The role of renewable energy on CO2 emission in the power industry: the impact of tendering as a possible mechanism

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Date:
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Author:
Witson Peña Tello

Advisor:
Alexandros Cavgias Martins Fraga

Máster ERCSP
Máster Universitario en Economía, Regulación y Competencia en los Servicios Públicos

UNIVERSITAT DE BARCELONA

Abstract

Carbon dioxide (CO_2) is the most important greenhouse gas that produces global warming and climate change. Despite most countries agreed on ambitious targets of CO_2 cuts, there is less consensus on the tools through which these targets will be achieved. The deployment of renewable energy into the power industry is one of the core elements for decarbonizing one of the industries with the largest contributor to CO_2 emissions. But we still know little about how different regulatory policies for renewable energy impact CO_2 emissions from power generation. This study sheds light on these gaps by using three complementary methodologies: Kaya's decomposition technique for identifying the main drivers of CO_2 emissions from power generation, the panel data approach for testing the relationship between renewable energy share in the generation mix and CO_2 emission, and matching procedure to estimate the possible causal effect on CO_2 emission of auction policy promoting renewable energy in the power industry. Results show that GDP per capita is the main driver pulling up CO_2 emission and renewable energy share in power generation is the main driver counteracting it. Furthermore, auction policy, as one way to promote renewable energy, seems to have a causal effect on CO_2 emissions per capita from power generation in countries that implemented it compared to a control group of countries that did not implement this policy.

Keywords: CO_2 emission, renewable energy, power generation, auctions, panel data, matching

CONTEND

1. Introduction

Global warming is one of human's greatest challenges to overcome. Carbon dioxide (CO_2) is the most important greenhouse gas that produces global warming. Electricity and heat generation was the largest contributor to greenhouse gas emissions in 2016 (Ge & Friedrich, 2020), of which power generation stands for 77%.

Paris Agreement on climate change, reached at the United Nations COP21 meeting in 2015 and went into effect in 2016, brought new vigor to global efforts to address climate change by limiting global warming to well below 2, preferably to 1.5 degrees Celsius, compared to pre-industrial levels (United Nations, 2020). Despite most countries agreed on ambitious targets of greenhouse emission cuts, there is less consensus on the tools through which these targets will be achieved.

The deployment of renewable energy into the power industry is one of the core elements for the transition from fossil fuels to clean electricity generation and, therefore, the power industry plays a key role in reducing CO_2. Not surprisingly, many countries use clean renewable energy sources or have plans to adapt them in the future into their power generation portfolio. By the end of 2019, of the more than 200 Intended Nationally Determined Contributions (INDC) plans submitted by countries after Paris Agreement, 132 mentioned renewables in the context of the power industry (IRENA, 2020).

While several studies have investigated the drivers of CO_2 emissions from power generation, most of them relied on decomposition techniques (Goh et al., 2018) and used data from a single country or region (Rodrigues et al., 2020). Moreover, we still know little about how different regulatory policies for renewable energy impact CO_2 emissions from power generation. According to IRENA (2020), the auctions scheme has gained traction since 2005 as the main instrument to promote renewable energy in the power industry. To the best of my knowledge, the contribution of this study is to develop a cross-country assessment from the sample of 129 countries between 1990 and 2018 to evaluate the drivers of CO_2 emission from power generation through a panel data approach and to estimate the possible causal effect on CO_2 emission of auction policy promoting renewable energy into generation mix.

I use three complementary methodologies to evaluate the drivers of CO_2 emissions from power generation and to investigate the possible causal effect on CO_2 emission of auction policy. First, I use Kaya's decomposition technique as a reference to have a first glance at the evolution of the main drivers of CO_2 emissions from power generation. Second, I use a panel data approach for testing the relationship between renewable energy share in the generation mix and CO_2 emissions per capita from power generation. Third, I use a matching procedure to investigate the possible causal effect on CO_2 emission of auction policy promoting renewable energy in the power industry.

The promotion of renewable energy is only an instrument that needs to be complemented with others to tackle the climate change challenge. So, in this study, I also outline a framework for energy and climate policies to address climate change in the power industry.

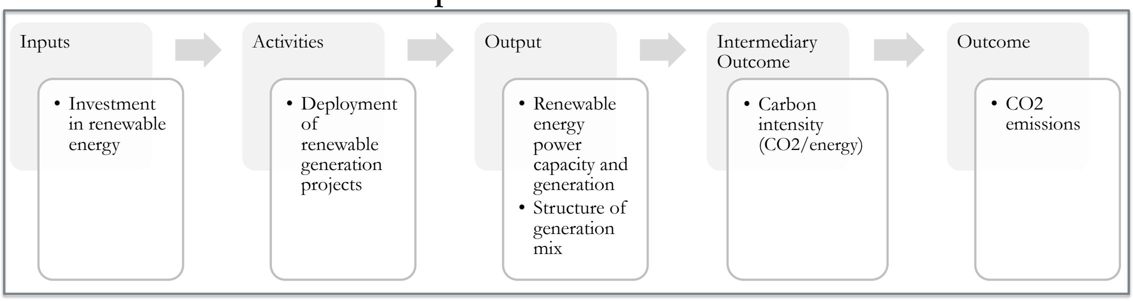
2. Literature review

Carbon dioxide (CO_2) is the most important greenhouse gas that produces global warming and climate change. Electricity and heat generation was the largest contributor to greenhouse gas emissions in 2016 (Ge & Friedrich, 2020), of which power generation stands for 77%.

Many studies have analyzed the drivers of CO2 emission from power generation, mostly through decomposition techniques such as Kaya identity (as an extension of IPAT), structural decomposition analysis (SDA), Index Decomposition Analysis (IDA), etc. (Goh et al., 2018) and for specific regions o countries (Rodrigues et al., 2020). For instance, Rodrigues et al., (2020), using an index decomposition analysis (IDA), have found that the expansion of renewable electricity is one of the main drivers of the decrease in CO2 emissions from electricity generation in Europe between 2007–2015. However, one drawback associated with the decomposition approach is the increasing complexity of result interpretation and analysis brought by interconnectivity and interdependency amongst effects. This affinity is expected to increase with the number of variables considered in the decomposition equation but could be surpassed by resorting to an econometric approach to determine what kind of causality is associated with these complementary effects (Lima et al., 2016).

The regulation policy for promoting renewable energy into power generation acts through the carbon intensity to impact the CO2 emission per capita. **Figure 1** summarizes the possible mechanism through which policy promoting renewable energy may impact CO2 emission from power generation.

Figure 1: Possible mechanism through policy promoting renewable energy may impact on CO2 emission

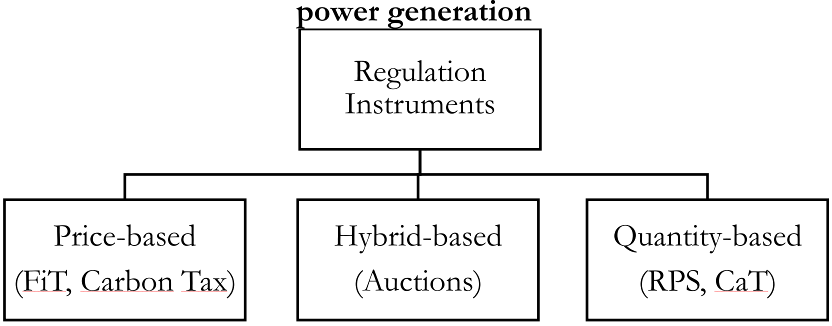


Elaborated by the author.

The policy promoting renewable energy has become the main climate change mitigation strategy (Sterner & Coria, 2012). From an economic theory viewpoint, the policy promoting renewable energy is a government intervention that seeks to correct negative externalities (pollution) through regulation (Gruber, 2016). **Figure 2** shows the main policies promoting renewable energy through market mechanisms (Bento et al., 2020) which could be based on (IRENA, 2020):

1) Price-based policies such as carbon tax and Feed-in policy that guarantees specified payments per unit over a fixed period (e.g. feed-in tariff – FIT) or payment floating on top of the wholesale electricity price (e.g., a feed-in premium).
2) Quantity-based policies like renewable portfolio standard (RPS) requiring the provision or use of a targeted renewable share from utility companies and cap and trade (CAT) which offers certainty over the environmental outcome (i.e., "cap" quantity) but leaves it to the market to set the price of carbon.
3) Hybrid-based policies as auction or tender, which is a mix of price and quantity instruments (Elizondo et al., 2014), provide stable revenue guarantees for investors (similar to the FIT mechanism) while at the same time ensuring a renewable generation quota (similar to an RPO).

