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Institutional and macroeconomic stability mediate the effect of auctions on renewable energy capacity

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ABSTRACT

Renewable energy (RE) auctions have become an increasingly popular policy instrument for decarbonizing the global energy matrix, and have been rapidly adopted by several countries worldwide. Previous research has used data from higher-income countries and two-way fixed effects models to estimate the impact of auctions on RE capacity, mostly with favorable results. However, these studies did not account for heterogeneous treatment effects across units to explore whether auctions are also effective in countries with unstable business environments. We analyze whether auctions also foster RE in countries experiencing macroeconomic instability or poor institutional quality. For this purpose, this study has drawn from multiple publicly available databases to build a dataset comprising 98 countries from 2000 to 2020. Our definition of RE includes solar, wind, and biomass sources. We first cluster countries by the quality of their business environment and then perform a differences-in-differences analysis considering staggered treatment adoption. We find that auctions positively affect RE capacity, yet the average treatment effects are higher for countries with better business environments. Thus, governments should exercise caution in adopting this instrument, especially in countries that experience macroeconomic or institutional instability. At the same time, dynamic treatment effects suggest that the policy needs time to show results.

1. Introduction

Energy systems account for the largest share of global anthropogenic greenhouse gas (GHG) emissions (Lamb et al., 2021). Approximately 70% of those energy-related emissions come from electricity and heat production to supply energy to industries and private housing (Dhakal et al., 2022). Thus, the rapid economic growth in low and middle-income countries is expected to increase their energy-related GHG emissions (Henriques and Borowiecki, 2017). Therefore, low-carbon electricity systems predominantly based on renewables must keep temperatures 1.5° below preindustrial levels (IPCC, 2022).

Many countries worldwide are decarbonizing their energy matrixes through renewable energy (RE) sources. This transition toward low-carbon energy systems has been supported by policies aiming to create an enabling environment for investments in this type of technology (Jordan and Huitema, 2014). RE auctions are examples of the institutional innovation being used to promote renewables. This policy has become increasingly popular recently, gradually replacing administratively established incentives, such as feed-in tariffs and RE tradable green certificates (Fitch-Roy et al., 2019; Grashof, 2021). RE auctions synthesize elements from price-based and quantity-based policies, ensuring fair remuneration for RE projects while avoiding excessive support costs (IRENA and CEM, 2015). Consequently, even low and middle-income countries without a track record in RE policies have adopted RE auctions (IRENA, 2019; Viscidi and Yepez, 2019).

A growing body of literature analyzes the effects of various policies on the deployment of RE (Bento et al., 2020; Bersalli et al., 2020; Jenner et al., 2013; Kersey et al., 2021; Kilinc-Ata, 2016; Liu et al., 2021; Romano et al., 2017). Although the evidence on auctions is still thin, several studies suggest they are an effective policy instrument (Bento et al., 2020; Bersalli et al., 2020; Jenner et al., 2013; Kilinc-Ata, 2016). Most of these studies, however, primarily focus on stable OECD or European economies. Despite the global optimism surrounding auctions and their rapid adoption, whether they are an appropriate instrument for all countries remains an open question. Furthermore, RE projects tend to be capital intensive (Mazzucato and Semieniuk, 2018) and

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involve lengthy and somewhat uncertain payback periods; these economic and political risks can undermine investors' willingness to fund RE (Gatzert and Vogl, 2016). This is especially relevant for many low-income countries, where the business environment is usually affected by devaluation, inflation, sovereign debt crises, a weak rule of law, ineffective contract enforcement, and political volatility. Evaluating auctions in such contexts is relevant because most of the renewable potential is in low- and middle-income countries, where we expect electricity demand to rise (Vanegas Cantarero, 2020).

We build on this body of literature by analyzing whether the impact of RE auctions varies according to the quality of the business environment in countries that have adopted RE auctions. The business environment comprises macroeconomic stability and institutional quality. Drawing from multiple publicly available databases, we have constructed a panel dataset for the 2000–2020 period, covering 98 countries with distinct macroeconomic and institutional profiles. In particular, we address the following research questions: 1) Do RE auctions affect the deployment of RE in contexts of macroeconomic instability and poor institutional quality? and 2) Does the effectiveness of auctions in promoting investments in RE vary across different technologies (i.e., solar, wind, and biomass)?

To our knowledge, this is the first quantitative study that uses data from many countries with varying macroeconomic and institutional conditions to analyze the effects of RE auctions in different business environments. Furthermore, we make an empirical contribution using two novel differences-in-differences (DiD) estimators for staggered treatment adoption (Callaway and Sant'Anna, 2021; Gardner, 2021), which allows us to account for heterogeneous treatment effects and differential timing and compare these results with those of the more traditional two-way fixed effects (TWFE) approach.

The remainder of this paper is structured as follows: Section 2 describes the conceptual nexus between auctions, RE capacity, and how the quality of the business environment may affect, theoretically, the efficiency of this policy instrument. Section 3 describes the primary data sources, and Section 4 details the empirical strategy used in the paper. Section 5 shows the results of our empirical analysis, which are then discussed in Section 6. The final section presents policy implications and further research opportunities.

