. On the other hand, if the p-value is greater than 0.3, this may indicate an excessive number of instruments, the matter that requires a reduction. Finally, if the p-value is less than 0.1, it may indicate problems with the validity of the instruments [64].

Table 4 shows the estimation of our model by using the GMM method in the Blundell and Bond system.

Table 4: Estimation results $\boldsymbol{Blundell\_Bond}$ method Dependant variable $log(CO2\_Emission)$	
$\boldsymbol{Blundell\_Bond}$ **Model**	
$lag(log(CO2\_Emission))$	0.918***(0.027)
$Dummy\ carbon\ tax$	-0.036**(0.014)
$log(GDP\_per\_capitaPPP)$	0.642**(0.297)
$log(Renewable\_EC)$	-0.107*(0.061)
$log(IndusVA)$	0.297*** (0.070)
$Sargan\ test$: $chisq\ (28) = 32.75046\ (p - value = 0.24478)$	
$Autocorrelation\ test$ (1): $normal = -2.150648\ (p - value = 0.04088)$	
$Autocorrelation\ test$ (2): $normal = -0.1297269\ (p - value = 0.89678)$	
$Wald\ test\ for\ coefficients$: $chisq\ (8) = 8194.206\ (p - value = < 2.22e - 16)$	
$Wald\ test\ for\ time\ dummies$: $chisq\ (4) = 10.38692\ (p - value = 0.034391)$	
Notes: $***\ Significant\ at\ the 1 percent\ level.$ $**\ Significant\ at\ the\ 5\ percent\ level.$ $*\ Significant\ at\ the\ 10\ percent\ level.$	

The results show a very high and significant coefficient at 1% associated with the lag of the dependent variable, indicating strong inertia of emissions: a 1% increase in emissions at t-1 leads to a 0.959% increase at time t.
For our variable of interest, the carbon tax reveals a negative and very significant effect, which confirms what we obtained from the Mundlak approach, as well as the literature on the subject.
Weak effect, but more robust than in our previous model (significance increased from 10% to 5%). This could indicate that the tax has a long-term effect, or that the GMM corrects for measurement bias.
The lagged GDP/capita has a positive effect (+ 0.642%), significant at 5%. This confirms the rebound effect of growth on emissions, which is more pronounced than in the previous model.
Delayed renewables reduce emissions by 0.107%, significant at 10%. Less strong effect than in the Mundlak model, possibly due to adjustment delays.
Industry's share of GDP shows a positive and significant effect, stronger than the previous model.
Our dynamic GMM model is valid and well specified (conclusive Sargan and AR(2) tests). It reveals an extremely strong persistence of CO_2 emissions, a modest and significant impact of the carbon tax, and a key role for renewable energies. These results argue in favor of climate policies combining economic instruments (carbon tax) and investment in clean energy.

Conclusion and implications

We have used a comprehensive database of 35 countries to study the impact of climate policies on carbon dioxide emissions a posteriori, with data on carbon emissions and macroeconomic variables over the period 2016-2022, as well as data on climate policies. We consider the implementation of the carbon tax and the transition to renewable energies as climate policies. Overall, we find that carbon taxes and investment in renewable energy are associated with a reduction in carbon emissions.
The results confirm a number of important trends:

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- Carbon emissions are highly persistent, which means that they are difficult to reduce quickly.
- Environmental policies (carbon tax, renewable energies) are having a significant effect on reducing emissions.
- Economic growth tends to increase emissions, but this effect is moderate.
- Accelerate the transition to renewable energies, as their impact is still low.

Policy recommendations

The effectiveness of a carbon tax depends on a number of essential conditions. The revenue generated must be reinvested in environmental protection and sustainable technologies, thereby increasing transparency and public support. To ensure social acceptance, the tax must be part of a coherent environmental strategy, including the elimination of harmful tax niches. A balanced tax framework is needed, combining sanctions against polluting behaviour with environmental incentives, thereby discouraging harmful activities while stimulating green initiatives. Countries that visibly reinvest these revenues achieve a broader consensus, as illustrated by Sweden, a pioneer in 1991. It introduced a gradual schedule of tax increases, accompanied by tax reforms and measures to protect vulnerable sectors. Thanks to this gradual approach, the tax has risen from 28 to 127 dollars per tons in 30 years, without compromising economic competitiveness. Finally, to avoid penalizing local industries in the face of international competition, mitigation mechanisms, such as quotas or exemptions, are often incorporated into carbon pricing systems.

Authors' contributions

All authors contributed equally in the elaboration of this article.

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Ethics approval and consent to participate

Not Applicable. The study is totally based on available dataset from WDI. We confirm that all methods were performed in accordance with the relevant ethical guidelines and regulations.

Consent for publication

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Competing interests

There are no competing interests by the authors of this paper.

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Highlights (for Review)

Article objective

The purpose of this article is twofold:

1. **Measuring the impact of the carbon tax on CO2 emissions**: Using **Dynamic Panel Data Approach**, we analyze how the carbon tax influences CO2 emissions in different countries.
2. **Evaluate the effect on the adoption of renewable energies**: We compare the adoption of renewable energies in countries with and without a carbon tax, taking into account the public policies in place.

Methodology

The study is based on panel data spanning several decades, incorporating economic and environmental variables. Mundlak's and Blundell and Bond's approach make it possible to take unobserved specific effects into account and provide robust estimates of the impacts of carbon tax policies.

Results and implications

The results of our analysis reveal that countries that have introduced a carbon tax have generally succeeded in reducing their CO2 emissions more significantly than those that have not. What's more, these countries also have a faster uptake of renewable energies, suggesting that carbon taxes can be an effective tool not only for reducing emissions but also for promoting energy transition.

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