Figure 2: Traditional regulation instruments for promoting renewable energy into power generation

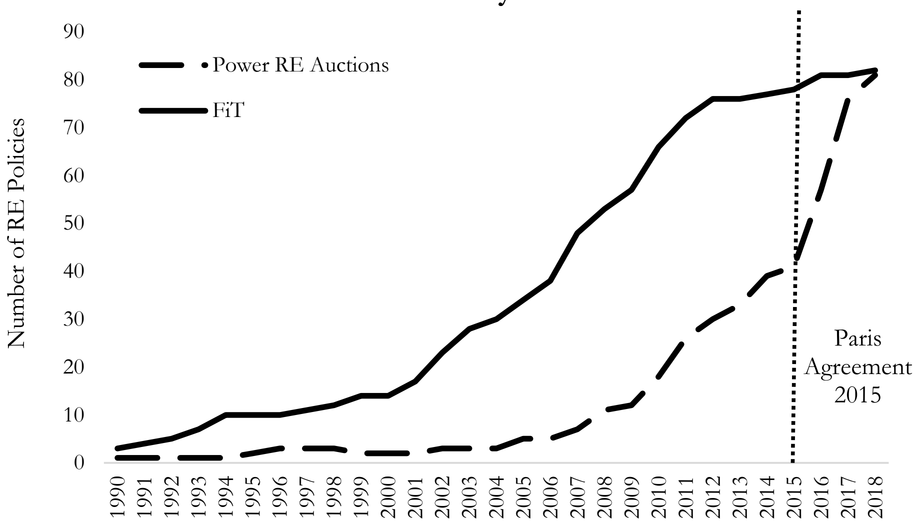


Source: Bento et al. (2020).

Price-based policy (FiT) and hybrid-based policy (auctions) are the most widely used instruments to promote renewable energy into the power industry. By the end of 2018, there were 113 jurisdictions (not necessarily countries since there are states or region level inside a country considered as jurisdictions) with FiT and 98 with auctions (IRENA, 2020). FiT has been used since the 1970s and, more recently, auctions started being implemented at the start of the 1990s. The United States, through the US PURPA policy, was the first country to implement an early version of the Feed-in policy in 1978. Likewise, United Kingdom, through the Non-Fossil Fuel Obligation, was the first country to implement auctions scheme in 1990 but the results were not very positive, so it was replaced by the RPS in 2002, although it reintroduced auctions system in 2011 (Woodman et al., 2019).

Figure 3 depicts that FiT scheme had been the most dynamic instrument for renewable energy development between 1990 and 2005, but interest has shifted away from FiT and towards competitive tendering schemes such as auctions, as a way to improve cost-effectiveness and increase control over renewable capacity levels (IRENA, 2020). Furthermore, this increased trend of auctions has gained traction since the Paris Agreement was signed in 2015.

Figure 3: Number of Countries that implemented FiT and auction in the power industry



Source: Elaborated by the author using data from IRENA, IEA, AURES II.

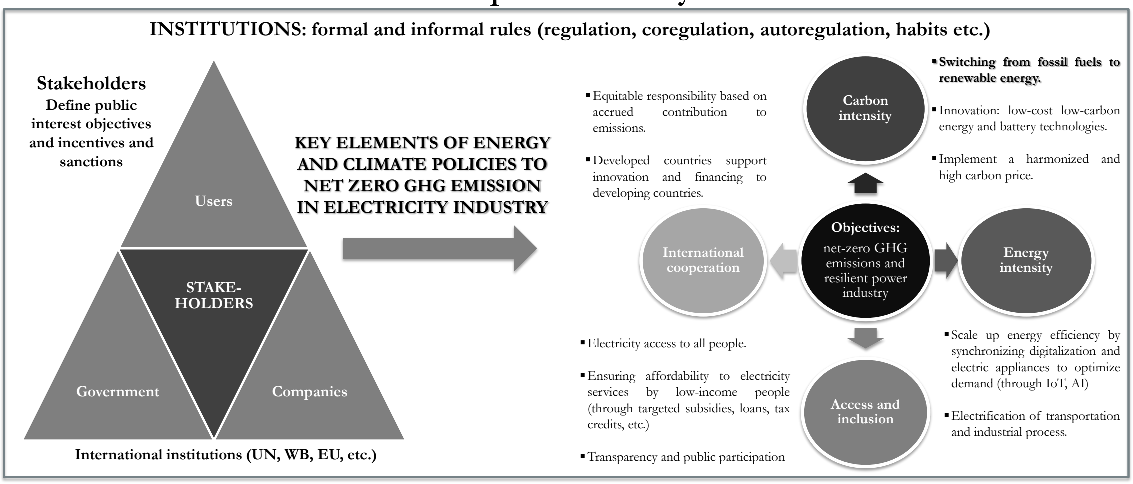
Nevertheless, policy regulation promoting renewable energy is only an instrument that needs to be complemented with others to tackle the climate change challenge. Since policy regulation is a means and not an end per se, the objectives of these instruments are set by stakeholders (users, companies, and governments) to achieve the public interest goals of each country. These targets can range from reaching net-zero greenhouse gas emissions to limit global temperature rise to 1.5°C above pre-industrial levels (between 1850 and 1900), getting a resilient power industry, etc. In the case of climate change, most countries worldwide agree on the objectives of reducing greenhouse emissions globally, but not necessarily on the institutions through which these objectives will be fulfilled.

The elements of energy and climate policies to address climate change could be focused on:

1) International cooperation since global warming is a global issue. According to Nordhaus (2021), international climate policy is still at a dead end because of the global free-rider and double externality problems (the social cost of fossil fuels and social benefits of clean energy technology not properly internalized). Moreover, international agreements (like Paris Agreement) are voluntary in participation and do not have costly penalties for non-participation. We do not have a global compact structure with carrots and sticks to tackle climate change, so developed countries could provide support for clean energy innovation and financing to developing countries given the greater responsibility of the first ones in the accrued contribution to greenhouse gas emissions.
2) Carbon intensity reduction through continuing switching from fossil fuels to renewable energy and to incentivize the innovation for low-carbon energy technology.
3) Energy intensity decreasing through scaling up energy efficiency by synchronizing digitalization and electric appliances to optimize demand (through IoT, AI) and the electrification of still challenging sectors such as transportation.
4) Access and inclusion mechanisms by providing electricity access to all worldwide population and making affordable the electricity service to low-income citizens through targeted subsidies, loans, tax credits, etc.

In **figure 4**, I summarize a framework for the formation of energy and climate policies to tackle climate change in the power industry.

Figure 4: Framework for energy and climate policies to address climate change in the power industry



Source: Elaborated by the author using information from IEA, Nordhaus (2021), Word in Our Data.

3. Data and methodology

3.1. Variables and data

In the empirical analysis, I used a sample of 129 countries for unbalanced panel data (though still strongly balanced) between 1990 and 2018. This dataset includes 79 and 69 countries that had implemented price-based policy (FiT) and hybrid-based policy (auctions) to promote renewable energy into the power industry up to 2018, respectively. By the end of 2018, 61% and 53% out of the total sample have implemented FiT and auction policies, respectively.

This study uses seven variables of which six could be categorized as controls of demand-shifter contributors (GDP and electricity consumption per capita), supply-shifter contributors (renewable electricity output share in total power generation and energy intensity), and policies (auction and FiT). **Figure 5** summarizes the variables and their respective sources used for the empirical analysis.

Figure 5: Variables and data sources

Type	Variables	Acronym	Units	Sources*	Means (sd**)
Outcome	CO2 emission per capita from power generation	emission	Metric tons per capita	IEA / Climate Watch	2.50 (3.56)
Independent variables					
Controls	GDP per capita	gdp	Purchasing power parity (PPP), constant 2017 international $)	World Bank	19,987 (20,034)
	Renewable energy into generation mix	reshare	% of total power generation	World Bank / IEA	34.01 (33.44)
	Energy intensity	eintensity	Power generation /GDP (kWh per $)	World Bank / EIA	0.20 (0.19)
	Electric power consumption (*Used only for matching*)	consum	kWh per capita	World Bank / IEA	3,943 (5,325)
Policy (Dummy variables)	RE auctions	rea	Dummy	World Bank, IEA, Aures II	0.11 (0.31)
	Feed-in policy	refit	Dummy	World Bank, IEA, Aures II	0.29 (0.45)

*Note: Energy Information Administration (EIA), International Energy Agency (IEA)
**Standard deviations (sd) in parentheses.