2. Auctions, renewable capacity, and the business environment

In RE auctions, the government calls for tenders to procure a certain amount of RE capacity, RE generation, or a fixed total budget, and companies compete to supply those volumes. Although a growing body of literature has recently analyzed the efficiency of different policies to foster RE capacity, empirical evidence on auctions is still scarce. Jenner et al. (2013) studied the effect of several RE policies from 1992 to 2008 for 26 European countries. The authors found mixed results, in which tendering schemes have positive results in interaction with feed-in tariffs for wind but not for solar capacity. Kilinc-Ata (2016) studied 27 EU countries and 50 U.S. states from 1990 to 2008 and found a positive but modest impact of auctions over the share of RE capacity. A similar result was found by Bento et al. (2020) for 20 OECD economies in the period 2004–2014, showing that the implementation of auctions results in higher investments in RE for the period but emphasizing that the implementation conditions are essential for these mechanisms to work (they illustrate this using Italy as an example, where there was a downturn in the investments after the first policy change).

The previous results were found largely in developed economies, whose macroeconomic variables and institutional conditions are normally more stable. Studies focusing on lower and middle-income countries often research a few case studies and use qualitative assessments. For example, Winkler et al. (2018) and Bayer et al. (2018) used six and four country cases, respectively, and neither of them is conclusive regarding the effectiveness of tendering mechanisms. Studies that focused on particular countries, such as Brazil (Bayer, 2018), South Africa (Kitzing et al., 2022), and India (Shrimali et al., 2016), also showed inconclusive results regarding the effects of auctions. To the best of our knowledge, only two papers include a quantitative assessment of auctions in a more comprehensive study design, including not only OECD or European countries but also low and middle-income countries. Hille and Oelker (2023) included a sample of 189 countries for 2005–2018 and found a positive impact of tendering schemes over solar and wind installed capacity. Bersalli et al. (2020) included a set of 30 European and 20 Latin American countries and found that auctions positively affect the yearly rate of RE added capacity. *Appendix A* presents a more detailed synopsis of the literature review.

Even when some of the presented papers include a more comprehensive sample of countries, none specifically addresses the role of institutional and macroeconomic aspects on the efficiency of auctions over the rate of RE capacity. This question is relevant, however, considering that auctions have become a popular policy instrument in recent years. According to the IEA (2021), the volume of RE capacity auctioned has quadrupled between 2015 and 2020. By 2020, 116 countries had held auctions at least once (REN, 2021, p. 40). Most recent newcomers to auctions are countries in Asia, South America, and Sub-Saharan Africa, which usually face macroeconomic instability and lower institutional quality compared with OECD or European countries. Can auctions perform well in countries with unstable business environments despite their rapid adoption? Authors who have explored the role of institutional quality over the deployment of RE in the energy matrix (Cadoret and Padovano, 2016; Sequeira and Santos, 2018; Uzar, 2020) have proposed that democratization and good institutional quality have a positive impact in the long run on RE investments. However, this paper is concerned with how the quality of the business environment may condition the efficiency of RE auctions to promote RE capacity.

Some features of auctions make them a suitable instrument to promote RE in countries with weak business environments. The first element is the reduction of information asymmetries between energy buyers and sellers (IRENA and CEM, 2015). The government only partially knows the actual marginal costs of the energy produced, leading to a potential overcompensation of costs (especially for mature technologies). Auctions promote competition and encourage price discovery, reducing public expenses to remunerate RE (Barnea et al., 2022; Polzin et al., 2019). Tendering schemes also allow better control of the volumes provided (del Río, 2017). Therefore, countries with limited public budgets might benefit from auctions, which are cost effective for procuring RE. A second argument relates to risk mitigation for the government and private investors. Auction winners sign a legally binding agreement (usually a long-term contract) that specifies the quantity to supply and the price received. This provides more robust warranties to investors against sudden policy changes (IRENA, 2017). Polzin et al. (2019) proposed that auctions effectively reduce risks and contribute to attracting early-stage capital. Enforcement issues, potential penalties, and conflict settlement are more evident within this legal framework. Moreover, auctions can be designed to provide clear-cut safeguards against inflation or devaluation (Viscidi and Yepez, 2019). From the policymaker's side, financial or physical prequalifications usually improve the instrument's effectiveness (Matthäus, 2020).

However, depending on the macroeconomic and institutional settings in which auctions are held, they could be less effective in deploying RE or may even lead to undesirable outcomes. The first critique relates to noncompetitive locations or small markets where competition is not guaranteed. While auctions could be tailored to promote competition in contexts of high market concentration, the risk of collusion typically reduces its efficiency (Compte et al., 2005). In the last two decades, many developing countries have introduced reforms to their electricity markets, such as dismantling public monopolies, unbundling production and distribution, and fostering the entry of international power producers. However, these reforms have had varying success rates; they have not always intensified competition or reduced electricity prices

(Nagayama, 2007; Zhang et al., 2008).

A second critique relates to transaction costs (del Río and Linares, 2014). Hidden transaction costs may undermine the savings for governments while restricting the chance to bid to big firms (which are those most likely to undertake the administrative burden of the process). While this is a general problem of auctions as a policy instrument, weak institutional settings may amplify transaction costs (North, 1987). The third potential disadvantage comes from the high levels of corruption and an overall lack of trust in the government. The literature on public procurement systems indicates that lower quality tends to be observed in the procured goods or contracted infrastructure in contexts with high levels of corruption (Dastidar and Mukherjee, 2014). Furthermore, high levels of corruption can lead to overpricing (Arozamena and Weinschelbaum, 2009; Finocchiaro Castro et al., 2014). The final critique relates to underbidding and the winner's course. Competitive pressures might force bidders to offer prices that barely cover marginal costs, which may be particularly relevant to many bidders (Hong and Shum, 2002). In such contexts, sudden exchange or interest rate alterations in unstable environments can severely affect bidders' projected revenues, leading to early project desertion (Bose and Sarkar, 2019). The failure to build the infrastructure can be an issue even in auction programs with high realization rates.