Figure 6 depicts a correlation matrix of CO2 emission per capita from power generation and their potential predictors. As one can expect CO2 emission per capita is positively correlated with GDP per capita and negatively correlated with renewable energy share into the generation mix. Conversely, CO2 emission per capita is positively correlated with energy intensity. Additionally, CO2 emission per capita is negatively correlated with auctions and FiT policies. Finally, GDP and electricity consumption per capita are weakly correlated with auctions policy.

Figure 6: Correlation matrix of the power generation CO2 emission per capita and potential predictors (sample of 129 countries)

	CO2 emission per capita	GDP per capita	RE auction (rea)	RE FiT (refit)	RE generation share	Energy intensity	Power consumption
CO2 emission per capita	1.000						
GDP per capita	0.606	1.000					
RE auction (rea)	-0.070	0.016	1.000				
RE FiT (refit)	-0.004	0.223	0.210	1.000			
RE generation share	0.474	0.265	-0.022	0.087	1.000		
Energy intensity	0.121	0.017	-0.075	-0.047	0.199	1.000	
Power consumption	0.518	0.715	-0.034	0.121	-0.053	0.387	1.000

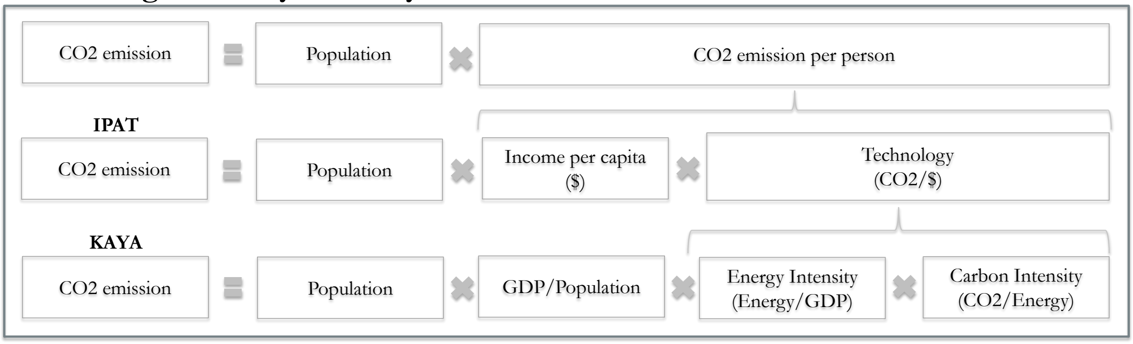
3.2. Methodology

I use three complementary methodologies to evaluate the drivers of CO2 emissions from power generation and to investigate the possible causal effect on CO2 emission of auction policy. First, I use Kaya's decomposition technique as a reference to have a first glance at the evolution of the main drivers of CO2 emissions from power generation. Second, I use a panel data approach for testing the relationship between renewable energy share in the generation mix and CO2 emissions per capita from power generation. Third, I use a matching procedure to investigate the possible causal effect on CO2 emission of auction policy promoting renewable energy in the power industry.

3.2.1. Kaya identity

In this study, I use Kaya identity as a reference to have a first glance at the evolution of the main drivers of CO2 emissions as cited by the Intergovernmental Panel on Climate Change - IPCC (Edenhofer et al., 2014). Kaya, developed by Japanese energy economist Yoichi Kaya in 1990, is one of the main ways to decompose the factors contributing to total emissions by the product of population, GDP per capita, energy intensity (energy/GDP), and the carbon intensity of the energy system (Edenhofer et al., 2014). **Figure 7** shows Kaya's decomposition of CO2 emission.

Figure 7: Kaya identity to break down the drivers of CO2 emissions



Source: Ourworldindata (2016).

3.2.2. Panel data

As a second empirical strategy, I want to test the relationship between renewable energy share in the generation mix and CO2 emissions per capita from power generation. In doing so, I considered as the determinants of the evolution of CO2 emission from power generation the GDP per capita, energy intensity, and renewable energy share in the generation mix (as a proxy of carbon intensity in the power industry). Thus, I estimate the following reduced-form equation:

$$\log(emission)_{it} = \beta_0 + \beta_2 X_{it} + \delta_t + \varepsilon_{it} \qquad (1)$$

i = 1,2,…129 t = 0,1,2...28.

Where:

- $emission_{it}$: CO2 emission per capita from power generation for country i and period t.
- X_{it}: a vector of control variables recognized in the literature as the main drivers of CO2 emission from power generation.
- δ_t: year dummies to control for yearly shocks, which are common to all countries. There are 29 dummy variables for each year from 1990 and 2018
- ε_{it}: error term.

Since the dataset used presents a panel structure, I use different techniques typically applied to this framework: pooled, random effects, fixed effects, and dynamic model. All models have their upsides and downsides (Verbeek, 2017). The main advantage of the **pooled model** is considered the effect of time-invariant explanatory variables, but it does not control for unobserved individual heterogeneity, and it only identifies the aggregate effect over a period (which could not be useful to examine changes in policies). The **fixed-effects** model does not consider the effect of time-invariant explanatory variables, but accounts for omitted time-invariant factors and identifies changes from one period to another which could be appropriate for policy evaluation. The **random-effects** model can capture the within and between variations of the data and is always efficient but could be inconsistent if random effects are correlated with independent variables. The **dynamic model** may be used in this study because the dependent variable (CO2 emission per capita) may show temporal inertia.

3.2.3. Matching

As a third empirical strategy, I want to investigate what are the possible effects on CO2 emission per capita of the main two policies promoting renewable energy in the generation mix: the price-based policy (FiT) and hybrid-based policy (auctions). In doing so, I introduce renewable energy policies (RE policy) into equation (1) but without considering renewable energy share into the generation mix because this is the intermediary output through which carbon intensity impacts the CO2 emission from power generation.

$$\log(emission)_{it} = \beta_0 + \beta_1 REpolicy_{it} + \beta_2 X_{it} + \delta_t + \varepsilon_{it} \qquad (2)$$

$i = 1,2,\ldots 129 \quad t = 0,1,2\ldots 28.$

Where:

- $RE\ policy_{it}$: dummy variable that takes a value of 1 when country i implemented Fit and/or auction instruments in the power industry in period t.

As the first step, I just estimate equation (2) by OLS to test for the statistical significance of these policies (Fit and auctions). As will be shown in the results section (4), only auction policy seems to be statistically significant. Although OLS regression attempts to simulate random assignment by controlling for observable variables that matter, it still faces omitted variables bias, systematic differences between groups other than the difference we are focused on (Angrist; Joshua D. & Pischke; Jörn-Steffen, 2015).

So, I use the matching procedure as a second step to create a valid counterfactual for applying auctions policy (treatment). Matching could eliminate the selection bias from a nonrandom sample by calculating sampling probabilities from a first stage logit conditioned on observable characteristics and then forming the treatment and control group based on these probabilities, so mimicking randomization (Jena et al., 2012).

To do so, I first estimate the probability of being treated conditional on the pre-existing observable characteristics that differ between treated and control groups with a logit model, obtaining the propensity score for each observation. Then, I match the observations in the treated and control groups with the propensity score using the first nearest neighbor algorithm (which matches treated observations with the control that has the closest propensity score). Next, it drops all the observations without common support and re-estimate equation (2).

Although the matching procedure reduces large biases in the sample, hidden biases may remain because matching only controls for observed variables. Additionally, matching is sensitive to a large sample, particularly, from control group observations.

3.3. Econometric issues

Before estimating any model specification, I performed some tests for possible problems of unit roots in the dependent variable, non-normality of variables, heteroscedasticity, and temporal autocorrelation in the error term.

The tests indicate that the dependent variable does not follow a unit roots, the variables do not seem to be normally distributed, the standard errors are not robust to heteroscedasticity, and have first-order autocorrelation (for further detail see **Appendix 1**). So, we correct heteroscedasticity and autocorrelation with the more robust clusters standard errors allowed by the data.