As presented in this section, even when there are favorable results of auctions over total RE investments, it is still unclear from a theoretical and empirical standpoint whether auctions are an effective instrument for fostering RE capacity in countries with unstable business environments. Despite the instrument's popularity and the increasing number of adopters from low and middle-income countries, given the arguments presented in this section, auctions will not necessarily contribute to deploying RE capacity in such institutional and macroeconomic contexts. This is what this paper will explore. The following two sections present the data and methods used for this purpose.

3. Data and descriptive statistics

We built a database with information from publicly available data sources for 98 countries. Of these, 70 implemented auctions between 2000 and 2020. We compiled data from 98 countries on their RE energy policies and installed capacity, socioeconomic characteristics, natural endowment, and business environment for this period.[1] Table 1 presents descriptive statistics, definitions, and sources for each variable used in the analysis.

We used multiple sources to code information for auctions, our treatment variable (we explain this further in Section 4.1). This includes reports and databases from the AURES II project, the International Renewable Energy Agency (IRENA), the Inter-American Development Bank, and previous papers (del Río and Kiefer, 2021; Kruger et al., 2018; Matthäus, 2020). We also coded information for feed-in policies (tariffs and premiums). We control for feed-in policies because they are the most popular and widely adopted type of policy (Ferroukhi et al., 2018, p. 22), and it is the policy most gradually being replaced by auctions (REN, 2021, p. 79). For our outcome variable, we collected information from the IRENA on the capacity of solar, wind, and biomass technologies, which is expressed as a share of the total installed capacity (explained in detail in Section 4.1).

Our empirical analyses control for variables that characterize the countries' socioeconomic profiles and natural endowment. First, we use GDP per capita from the World Bank to capture economic growth and overall income level. We use World Bank and Ember's Global Electricity Review data to capture countries' dependency on fossil fuels and energy imports. For this purpose, we use variables representing oil rents, CO_2 emissions per capita, the share of electricity produced through fossil sources, and net electricity imports. Finally, given that the adoption of RE depends on the natural resources available, we use data from the Global Solar Atlas and the Global Wind Atlas by the World Bank to control for solar potential and wind speed and data from United Nations on forest biomass stock as a proxy for biomass potential.

Previous studies on auctions included covariates related to the level of development (i.e., GDP or income) and political status (i.e., type of political system or the strength of the fossil lobby). Nevertheless, in this paper, we want to comprehensively address the quality of the business environment, defined as a combination of macroeconomic stability and institutional quality factors. Macrolevel stability is based on the four points established by the Maastricht convergence criteria: price stability, sustainable public finances, exchange rate stability, and long-term interest rates (European Central Bank, 2020). We use the variable inflation from the International Monetary Fund (IMF) for price stability. We also include dummy debt and currency crisis variables to reflect sustainable public finances and exchange rate stability. These data come from Laeven and Valencia (2020) and Nguyen et al. (2021). Additionally, the IMF financial development index is used as a proxy for the long-term quality of the financial system. For institutional quality, we use the six composite indicators reported in the Worldwide Governance Indicators (GWI) database, published by the World Bank (Kaufmann et al., 2010).

4. Empirical strategy

The paper aims to determine whether RE auctions are an effective mechanism for promoting investments in RE capacity in unstable business environments. For that purpose, we adopt a causal inference analysis to establish the links between adopting auctions (considered the treatment) and the changes in the share of RE capacity (the outcome), subsetting the countries according to the quality of their business environment. Given the nature of our problem, we cannot assign the treatment randomly to avoid self-selection. Under randomized designs, the adoption of the treatment is independent of the attributes of the individuals; thus, it is possible to ensure that the final observed effect is a direct consequence of the treatment. However, this is not an applicable method for policy choices at the country level. In this study, we work with observational data and use quasiexperimental techniques to establish causality.

Many of the quantitative studies presented in Section 2 relied on TWFE models to evaluate the effects of RE policies (see *Appendix A* for a detailed summary of the methods used by previous papers). Nevertheless, TWFE regression provides biased estimations under differential timing in adoption with heterogeneous treatment effects (Borusyak et al., 2021; Goodman-Bacon, 2021). This is relevant to our case because, as countries have adopted auctions at different points in time, it is unlikely that the policy outcomes are perfectly homogeneous across all countries in the sample. Therefore, we applied difference-in-difference techniques, one of the most common quasi-experimental methods used in Economics. Furthermore, we also considered that not every country adopts the policy (i.e., the treatment) simultaneously.

In particular, our empirical strategy comprises four steps:

1. *Definition of the treatment and outcome variables:* The two most important variables in our setting are the definition of the treatment (in this case, auctions) and the outcome (the result we are evaluating). This is explained in Section 4.1.
2. *Identifying the determinants of RE auction adoption:* We start our empirical analyses by checking to what extent self-selection might be a concern, emphasizing whether countries with specific institutional or macroeconomic features are more likely to adopt auctions. This is presented in Section 4.2.
3. *Subsampling according to the business environment:* Given the purpose of our paper, we need to incorporate the quality of the business environment in the analysis. Therefore, we apply Principal

[1] Because some variables have missing information for 2020, most of the analysis are run considering a fully balanced panel for the period 2000–2019.