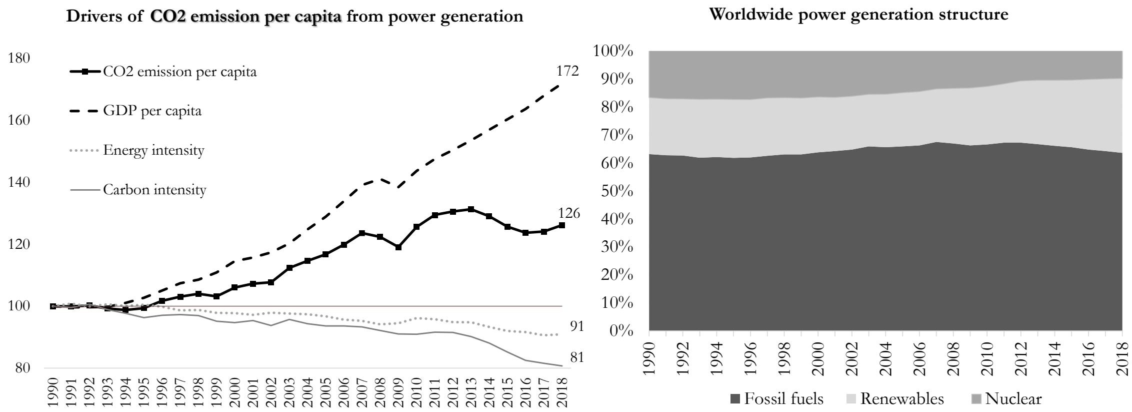
In the empirical analysis, there could be a possible endogeneity problem. Endogeneity may have different reasons such: unobserved individual heterogeneity stemming from countries (e.g. renewable energy potential natural resources), omitted variables (e.g. renewable technology cost reductions), simultaneous determination of dependent and independent variables, autocorrelation with lagged dependent variables, measurement errors in the explanatory variables, etc. We are dealing, partly, with this problem with the matching procedure.

4. Results

In this section, I present the results from Kaya's decomposition technique for identifying the main drivers of CO2 emissions from power generation, the panel data approach for testing the relationship between renewable energy share in the generation mix and CO2 emission, and matching procedure to estimate the possible causal effect on CO2 emission of auction policy promoting renewable energy in the power industry.

Figure 8 shows a decomposition of the factors contributing to CO2 emissions per capita from power generation that I elaborated on using data from official sources. As it is shown, GDP per capita is the main factor explaining the increase of CO2 emissions per capita while energy and carbon intensities act as factors pulling down the CO2 emission per capita. For example, switching from fossil fuels to renewable energy into the generation mix tends to lower the carbon intensity factor and, consequently, reduce CO2 emissions.

Figure 8: Kaya decomposition for main drivers of CO2 emissions per capita and power generation structure worldwide



Source: Elaborated by the author using data from Climate Watch, EIA, IEA, World Bank.

In **figure 9**, I summarize the results of coefficients estimated by different panel data models in logs to find out the magnitudes and signs of the main drivers of CO2 emission per capita from power generation: pooled, random effects, fixed effects, and dynamic models (for further detail see **Appendix 2**). Regardless of the model used all the drivers are statistically significant and have the expected signs, except for energy intensity which turned out to be positive correlated with the CO2 emission, probably, because of the rebound effects which could lead to an increase in energy consumption and greenhouse gas emissions (Chitnis et al., 2014) and only around one-third of final energy use is covered by policies that mandate energy efficiency improvements worldwide up to 2018 (IEA, 2020).

In our estimation, the carbon intensity indicator is captured by the renewable energy share in the generation mix. This driver was the main factor pulling down CO2 emissions in the power industry and has stable coefficients regardless of the model specification. The elasticities estimates are between -0.022 and -0.025, meaning that an increase of 10% percentage points in renewable energy share into the generation mix could reduce between 0.2% and 0.3% the CO2 emission per capita from power generation.

Figure 9: Summary of the estimates by panel data model specifications: log CO2 emission per capita from power generation (log emission)

Variables	Pooled	Random effects	Fixed effects	Dynamic AR(1)
Log GDP per capita (lgdp)	0.7616*** (0.1062)	0.6490*** (0.1716)	0.6016*** (0.1830)	0.4516*** (0.1028)
RE generation share (reshare)	-0.0250*** (0.0008)	-0.0225*** (0.0021)	-0.0219*** (0.0021)	-0.0231*** (0.0022)
Log energy intensity (leintensity)	0.5769*** (0.0387)	0.5769*** (0.1050)	0.5823*** (0.1068)	0.3116*** (0.0936)
Lag (controls)	Yes	Yes	Yes	Yes
Lag (log emission)				Yes
R^2	0.8688	0.8690	0.8680	-
Number observations	3,303	3,303	3,303	3,142

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

Since the structure of the still increasing share of removable energy into the generation mix is the main driver that counteracts the CO2 emission per capita from power generation, a natural step is to investigate the possible policies through which renewable energy has impacted the CO2 emissions from power generation. Particularly, we are interested in finding out the causal effect of price-based policy (FiT, a variable called refit) and hybrid-based policy (auctions, a variable called rea) being the most widely used instruments to promote renewable energy into power generation.

In **figure 11**, I start by estimating a simple OLS to dive into the statistical significance of these policies. Our results show that the coefficient of price-based policy (refit) is not statistically significant despite having the right sign. Meanwhile, hybrid-based policy (rea) is statistically significant and seems to be negative correlated with CO2 emission per capita from power generation. Consequently, **I focus only on auctions scheme (rea) as a possible policy through which renewable energy may affect CO2 emissions**. Although OLS regression attempts to simulate random assignment by controlling for observable variables, it still faces omitted variables bias.

Thus, I use the matching procedure to create a possible valid counterfactual from a nonrandom sample which could eliminate the selection bias by calculating sampling probabilities from a first stage logit conditioned on observable characteristics in the pre-treatment period and then forming the treatment and control group based on these probabilities. To this end, I have chosen GDP per capita and electricity consumption per capita because these observed covariates are not affected by the treatment (countries that have implemented or not auctions for renewable energy deployment into the power industry).

Accordingly, I can provide evidence that the treated and control groups had similar observable characteristics by performing an equality of means test for the explanatory variables (GDP and electricity consumption per capita) on the treated and control groups between 1990-1994 where auctions mechanism for renewable energy into power industry was not implemented at large scale. Although in this period, United Kingdom, through the

Non-Fossil Fuel Obligation, was the first and the only country that had implemented an early auction scheme in 1990 for renewable energy, the results were not very positive, so it was replaced by a quotas scheme (called RPS) in 2002 and later it reintroduced a modern auction system in 2011(Woodman et al., 2019). Despite this, I am considering 1990-1994 as a pre-treatment period. The null hypothesis of the t-test is equality of means of observable characteristics between control and treated groups in the pre-treatment period. In **figure 10**, the tests show that we cannot reject the null hypothesis, so there are no statistically significant differences (Diff) in the pre-existing characteristics of the treated and control groups (for further detail see **Appendix 3**). That is, there is evidence of similar observable pre-existing characteristics between treated and control groups.

Figure 10: T-test for observable characteristics in the pre-treatment period (1990-1994)

Variables	Mean		Ha: diff != 0	Results
	Treated	Control	Pr(|T| > |t|)	(ho)
GDP per capita* ($ per person)	16,073	16,425	0.748	Not reject (no Diff)
Power consumption per capita (kWh per person)	3,118	3,306	0.486	Not reject (no Diff)

*Note: GDP per capita is in Purchasing Power Parity o PPP) in constant 2017 international $ per person.

After matching the observations in the treated and control groups with the propensity score using the first nearest neighbor algorithm (which drops all the observations without common support), I re-estimate equation (2). As it is shown in **figure 11**, the coefficient of the auctions mechanism (rea) is statistically significant, meaning that countries that implemented auctions policy may have reduced their power generation CO2 emission than those that did not implement it (for further detail see **Appendix 4**).

Figure 11: Summary of the re-estimation of equation 1 by OLS, pooled and random effect models for the potential impact of auction on CO2 emission from power generation (log emission)

Variables	**OLS**	**Matching procedure**	
		Pooled	**Random effects**
RE auctions (rea)	-0.02382* (0.0142)	-0.0445* (0.0248)	-0.0294*** (0.0113)
Feed-in policy (refit)	-0.0035 (0.0081)		
Log GDP per capita (lgdp)	0.5897*** (0.1303)	0.9066*** (0.1845)	0.8889*** (0.2100)
Log energy intensity (leintensity)	0.2154** (0.1105)	0.2627 (0.2143)	0.3073** (0.1561)
Lag (log controls)	Yes	Yes	Yes
Lag (log emission)	Yes	Yes	Yes
R^2	0.9859	0.9884	0.9840
Number observations	3,284	398	398

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

5. Conclusions

This study sought to develop a cross-country assessment from a sample of 129 countries between 1990 and 2018 to evaluate the drivers of CO2 emission from power generation through a panel data approach and to estimate the possible causal effect on CO2 emission of auction policy promoting renewable energy into generation mix. To the best of my knowledge, this is the contribution of this study.