Table 1
Description of the variables used in this study.

Variable	n	min	max	median	mean	std. dev	Period Available	Unit	Description	Source
Number of years with auctions	2058	0	18.0	4.0	4.5	4.4	Time invariant	Count	Total number of years since the first auction up to 2020.	See *Appendix B*
Auctions	2058	0	1.0	0	0.2	0.4	2000–2020	Dummy	AUC3 = 1 if treatment is in place; AUC3 = 0 otherwise	See *Appendix B*
Feed-in policies	2058	0	1.0	0	0.4	0.5	2000–2020	Dummy	FIT = 1 if feed-in-policies (tariffs or premiums) are in place for a country in a specific year; FIT = 0 otherwise.	REN 21 Global Data Pack 2021 and complementary sources
Share of wind, solar and biomass	2058	0	62.0	2.5	6.5	9.2	2000–2020	%	Participation of wind, solar and biomass capacity over total system capacity in a specific year	IRENA
Share of wind	2058	0	40.8	0.1	2.8	5.5	2000–2020	%	Participation of wind capacity over total system capacity in a specific year	IRENA
Share of solar	2058	0	23.8	0.1	1.6	3.7	2000–2020	%	Participation of solar capacity over total system capacity in a specific year	IRENA
Share of biomass	2058	0	26.8	0.7	2.1	3.4	2000–2020	%	Participation of biomass capacity over total system capacity in a specific year	IRENA
GDP per cápita in 2015 dollar (4)	2058	259	112,373	7,828	16,757	20,073	2000–2020	Constant 2015 USD	GDP per capita	World Bank
Oil rents	1960	0	58.2	0	3.2	8.5	2000–2019	% of GDP	Difference between the value of crude oil production at regional prices and total costs of production	World Bank
Net imports of electricity	2058	−77.0	66.7	0	−0.2	12.2	2000–2020	TW	Net imports of electricity from all sources	EMBER
CO2 emissions per cápita (4)	2058	0.1	67.0	4.4	6.4	7.2	2000–2020	Tonnes per person	CO2 emissions per capita	OWiD
Share of electricity from fossil sources	2058	0	100.0	62.5	58.7	32.6	2000–2020	% of total electricity generation	Share of electricity generation from coal, oil and gas sources combined	OWiD
Solar potential (1)	2058	2.0	6.4	4.8	4.6	1.1	Time invariant	kWh/m2/day	Solar theoretical potential, measured by Global Horizontal Irradiation Index (GHI, country median, long-term)	Solargis - World Bank
Wind potential (1)	2058	3.3	9.9	6.5	6.5	1.3	Time invariant	meters/ second	Mean wind speed at height 100 m (for 50% windiest areas)	Global Wind Atlas
Biomass potential (1)	2058	0	289.3	99.7	107.1	59.9	Time invariant	tonnes/ hectare	Above-ground biomass stock in forest in year 2010	United Nations
FDI (2)	1960	3.5	100.0	35.2	39.7	23.4	2000–2019	Index (0–100)	Financial development index that measures depht, access and efficiency of financial institutions and financial markets	IMF
Inflation	2058	−8.2	168.6	3.3	5.0	7.5	2000–2020	%	Annual average of monthly rates of inflation for a specific year	IMF
Currency crisis	1960	0	1.0	0	0	0.2	2000–2019	Dummy	currency_crisis = 1 if the country experienced a currency crisis in the specific year; currency_crisis = 0 otherwise	Laeven and Valencia (2020) and Nguyen et al. (2021)
Debt crisis	1960	0	1.0	0	0.1	0.3	2000–2019	Dummy	debt_crisis = 1 if the country experienced a debt crisis in the specific year; debt_crisis = 0 otherwise	Laeven and Valencia (2020) and Nguyen et al. (2021)
Regulatory quality (rqe) (3)	2058	0	100.0	52.2	54.6	21.6	2000–2020	Index (0–100)	Ability of the government to formulate and implement sound policies and regulations	WGI Database (World Bank)
Rule of law (rle) (3)	2058	0	100.0	42.4	47.7	25.7	2000–2020	Index (0–100)	Quality of contract enforcement, property rights, the police, and the courts	WGI Database (World Bank)
Government effectiveness (gee) (3)	2058	0	100.0	40.1	45.2	23.9	2000–2020	Index (0–100)	Quality of public and civil services and the quality of policy formulation and implementation	WGI Database (World Bank)
Control of corruption (cce) (3)	2058	0	100.0	36.0	43.2	24.8	2000–2020	Index (0–100)	Extent to which public power is exercised for private gain	WGI Database (World Bank)

(*continued on next page*)

Table 1 (*continued*)

Variable	n	min	max	median	mean	std. dev	Period Available	Unit	Description	Source
Political stability and no violence (pve) (3)	2058	0	100.0	59.1	58.5	20.6	2000–2020	Index (0–100)	Likelihood that the government will be destabilized or overthrown by unconstitutional or violent means	WGI Database (World Bank)
Voice and accountability (vae) (3)	2058	0	100.0	56.4	57.0	24.5	2000–2020	Index (0–100)	Freedom to select government, freedom of expression, freedom of association and free media	WGI Database (World Bank)

(1) Complementary sources were used in case of missing data.
(2) The original index goes from 0 to 1, but it was rescaled from 0 to 100 to facilitate the interpretation of the coefficient.
(3) The original index goes from −2.5 to 2.5, but it was rescaled from 0 to 100 to facilitate the interpretation of the coefficient.
(4) For estimation purposes, these variables are included in its log form.

Component Analysis (PCA) and Cluster Analysis to reduce the dimensionality of the data and create subgroups for our research. This is detailed in Section 4.3.

4. *Calculation of average treatment effects on the treated:* Taking as inputs the results from steps 1 to 3, we calculate the average treatment effect on the treated (i.e., the impact of adopting auctions on the share of RE capacity for the countries in the sample). This is the primary goal of our analysis. A detailed explanation of the methods used is provided in Section 4.4.

A summary of the methodology presented in this section is shown in Fig. 1.

4.1. Definition of the treatment and outcome variables

There are different alternative measures for the incidence of renewable sources in the energy matrix (*Appendix A*). In this paper, we define the outcome variable in terms of capacity, i.e., the share of solar, wind, and biomass capacity over total installed capacity in the electricity system for country *i* in time *t*:

$$y_{it} = \frac{CapacitySolar_{it} + CapacityWind_{it} + CapacityBiomass_{it}}{Total\ System\ Installed\ Capacity\ (RE\ and\ non\ RE)_{it}} \tag{1}$$

We use electricity capacity rather than electricity generation because capacity more accurately reflects the long-term direction of the electricity system and is less dependent on short-term determinants (i.e., climate, fluctuation in fossil costs or short-term policy preferences). We include wind and solar energy because these are the two most widely adopted RE sources. We also incorporate biomass, given its role in providing stable capacity to the system. However, we exclude hydropower sources due to reported negative environmental impacts (Rosenberg et al., 2000). We also use individual measures for the share of solar, wind, and biomass as outcome variables.

As for the treatment variable, we consider the adoption of auctions for empirical purposes. In other words, countries that have implemented auctions between 2000 and 2020 are considered "treated," and countries that have not implemented auctions during this period are considered "controls" (regardless of any other RE policies or incentives they may have). We define the treatment as binary (1 if the country has adopted auctions; 0 otherwise) and irreversible (once the country has implemented auctions for the first time, it stays treated up to the end). Even if a country does not regularly run auctions every year, implementing an auction scheme has a double effect: first, it helps to create a lasting legal and institutional framework that leaves a scarring effect on the system; and second, it sends a signal to investors regarding the willingness of the authorities to promote RE (IRENA and CEM, 2015; Maurer and Barroso, 2011). *Appendix B* details each country's treatment start and the sources used to code this variable.

In our sample, 70 of the 98 countries implemented auctions between 2000 and 2020 (i.e., "treated"), whereas 28 did not (i.e., "controls").[2] Fig. 2 shows which countries are treated and which are controls.

4.2. Identifying the determinants of RE auction adoption

Because self-selection into treatment might be a concern, we test whether countries with specific institutional or macroeconomic features are more likely to adopt auctions. For this purpose, we follow an approach similar to Hoynes and Schanzenbach (2009). We run a regression in which we take as the dependent variable the number of years a country has been applying auctions (a proxy variable to explain the timing of adoption). Fig. 2 shows the length of the treatment for the treated units. We use a Poisson model, which is a regression model suitable for count data, of the following form:

$$z_i^{2020} = REN_i^{2000}\beta + ENE_i^{2000}\gamma + ECO_i^{2000}\rho + NAT_i\delta + INS_i^{2000}\theta + \varepsilon_i \tag{2}$$

z_i^{2020} is a count variable that reflects the number of years since country *i* implemented its first auction. The variable takes the value 0 for non-adopters. We regress this on pretreatment variables to identify what characteristics help explain if and when countries choose to adopt auctions. Because some of our independent variables (e.g. those related to the profile of the energy matrix in a country) could simultaneously affect and be affected by auctions, all our explanatory variables represent the status of countries in the year 2000 (indicated by the superscript), when none of the countries in our dataset had implemented auctions yet. The choice of explanatory variables in this analysis was informed by the scientific literature and technical reports that explain why countries adopt auctions as a policy instrument to foster RE. These include the following variables described in Equation (2):

REN_i^{2000} is a vector of variables reflecting the status of the renewable sector in the year 2000, including the percentage of RE capacity (Marques and Fuinhas, 2012) and if it already had feed-in policies in force at that time (Aguirre and Ibikunle, 2014; Bersalli et al., 2020; Kilinc-Ata, 2016; Romano et al., 2017; Zhao et al., 2013). ENE_i^{2000} is a group of variables reflecting the profile of the energy matrix in the year 2000. We include oil rents (Sequeira and Santos, 2018), the share of electricity generation from fossil fuels (Aguirre and Ibikunle, 2014; Marques and Fuinhas, 2012), emissions per capita (Bersalli et al., 2020; Cadoret and Padovano, 2016; Uzar, 2020), and net electricity imports (Bersalli et al., 2020; Jenner et al., 2013; Romano et al., 2017). NAT_i includes variables

[2] Originally, we collected data for 100 countries. However, the UK and Ireland were excluded from the analysis because both countries had RE auctions programs during the 1990s, before the start date of our analysis.