I have statistically confirmed that GDP per capita is the main driver pulling up CO2 emission per capita from power generation and carbon intensity is the main driver counteracting it. Furthermore, energy intensity turned out to be positive correlated with the CO2 emission, probably, because of the rebound effects which could lead to an increase energy consumption and greenhouse gas emissions, and only around one-third of final energy use is covered by policies that mandate energy efficiency improvements worldwide up to 2018.

Auction policy, as one way to promote renewable energy, seems to have a causal effect on CO2 emissions per capita from power generation in countries that implemented it compared to a control group of countries that did not implement this policy.

We also can draw some policy conclusions from the literature review and the results of this study:

1) Promoting renewable energy into the generation mix is one of the faster ways to decarbonize the electricity industry and is an easier way compared to other challenging sectors like transportation.
2) Auctions, which is a mix of price and quantity instruments, seem to be a good instrument to promote the introduction or the increase of renewable energy into power generation, particularly, in the context of downward-trend costs of renewable energy technologies (like solar and wind) which will lower the pressure to guarantee payments to renewable energy generators with FiT schemes. Furthermore, auctions are nowadays being using in the provision of renewable energy in rural and isolated areas and could a proper instrument to help in the transition from consumers to prosumers in a sharing economy context.
3) The promotion of renewable energy is only a policy that needs to be complemented with others to tackle climate change such as energy efficiency policies, electrification of the transportation sector, etc.
4) Countries worldwide agree on the objectives of reducing greenhouse emissions globally, but not necessarily on the institutions through which these objectives will be fulfilled and how the costs will be distributed among the countries. Since CO2 emission is a global issue plagued with free-rider and double externality problem and we do not have a global compact structure with carrots and sticks to tackle climate change, we need international cooperation where developed countries could provide support for clean energy innovation and financing to developing countries given the greater responsibility of the first ones in the accrued contribution to greenhouse gas emissions.

There are some caveats to be considered in this study:

1) CO2 emission from power generation comes from electricity and heat CO2 emissions which refer mainly, but not exclusively to electricity and heat but also includes auto producers and other energy industries (WRI, 2015). Nevertheless, it is a good proxy for CO2 emission from power generation.

2) Many countries have implemented different policies to promote renewable energy into the generation mix, so there are multiple promoting instruments apart from auctions and FiT with possible endogeneity implications.
3) Although the matching procedure reduces large biases in the sample, hidden biases may remain because matching only controls for observed variables. Additionally, matching is sensitive to a large sample, particularly, from control group observations.

Finally, policies promoting renewable energy may have been effective in reducing CO2 in the power industry in some countries or regions, but at what cost in terms of efficiency and equity (with possible distributional effects)? This a forthcoming research that I want to dig into in the future.

6. Appendices

6.1. Appendix 1: Tests for unit roots, multivariate normality, heteroscedasticity, and autocorrelation

For the dependent variable (CO2 emission per capita from power generation), I performed a fisher-type unit-root test based on augmented Dickey-Fuller for unbalanced panel data. The test indicates that the dependent variable does not follow a unit-roots, so there is a non-stationarity problem with this variable.

```
. xtunitroot fisher emission, dfuller lags(0)
(3 missing values generated)

Fisher-type unit-root test for emission
Based on augmented Dickey-Fuller tests
---------------------------------------
Ho: All panels contain unit roots           Number of panels       =    129
Ha: At least one panel is stationary        Avg. number of periods =  28.98

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 0 lags
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(258)  P       475.9949       0.0000
 Inverse normal            Z        -0.8713       0.1918
 Inverse logit t(634)      L*       -2.8956       0.0020
 Modified inv. chi-squared Pm        9.5967       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

I also perform the multivariate normality test (mvtest normality) to contrast the normality of the distribution of the analyzed variables. The null hypothesis of the test is that variables are normally distributed (Ho: The distribution of the variables is normal). This test shows that the null hypothesis of normality of all variables is rejected at the 1% level of significance (with $p < 0.01$), which means that the variables do not seem to be normally distributed. But normality problem is compensated when we have large-sample inference which is the case from our worldwide sample of 129 countries.

```
. mvtest normality emission gdp eintensity reshare consum rea refit

Test for multivariate normality

    Doornik-Hansen                  chi2(14) =74337.724   Prob>chi2 =  0.0000
```

Breusch-Pagan/Cook-Weisberg test for heteroscedasticity was performed. The null hypothesis (Ho) is that there is a constant variance (no heteroskedasticity). This test implies that we reject the null hypothesis of constant variance (homoskedasticity), so there is a problem of heteroskedasticity. Consequently, the standard errors are not robust to heteroscedasticity, and we will correct it by using the option "robust" in Stata when we estimate the regression.

```
      Source |       SS           df       MS      Number of obs   =     3,430
-------------+----------------------------------   F(33, 3396)     =    701.93
       Model |  9143.17629        33  277.065948   Prob > F        =    0.0000
    Residual |  1340.46186     3,396  .394717864   R-squared       =    0.8721
-------------+----------------------------------   Adj R-squared   =    0.8709
       Total |  10483.6382     3,429  3.05734563   Root MSE        =    .62827

------------------------------------------------------------------------------
   lemission |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         rea |  -.0526808   .0373457    -1.41   0.158    -.1259032    .0205415
       refit |   -.018706   .0270045    -0.69   0.489    -.0716528    .0342407
        lgdp |   .8960776   .0112921    79.35   0.000     .8739376    .9182176
     reshare |  -.0279784   .0003639   -76.88   0.000    -.0286919   -.0272649
 leintensity |   .7430134   .0142891    52.00   0.000     .7149973    .7710294
       year0 |  -.0184016   .0914028    -0.20   0.840    -.1976117    .1608085
       year1 |          0  (omitted)
       year2 |   .0620646   .0886076     0.70   0.484    -.1116649    .2357942
       year3 |   .0198959   .0880719     0.23   0.821    -.1527833    .1925751
       year4 |   .0416539   .0882906     0.47   0.637    -.1314541    .2147619
       year5 |   -.002982   .0867281    -0.03   0.973    -.1730266    .1670626
       year6 |   .0124636   .0868759     0.14   0.886    -.1578707    .1827979
       year7 |  -.0050705   .0868791    -0.06   0.953    -.1754111    .1652701
       year8 |   .0198159   .0870781     0.23   0.820     -.150915    .1905467
       year9 |  -.0350879   .0865599    -0.41   0.685    -.2048027    .1346268
      year10 |  -.0711575   .0864101    -0.82   0.410    -.2405786    .0982637
      year11 |  -.0792028   .0866112    -0.91   0.361    -.2490182    .0906127
      year12 |  -.0857187   .0864867    -0.99   0.322      -.25529    .0838526
      year13 |  -.1014944   .0862009    -1.18   0.239    -.2705054    .0675166
      year14 |  -.1201741   .0860585    -1.40   0.163    -.2889057    .0485575
      year15 |  -.1082044   .0861156    -1.26   0.209    -.2770481    .0606392
      year16 |   -.109607   .0860141    -1.27   0.203    -.2782516    .0590377
      year17 |  -.1038205   .0863708    -1.20   0.229    -.2731646    .0655236
      year18 |  -.1127725    .086508    -1.30   0.192    -.2823855    .0568406
      year19 |  -.1172867   .0866087    -1.35   0.176    -.2870971    .0525237
      year20 |  -.1187737   .0870883    -1.36   0.173    -.2895245     .051977
      year21 |  -.0935379   .0875406    -1.07   0.285    -.2651755    .0780997
      year22 |  -.0445563   .0878621    -0.51   0.612    -.2168242    .1277117
      year23 |  -.0944195   .0873666    -1.08   0.280    -.2657159    .0768769
      year24 |  -.0873459   .0873342    -1.00   0.317    -.2585787    .0838869
      year25 |  -.1225042   .0871937    -1.40   0.160    -.2934617    .0484534
      year26 |  -.1343807   .0878978    -1.53   0.126    -.3067186    .0379572
      year27 |  -.1443247   .0886354    -1.63   0.104    -.3181089    .0294595
      year28 |   -.095838   .0890458    -1.08   0.282    -.2704268    .0787508
       _cons |   -6.18377   .1338949   -46.18   0.000    -6.446293   -5.921247
------------------------------------------------------------------------------

. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity 
         Ho: Constant variance
         Variables: fitted values of lemission

         chi2(1)      =    37.21
         Prob > chi2  =   0.0000
```

Wooldridge test for autocorrelation is performed. The null hypothesis (Ho) is that does not exist a first-order autocorrelation. This test indicates that we reject the null hypothesis of no first-order autocorrelation at 1% of the statistical significance level, so we have an autocorrelation problem. This problem can be corrected by allowing for an arbitrary variance-covariance structure and by computing the standard errors in clusters by country.

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,     125) =     61.358
           Prob > F =      0.0000
```

6.2. Appendix 2: Panel data results

global ylist lemission
global xlist L(0/1).lgdp L(0/1).reshare L(0/1).leintensity year0 year1 year2 year3 year4 year5 year6 year7 year8 year9 year10 year11 year12 year13 year14 year15 year16 year17 year18 year19 year20 year21 year22 year23 year24 year25 year26 year27 year28

```
. xtpcse $ylist $xlist, correlation(psar1) hetonly

Number of gaps in sample:  18
(note: computations for rho restarted at each gap)
note: year0 omitted because of collinearity
note: year1 omitted because of collinearity
(note: estimates of rho outside [-1,1] bounded to be in the range [-1,1])

Prais-Winsten regression, heteroskedastic panels corrected standard errors

Group variable:   id_nro                        Number of obs     =      3,303
Time variable:    year                          Number of groups  =        127
Panels:           heteroskedastic (unbalanced)  Obs per group:
Autocorrelation:  panel-specific AR(1)                        min =          3
                                                              avg =  26.007874
                                                              max =         28
Estimated covariances      =       127          R-squared         =     0.8688
Estimated autocorrelations =       127          Wald chi2(33)     =    5229.31
Estimated coefficients     =        34          Prob > chi2       =     0.0000

------------------------------------------------------------------------------
             |           Het-corrected
   lemission |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        lgdp |
         --. |   .7615792   .0617618    12.33   0.000     .6405282    .8826301
         L1. |   .1998783   .0618736     3.23   0.001     .0786084    .3211482
             |
     reshare |
         --. |   -.024995   .0008126   -30.76   0.000    -.0265877   -.0234023
         L1. |  -.0031315   .0007703    -4.07   0.000    -.0046413   -.0016216
             |
 leintensity |
         --. |   .4195664   .0386888    10.84   0.000     .3437376    .4953951
         L1. |   .2184335   .0373352     5.85   0.000      .145258    .2916091
             |
       year0 |          0  (omitted)
       year1 |   .2296149   .0679151     3.38   0.001     .0965037    .3627262
       year2 |   .2457643   .0666884     3.69   0.000     .1150573    .3764712
       year3 |   .2363115   .0650041     3.64   0.000     .1089058    .3637172
       year4 |   .2242046   .0641109     3.50   0.000     .0985495    .3498597
       year5 |   .2094284   .0634134     3.30   0.001     .0851404    .3337164
       year6 |   .1924647   .0625273     3.08   0.002     .0699135    .3150159
       year7 |   .1801695   .0615355     2.93   0.003     .0595621     .300777
       year8 |   .1979669   .0606664     3.26   0.001      .079063    .3168708
       year9 |   .1430511   .0597727     2.39   0.017     .0258987    .2602035
      year10 |   .1050972   .0588182     1.79   0.074    -.0101844    .2203787
      year11 |   .0944125   .0579684     1.63   0.103    -.0192035    .2080285
      year12 |   .0777379   .0569369     1.37   0.172    -.0338564    .1893322
      year13 |   .0793736   .0559493     1.42   0.156    -.0302851    .1890323
      year14 |   .0647454   .0544948     1.19   0.235    -.0420624    .1715533
      year15 |   .0766629   .0529452     1.45   0.148    -.0271077    .1804335
      year16 |   .0867149   .0513251     1.69   0.091    -.0138804    .1873102
      year17 |   .0690625   .0496623     1.39   0.164    -.0282738    .1663988
      year18 |   .0515064   .0476559     1.08   0.280    -.0418975    .1449103
      year19 |   .0378245   .0460916     0.82   0.412    -.0525135    .1281625
      year20 |   .0487919   .0438562     1.11   0.266    -.0371647    .1347486
      year21 |    .034262   .0413871     0.83   0.408    -.0468552    .1153792
      year22 |   .0675289   .0384069     1.76   0.079    -.0077473    .1428051
      year23 |   .0583143   .0354179     1.65   0.100    -.0111034     .127732
      year24 |   .0744177    .031765     2.34   0.019     .0121594    .1366761
      year25 |   .0458045    .027797     1.65   0.099    -.0086766    .1002856
      year26 |   .0191979   .0226531     0.85   0.397    -.0252014    .0635972
      year27 |   .0003932    .015765     0.02   0.980    -.0305057    .0312921
      year28 |          0  (omitted)
       _cons |  -7.173565   .3932228   -18.24   0.000    -7.944268   -6.402863
-------------+----------------------------------------------------------------
      rhos =  .8612471          1          1  .8140264  .9996219 ...          1
------------------------------------------------------------------------------
```

```
. xtreg $ylist $xlist, robust re cluster (id_nro)
note: year0 omitted because of collinearity
note: year28 omitted because of collinearity

Random-effects GLS regression                   Number of obs     =      3,303
Group variable: id_nro                          Number of groups  =        127

R-sq:                                           Obs per group:
     within  = 0.5936                                         min =          3
     between = 0.8700                                         avg =       26.0
     overall = 0.8690                                         max =         28

                                                Wald chi2(33)     =    1515.94
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000

                               (Std. Err. adjusted for 127 clusters in id_nro)
------------------------------------------------------------------------------
             |               Robust
   lemission |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        lgdp |
         --. |   .6490333   .1715932     3.78   0.000     .3127168    .9853498
         L1. |   .2179795   .1770826     1.23   0.218     -.129096     .565055
             |
     reshare |
         --. |  -.0225271    .002075   -10.86   0.000     -.026594   -.0184601
         L1. |  -.0010931    .001495    -0.73   0.465    -.0040231     .001837
             |
  leintensity |
         --. |   .5769041   .1049585     5.50   0.000     .3711893     .782619
         L1. |   .1188968   .0893168     1.33   0.183     -.056161    .2939545
             |
       year0 |          0  (omitted)
       year1 |   .1601129   .0582555     2.75   0.006     .0459342    .2742916
       year2 |   .1862397   .0548326     3.40   0.001     .0787697    .2937096
       year3 |   .1921898   .0518466     3.71   0.000     .0905723    .2938074
       year4 |   .1873927    .053468     3.50   0.000     .0825973     .292188
       year5 |   .1607634   .0490362     3.28   0.001     .0646541    .2568726
       year6 |   .1577918   .0474015     3.33   0.001     .0648867     .250697
       year7 |   .1486179   .0428246     3.47   0.001     .0646831    .2325526
       year8 |   .1732297   .0438441     3.95   0.000     .0872969    .2591626
       year9 |   .1166042   .0442702     2.63   0.008     .0298363    .2033721
      year10 |   .0841189   .0414688     2.03   0.043     .0028416    .1653962
      year11 |   .0770407   .0435449     1.77   0.077    -.0083058    .1623871
      year12 |   .0569584   .0444404     1.28   0.200    -.0301431      .14406
      year13 |   .0544121   .0448913     1.21   0.225    -.0335733    .1423975
      year14 |   .0406199   .0430639     0.94   0.346    -.0437838    .1250235
      year15 |   .0506625   .0414416     1.22   0.222    -.0305615    .1318866
      year16 |   .0668886   .0411315     1.63   0.104    -.0137277    .1475048
      year17 |   .0557108   .0398247     1.40   0.162    -.0223442    .1337658
      year18 |   .0373382   .0429313     0.87   0.384    -.0468057     .121482
      year19 |    .012896   .0446723     0.29   0.773    -.0746601     .100452
      year20 |   .0179669   .0388692     0.46   0.644    -.0582153    .0941492
      year21 |   .0133416   .0374821     0.36   0.722    -.0601219    .0868051
      year22 |   .0547145   .0375673     1.46   0.145    -.0189161    .1283451
      year23 |   .0321933   .0406868     0.79   0.429    -.0475514     .111938
      year24 |   .0490645   .0367906     1.33   0.182    -.0230438    .1211727
      year25 |   .0227883   .0296524     0.77   0.442    -.0353293    .0809059
      year26 |   .0076778   .0253977     0.30   0.762    -.0421007    .0574563
      year27 |  -.0109849   .0200357    -0.55   0.584    -.0502542    .0282844
      year28 |          0  (omitted)
       _cons |  -6.329114   .6505703    -9.73   0.000    -7.604208   -5.054019
-------------+----------------------------------------------------------------
     sigma_u |  .44401706
     sigma_e |  .26354067
         rho |  .73948828   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Fixed-effects (within) regression | Number of obs = 3,303
Group variable: id_nro | Number of groups = 127

R-sq: | Obs per group:
within = 0.5940 | min = 3
between = 0.8681 | avg = 26.0
overall = 0.8680 | max = 28

| F(33,126) = 33.17
corr(u_i, Xb) = 0.3201 | Prob > F = 0.0000

(Std. Err. adjusted for 127 clusters in id_nro)

lemission	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
lgdp						
--.	.6016168	.1830824	3.29	0.001	.2393022	.9639315
L1.	.2228276	.1869306	1.19	0.235	-.1471025	.5927576
reshare						
--.	-.021872	.002139	-10.23	0.000	-.0261051	-.0176389
L1.	-.0003315	.0015434	-0.21	0.830	-.0033859	.0027229
leintensity						
--.	.5822891	.1068385	5.45	0.000	.3708589	.7937193
L1.	.1093134	.0904945	1.21	0.229	-.0697726	.2883993
year0	0	(omitted)				
year1	.1321961	.0700148	1.89	0.061	-.0063611	.2707534
year2	.1603356	.0675659	2.37	0.019	.0266246	.2940466
year3	.1672911	.063253	2.64	0.009	.0421153	.2924669
year4	.1602533	.0643119	2.49	0.014	.032982	.2875246
year5	.137557	.0617378	2.23	0.028	.0153798	.2597343
year6	.1345838	.0600772	2.24	0.027	.0156929	.2534748
year7	.1279887	.0533011	2.40	0.018	.0225073	.2334701
year8	.1550025	.05467	2.84	0.005	.0468122	.2631928
year9	.0992997	.0553845	1.79	0.075	-.0103046	.208904
year10	.0684868	.0504613	1.36	0.177	-.0313747	.1683483
year11	.0630732	.0508336	1.24	0.217	-.037525	.1636714
year12	.0441479	.051875	0.85	0.396	-.0585112	.146807
year13	.0428723	.0524124	0.82	0.415	-.0608503	.1465948
year14	.0311222	.049968	0.62	0.535	-.067763	.1300073
year15	.0430176	.0466921	0.92	0.359	-.0493847	.1354199
year16	.061657	.0446805	1.38	0.170	-.0267643	.1500784
year17	.0536027	.0429358	1.25	0.214	-.031366	.1385713
year18	.0358863	.044263	0.81	0.419	-.0517088	.1234814
year19	.0086606	.0456211	0.19	0.850	-.0816221	.0989434
year20	.0141744	.0398316	0.36	0.723	-.0646512	.0930001
year21	.0102095	.0382176	0.27	0.790	-.065422	.0858411
year22	.0528602	.0380355	1.39	0.167	-.0224109	.1281313
year23	.0296797	.0407095	0.73	0.467	-.0508831	.1102426
year24	.0462215	.0359494	1.29	0.201	-.0249212	.1173643
year25	.0215051	.0290433	0.74	0.460	-.0359707	.078981
year26	.0080645	.0246588	0.33	0.744	-.0407346	.0568635
year27	-.0095019	.0198281	-0.48	0.633	-.0487412	.0297373
year28	0	(omitted)				
_cons	-5.92568	.9514103	-6.23	0.000	-7.808493	-4.042867
sigma_u	.70771301					
sigma_e	.26354067					
rho	.87821796	(fraction of variance due to u_i)				