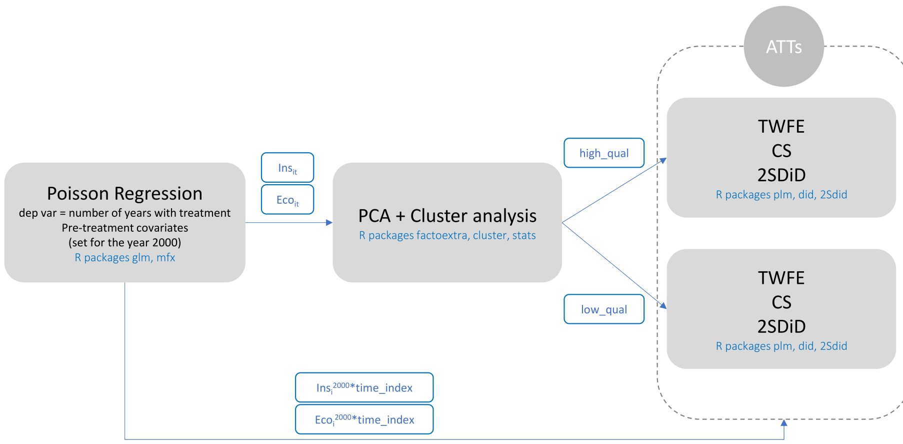

Fig. 1. Summary of the methodology. We use Poisson regression to explain the influence of institutional (Ins_{it}) and macroeconomic (Eco_{it}) variables in adopting auctions. Then, we use both sets of variables (Ins_{it} and Eco_{it}) to classify countries according to the quality of their business environment. Finally, we calculate the average treatment effects of adopting auctions using three estimators (TWFE, CS, and DiD), disaggregating the analysis by the quality of the business environment.

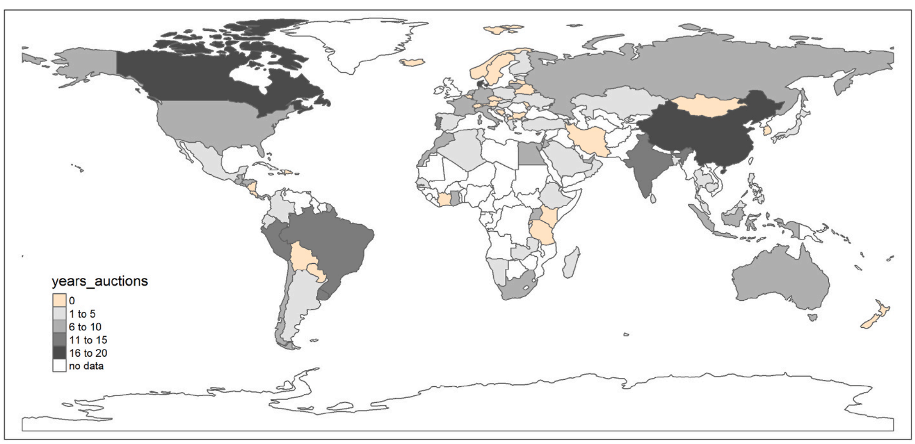

Fig. 2. Countries selected in the sample and length of the treatment.

that capture the natural endowment of the country (Aguirre and Ibikunle, 2014). These variables are time-invariant, so the superscript "2000" is not included. ECO_i^{2000} is a vector of variables related to the macrolevel instability in 2000 and INS_i^{2000} is a vector of variables that describe institutional quality in 2000. ε_i is the error term, which we cluster using the World Bank income groups in the year 2000. We use the R package *mfx* for calculation purposes, which allows us to recover marginal effects and calculate clustered standard errors (Fernihough and Henningsen, 2019).

Table 2 summarizes the estimation results for equation (1), considering only the best-performing model. These results are robust to different model specifications, as presented in *Appendix C*. All results are expressed in average marginal effects, meaning they reflect the predicted change in the dependent variable (number of years from the first auction up to 2020) from a unit change in the explanatory variables. For macroeconomic variables, financial development index (FDI) and inflation consistently have significant coefficients across all model specifications. The positive sign for FDI indicates that a more developed financial infrastructure lowers the cost of capital to fund RE projects. However, considering how unpredictable costs and income become in inflationary contexts, a negative sign for inflation is expected. In terms of the institutional setting, the rule of law is significant. According to Kaufmann et al. (2010, p. 4), the rule of law indicates "the respect of citizens and the state for the institutions that govern economic and social interactions among them." The negative sign in this case is contrary to intuition. The first possible explanation for the negative sign is that the level of regulation might operate negatively in the mind of investors if they foresee over-regulation (Sisodia et al., 2016). A second explanation is that in highly corrupted countries, auctions may help reduce functionaries' discretion in handling procurement projects (Baldi et al., 2016).

Although these coefficients are statistically significant, their size is small to support that institutional or macrolevel variables consistently affect the decision to adopt auctions. For instance, an increase of 1 point in FDI is associated with 0.104 extra years in the length of the treatment, and a 1-point increase in inflation explains a reduction in 0.070 years. For *rle*, a change of approximately 1 point explains a change of 0.093 years in the length of the treatment. These results have implications for the identification strategy because the small size of the coefficients indicates that the quality of the business environment has only a marginal influence on the choice for RE auctions. Thus, based on these observed variables, we cannot conclude that substantial and systematic differences between countries affect the decision to adopt auctions early on. Nonetheless, we still include the variables FDI, inflation, and the rule of law in our causal inference models. By adding these variables, we are controlling for covariates that could be correlated with the outcome and treatment adoption.