```
. xtabond $ylist $xlist, robust
note: year0 dropped from div() because of collinearity
note: year1 dropped from div() because of collinearity
note: year0 dropped because of collinearity
note: year1 dropped because of collinearity

Arellano-Bond dynamic panel-data estimation     Number of obs     =      3,142
Group variable: id_nro                          Number of groups  =        126
Time variable: year
                                                Obs per group:
                                                              min =          2
                                                              avg =   24.93651
                                                              max =         27

Number of instruments =    412                  Wald chi2(34)     =    2667.74
                                                Prob > chi2       =     0.0000
One-step results
                                  (Std. Err. adjusted for clustering on id_nro)
------------------------------------------------------------------------------
             |               Robust
   lemission |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   lemission |
         L1. |   .6646601   .0492614    13.49   0.000     .5681096    .7612106
             |
        lgdp |
         --. |   .4515662   .1027998     4.39   0.000     .2500823    .6530501
         L1. |  -.3459391   .0916517    -3.77   0.000    -.5255731   -.1663052
             |
     reshare |
         --. |  -.0231269   .0022444   -10.30   0.000    -.0275259   -.0187279
         L1. |   .0159497   .0018375     8.68   0.000     .0123482    .0195513
             |
 leintensity |
         --. |   .3116829   .0936251     3.33   0.001      .128181    .4951847
         L1. |   -.074468   .0878786    -0.85   0.397    -.2467069    .0977708
             |
       year2 |   .0026571   .0211047     0.13   0.900    -.0387074    .0440216
       year3 |  -.0089042   .0204184    -0.44   0.663    -.0489235    .0311151
       year4 |  -.0183269   .0284953    -0.64   0.520    -.0741766    .0375229
       year5 |  -.0077273   .0233188    -0.33   0.740    -.0534314    .0379767
       year6 |  -.0111933    .021826    -0.51   0.608    -.0539714    .0315848
       year7 |  -.0066731   .0247036    -0.27   0.787    -.0550912     .041745
       year8 |   .0286125   .0283617     1.01   0.313    -.0269754    .0842004
       year9 |  -.0384469   .0281459    -1.37   0.172    -.0936119    .0167181
      year10 |  -.0310446   .0300883    -1.03   0.302    -.0900166    .0279275
      year11 |  -.0107751   .0325176    -0.33   0.740    -.0745084    .0529581
      year12 |  -.0192057   .0259502    -0.74   0.459    -.0700671    .0316557
      year13 |  -.0003008   .0330104    -0.01   0.993    -.0649999    .0643983
      year14 |  -.0201343   .0345313    -0.58   0.560    -.0878145    .0475459
      year15 |   .0122529   .0372265     0.33   0.742    -.0607097    .0852155
      year16 |   .0258595   .0458355     0.56   0.573    -.0639765    .1156954
      year17 |   .0039114   .0474658     0.08   0.934    -.0891198    .0969425
      year18 |  -.0016495   .0489573    -0.03   0.973     -.097604     .094305
      year19 |   -.010134   .0507186    -0.20   0.842    -.1095406    .0892726
      year20 |   .0160439   .0505352     0.32   0.751    -.0830032    .1150911
      year21 |   .0060112   .0514506     0.12   0.907    -.0948301    .1068525
      year22 |   .0484741   .0535992     0.90   0.366    -.0565784    .1535266
      year23 |   .0201071   .0577044     0.35   0.728    -.0929915    .1332057
      year24 |   .0473882   .0614628     0.77   0.441    -.0730768    .1678531
      year25 |   .0067596   .0590224     0.11   0.909    -.1089221    .1224414
      year26 |   .0092714   .0607272     0.15   0.879    -.1097518    .1282946
      year27 |   .0067029   .0588831     0.11   0.909    -.1087058    .1221116
      year28 |   .0291243   .0636402     0.46   0.647    -.0956083    .1538569
       _cons |  -.3449794     .92171    -0.37   0.708    -2.151498    1.461539
------------------------------------------------------------------------------
Instruments for differenced equation
        GMM-type: L(2/.).lemission
        Standard: D.lgdp LD.lgdp D.reshare LD.reshare D.leintensity
                  LD.leintensity D.year2 D.year3 D.year4 D.year5 D.year6
                  D.year7 D.year8 D.year9 D.year10 D.year11 D.year12
                  D.year13 D.year14 D.year15 D.year16 D.year17 D.year18
                  D.year19 D.year20 D.year21 D.year22 D.year23 D.year24
                  D.year25 D.year26 D.year27 D.year28
Instruments for level equation
        Standard: _cons
```

6.3. Appendix 3: Matching results

```
. global treatment reatreated

. global ylist emission

. global xlist gdp consum if year<=1994

. global breps 10000

. psmatch2 $treatment $xlist, outcome($ylist) n(1) common logit qui
```

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
emission	Unmatched	2.47332334	1.67349019	.799833151	.240949915	3.32
	ATT	2.39550151	2.6449544	-.249452897	.332242321	-0.75

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support Off suppo	On suppor	Total
Untreated	0	255	255
Treated	5	329	334
Total	5	584	589

```
. pstest $xlist, t($treatment)
```

Variable	Mean Treated	Mean Control	%bias	t-test t	t-test p>|t|	V(T)/V(C)
gdp	16073	16425	-2.1	-0.32	0.748	1.30*
consum	3118.3	3305.6	-4.5	-0.70	0.486	2.03*

* if variance ratio outside [0.81; 1.24]

Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
0.001	0.62	0.733	3.3	3.3	6.2	2.13*	100

* if B>25%, R outside [0.5; 2]

6.4. Appendix 4: Policy data results

global ylist lemission
global xlist rea refit L(0/1).lgdp L(0/1).leintensity L1.lemission year0 year1 year2 year3 year4 year5 year6 year7 year8 year9 year10 year11 year12 year13 year14 year15 year16 year17 year18 year19 year20 year21 year22 year23 year24 year25 year26 year27 year28

```
. reg $ylist $xlist, robust cluster (id_nro)
note: year0 omitted because of collinearity
note: year1 omitted because of collinearity

Linear regression                               Number of obs     =      3,284
                                                F(34, 126)        =   16725.40
                                                Prob > F          =     0.0000
                                                R-squared         =     0.9859
                                                Root MSE          =     .20476

                                (Std. Err. adjusted for 127 clusters in id_nro)
------------------------------------------------------------------------------
             |               Robust
   lemission |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         rea |  -.0238208   .0141471    -1.68   0.095    -.0518175    .0041758
       refit |  -.0034501   .0081321    -0.42   0.672    -.0195433    .0126431
             |
        lgdp |
         --. |   .5897176   .1303526     4.52   0.000     .3317536    .8476817
         L1. |  -.5719625   .1300278    -4.40   0.000    -.8292836   -.3146414
             |
 leintensity |
         --. |   .2154199   .1105697     1.95   0.054    -.0033943    .4342341
         L1. |  -.2120665   .1075587    -1.97   0.051     -.424922    .0007889
             |
   lemission |
         L1. |     .97604   .0064491   151.35   0.000     .9632775    .9888026
             |
       year0 |          0  (omitted)
       year1 |          0  (omitted)
       year2 |    -.00298   .0314395    -0.09   0.925    -.0651979    .0592379
       year3 |  -.0723761   .0323727    -2.24   0.027    -.1364406   -.0083115
       year4 |  -.0288674   .0319018    -0.90   0.367    -.0920002    .0342653
       year5 |  -.0115458   .0316808    -0.36   0.716    -.0742412    .0511497
       year6 |  -.0405378   .0281458    -1.44   0.152    -.0962375     .015162
       year7 |  -.0100762   .0258587    -0.39   0.697    -.0612498    .0410975
       year8 |   .0086679   .0260762     0.33   0.740    -.0429362     .060272
       year9 |  -.0857348   .0304513    -2.82   0.006     -.145997   -.0254725
      year10 |  -.0620007   .0289494    -2.14   0.034    -.1192906   -.0047107
      year11 |  -.0194838   .0247049    -0.79   0.432     -.068374    .0294064
      year12 |  -.0437707   .0300659    -1.46   0.148    -.1032702    .0157287
      year13 |  -.0256112   .0212772    -1.20   0.231    -.0677182    .0164958
      year14 |  -.0507443   .0286055    -1.77   0.078    -.1073538    .0058652
      year15 |  -.0201688   .0231203    -0.87   0.385    -.0659231    .0255856
      year16 |   -.008336   .0266589    -0.31   0.755    -.0610932    .0444212
      year17 |  -.0396949   .0288296    -1.38   0.171    -.0967477     .017358
      year18 |  -.0616604   .0253096    -2.44   0.016    -.1117473   -.0115735
      year19 |    -.06615   .0289952    -2.28   0.024    -.1235306   -.0087694
      year20 |  -.0489842   .0319825    -1.53   0.128    -.1122766    .0143082
      year21 |   -.011347    .023382    -0.49   0.628    -.0576193    .0349253
      year22 |  -.0128479     .02534    -0.51   0.613    -.0629951    .0372992
      year23 |  -.0705975   .0245232    -2.88   0.005    -.1191281   -.0220669
      year24 |  -.0119715   .0289294    -0.41   0.680    -.0692218    .0452789
      year25 |  -.0466192    .031824    -1.46   0.145    -.1095979    .0163594
      year26 |   -.028527   .0243975    -1.17   0.245     -.076809     .019755
      year27 |  -.0574012    .030874    -1.86   0.065    -.1185001    .0036976
      year28 |  -.0479332   .0292203    -1.64   0.103    -.1057593    .0098928
       _cons |  -.1219043   .0727692    -1.68   0.096    -.2659123    .0221038
------------------------------------------------------------------------------
```

```
. xtpcse $ylist $xlist if _support==1, correlation(psar1) hetonly
(note: rho_i could not be computed for panel id_nro 32;
       assumed to be 0.)
(note: rho_i could not be computed for panel id_nro 39;
       assumed to be 0.)
(note: rho_i could not be computed for panel id_nro 40;
       assumed to be 0.)
(note: rho_i could not be computed for panel id_nro 52;
       assumed to be 0.)
(note: rho_i could not be computed for panel id_nro 105;
       assumed to be 0.)
(note: estimates of rho outside [-1,1] bounded to be in the range [-1,1])

Prais-Winsten regression, heteroskedastic panels corrected standard errors

Group variable:   id_nro                        Number of obs     =        398
Time variable:    year                          Number of groups  =        111
Panels:           heteroskedastic (unbalanced)  Obs per group:
Autocorrelation:  panel-specific AR(1)                        min =          1
                                                              avg =  3.5855856
                                                              max =          4
Estimated covariances      =       111          R-squared         =     0.9884
Estimated autocorrelations =       111          Wald chi2(6)      =   24840.70
Estimated coefficients     =         7          Prob > chi2       =     0.0000

------------------------------------------------------------------------------
             |           Het-corrected
   lemission |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         rea |  -.0444833   .0248166    -1.79   0.073    -.0931229    .0041563
             |
        lgdp |
         --. |   .9066033   .1845038     4.91   0.000     .5449825    1.268224
         L1. |  -.8283742   .1826124    -4.54   0.000    -1.186288   -.4704604
             |
 leintensity |
         --. |    .262709   .2143849     1.23   0.220    -.1574777    .6828956
         L1. |  -.2525523   .2159613    -1.17   0.242    -.6758287     .170724
             |
   lemission |
         L1. |   .9369967   .0156581    59.84   0.000     .9063073    .9676861
             |
       _cons |  -.6959384   .2059564    -3.38   0.001    -1.099606   -.2922712
-------------+----------------------------------------------------------------
        rhos = -.1322415   -.939013   -.013209  .7557878 -.0118611 ...   .5127978
------------------------------------------------------------------------------
```

```
. xtreg $ylist $xlist if _support==1, robust re cluster (id_nro)

Random-effects GLS regression                   Number of obs     =        398
Group variable: id_nro                          Number of groups  =        111

R-sq:                                           Obs per group:
     within  = 0.1777                                         min =          1
     between = 0.9943                                         avg =        3.6
     overall = 0.9840                                         max =          4

                                                Wald chi2(6)      =   34755.40
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000

                              (Std. Err. adjusted for 111 clusters in id_nro)
------------------------------------------------------------------------------
             |               Robust
   lemission |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         rea |  -.0294277   .0112492    -2.62   0.009    -.0514757   -.0073797
             |
        lgdp |
         --. |   .8889274   .2100415     4.23   0.000     .4772537    1.300601
         L1. |  -.8393678   .2042602    -4.11   0.000     -1.23971   -.4390252
             |
 leintensity |
         --. |   .3073096   .1561381     1.97   0.049     .0012846    .6133346
         L1. |  -.2984098   .1615402    -1.85   0.065    -.6150228    .0182033
             |
   lemission |
         L1. |   .9562163   .0179465    53.28   0.000     .9210418    .9913908
             |
       _cons |  -.4430213   .2347644    -1.89   0.059    -.9031511    .0171085
-------------+----------------------------------------------------------------
     sigma_u |  .09439322
     sigma_e |  .19234506
         rho |  .19409105   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

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