4.3. Subsampling according to the business environment

In this step, we classify countries according to the quality of their business environment, which is a necessary step to answer our research

Table 2
Addressing self-selection with a Poisson model.

Dep. Var.:Lengths of treatment (number of years with auctions in the period 2000–2020)	
Share of wind, solar and biomass	0.228***
	(0.068)
Feed-in policies	1.889
	(1.701)
share of electricity from fossil sources	−0.016
	(0.015)
Oil rents	−0.081***
	(0.026)
CO2 emissions per capita	0.471
	(0.296)
Net imports of electricity	−0.011
	(0.044)
Solar potential	1.225***
	(0.350)
Wind potential	0.460*
	(0.235)
Biomass potential	−0.005**
	(0.002)
FDI	0.104***
	(0.016)
Inflation	−0.070***
	(0.023)
Currency crisis	6.467*
	(3.914)
Debt crisis	−0.334
	(1.943)
Rule of law	−0.093***
	(0.025)
Num. obs.	98
Deviance	350.49
AIC	626.03

***p < 0.01; **p < 0.05; *p < 0.1.
(Standard errors).
Errors clustered by Income Group for year 2000 (World Bank).

questions. We work with the four macroeconomic and six institutional variables related to business environment (see Table 1) and combine two tools—principal component analysis (PCA) and cluster analysis—which are suitable for reducing the dimensionality of a dataset and finding subgroups within a particular sample. This is useful in our case for defining subgroups of countries according to the characteristics of the business environment. We conduct these analyses using the sum of currency and debt crises for the period and the country averages for the other variables.

First, we run a PCA analysis to reduce the dimension of the data using the R package *stats*. Then, we extract the scores of the first three dimensions that explain most of the variability and run a cluster analysis of those scores using the k-medoids approach (partitioning around medoids). This approach is more robust than the k-means, being less sensitive to outliers (Kaufman and Rousseeuw, 1990). Finally, we use the R packages *factoextra* (Kassambara and Mundt, 2020) and *cluster* (Maechler et al., 2022) for the estimation procedure. With this approach, we end up with the business environments of 40 countries classified as high quality and the remaining 58 classified as low quality. The methodological details are presented in *Appendix D*, and the countries classified in each group are shown in *Appendix E*.

4.4. Calculation of average treatment effect on the treated

To estimate the causal effects of auctions on the deployment of RE, we use a DiD estimator. The canonical form of DiD, which includes two groups (treated and untreated) and two periods (before and after treatment), recovers, under the parallel trend assumption, what is known as the *average treatment effect on the treated* (ATT). This is the difference between the treated potential outcome (y_t^1) and the untreated potential outcome (y_t^0) for all the units that have been treated and is expressed as follows:

$$ATT = E\left[y_t^1 - y_t^0 \middle| treated = 1\right] \tag{3}$$

With multiple periods, not every unit might receive the treatment simultaneously (known as “differential timing”). The standard approach, in this case, is the TWFE model with the following model specification:

$$y_{it} = \theta_t + \vartheta_i + \gamma X_{it} + \beta treat_{it} + \varepsilon_{it} \tag{4}$$

where θ_t are period fixed effects, ϑ_i are individual fixed effects, X_{it} is a set of covariates, and $treat_{it}$ is a binary variable that reflects the treatment status (1 if individual i is treated in period t; 0 otherwise). In this case, β is the parameter of interest. This is the first type of model used in this paper.

Previous studies that analyze the impacts of RE auctions have relied on TWFE for their empirical analyses (see *Appendix A*). However, estimating the parameter β may be biased when treatment effects are heterogeneous across units. For example, Goodman-Bacon (2021) shows that β is a weighted average of all the possible two-group-two-period combinations in the data. In this weighted average, the early (or past) treated units are used as controls for the later (or future) treated units (Goodman-Bacon, 2021). Because in this case the units used as controls are already treated, the parameter β in the TWFE may be biased.

Many of the recent developments in the DiD methods seek to account for heterogenous treatment effects in differential timing settings (Athey and Imbens, 2022; Borusyak et al., 2021; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfœuille, 2020; Gardner, 2021; Sun and Abraham, 2021). Based on this premise, we run two additional models.

The first DiD model we will use is the one developed by Callaway and Sant'Anna (2021) (hereafter CS). Their target parameter for identification is defined as the *group-time average treatment effect*. This is an extension of the ATT in the canonical 2 × 2 DiD but accounts for the fact that units adopt the treatment in cohorts (groups). It is specified as follows:

$$ATT\ (g,t) = E\left[y_t^g - y_t^0 \middle| G_g = 1\right] \tag{5}$$

This is the average treatment effect for treated units that belong to a particular cohort (g) at a specific time (t).

One of the most attractive features of CS compared with similar methodologies is aggregation. With many groups and periods, the large number of group-time average treatment effects may not be informative, so aggregated measures are preferable. The authors propose an aggregation procedure of the form:

$$\theta = \sum_{g \epsilon G} \sum_{t=2}^{\tau} w(g,t)^{*} ATT(g,t) \tag{6}$$

In this case, $w(g,t)$ represents a weighting method, the choice of which depends on the type of information needed and the specific research questions.[3] At the same time, the methodology allows accounting for overall treatment effect parameters, i.e., summarizing everything into one parameter to show the overall effect of the treatment. According to the authors, the best way to obtain a general-purpose parameter is the following (Callaway and Sant'Anna, 2021, p. 12):

$$\theta_{sel}^{o} = \sum_{g \epsilon G} \theta_{sel}(g)^{*} P(G = g | G \leq \tau) \tag{7}$$

[3] The authors propose three aggregation methods: dynamic (how the treatment effect varies with the length of exposure to the treatment), group (how the treatment effect varies according to cohort membership), and calendar (how the treatment effect varies according to calendar time).

This indicator is the sum of the average effect of participating in the treatment for each cohort ($\theta_{sel}(g)$) weighted by the probability of belonging to that specific group ($P(G = g|G \leq \tau)$), which in practical terms is the relative share of a group over the total number of treated units. This aggregated measure shows the average treatment effect for every unit treated during the period under analysis.[4] Given the small cohort size in our data, we will only focus on this type of aggregated measure.

For estimation purposes, we use the R package DiD developed by the authors (Callaway and Sant'Anna, 2022a). This package allows setting several estimation parameters: the estimation procedure (outcome regression,[5] in our case), the aggregation procedure (group effects, in our case), and the comparison group ("not yet treated," in our case). In addition, to test for parallel trends before treatment, we use the event-study plots (Callaway and Sant'Anna, 2022a), presented later in the paper (Fig. 6).

The second DiD model we use follows a somewhat different estimation procedure. It is called two-stage DiD (hereafter 2SDID) and was developed by Gardner (2021). The intuition behind this method is that the untreated potential outcomes ($y_t^0 \big| \, treated = 0$) decompose into group and time effects (Cunningham, 2021). Thus, the error term in the TWFE (ε_{it}) is "not mean zero conditional on group membership, period and treatment status" (Gardner, 2021, p. 6). Compared to CS, which works with group-time effects as building blocks for the analysis, this method follows an imputation approach, i.e., it imputes the value of the counterfactual $y_t^0 \big| treated = 1$ using untreated units. It has the advantage of simplicity and shows efficiency gains compared with CS when the parallel trend assumption holds (Borusyak et al., 2021). However, when the parallel trend assumption holds conditionally, 2SDID is less stringent for dealing with covariates than CS.

The procedure proposed by the author takes two steps. The first requires removing those group and period fixed effects using untreated observations to predict the outcome. So, we run a TWFE regression of the type:

$$y_{it} = \theta_i + \vartheta_t + \varepsilon_{it} \tag{8}$$

where θ_p are period fixed effects, ϑ_g are group fixed effects. Then, we calculate the adjusted outcome as follows:

$$\widehat{y}_{it} = y_{it} - \widehat{\theta}_i - \widehat{\vartheta}_t \tag{9}$$

The second step requires using this transformation as the outcome and regressing it on the treatment D_{it} in the following way:

$$\widehat{y}_{it} = \beta^{2s} D_{it} + u_{it} \tag{10}$$

In this case β^{2s} recovers the true ATT. We use the R package did2s developed by Butts and Gardner (2021) for the empirical estimation. Observations are weighted by the size of their group cohort to keep coherence with the CS group aggregation (see *Appendix F*).

Finally, we include covariates in our models to cover at least a conditional parallel trend assumption. The approach for dealing with covariates varies according to the model. Callaway and Sant'Anna (2021) suggest that covariates should be chosen to explain the evolution of the outcome in the absence of treatment (i.e., covariate-specific trends). Gardner (2021) does not include covariates in his model. However, he suggests that including time-varying covariates in the first- and second-stage regressions may be a simple way to deal with them (Gardner, 2021, p. 9).[6]

In our analysis, we propose three alternative specifications for each of our models:

(i) *No controls* (assuming the parallel trend assumption is fulfilled unconditionally);
(ii) *Controls (1)*: A set of control variables related to the country's energy profile usually used in the literature. We control for feed-in policies; GDP per capita (in 2015 USD); fossil dependency (oil rents, share of electricity produced through fossil sources, and CO_2 emissions); import dependency (net imports of electricity); and the natural endowment for solar, wind, and biomass.
(iii) *Controls (2)*: The set of variables in controls (1) plus specific variables related to macroeconomic stability and institutional quality.

We first run all three estimators (TWFE, CS, and 2SDID) and the three specifications for the full sample of countries, and then we run additional regressions including only those countries with high-quality business environments (*high_qual*) and only those countries with low-quality business environments (*low-qual*). This allows us to estimate the average impact of RE auctions and analyze whether these outcomes vary depending on countries' business environments. Finally, to analyze the effects of auctions on different RE technologies, we run our three estimators using the specification "Controls (2)" by the total capacity of solar, wind, and biomass separately. In every model, the standard errors are clustered at the country level.

As reflected in Table 1, some variables are time-variant, whereas others are not. The TWFE and 2SDID models rule out time-invariant variables. In contrast, the CS package (2022a) explicitly requires pre-trend time-invariant variables and automatically sets time-varying covariates to a base period.[7] Therefore, we include time-variant variables where possible and interact time-invariant variables with a trend variable. In the 2SDID model, we add the same set of covariates in both stages of the regression. As for the macrolevel and institutional variables in controls (2), we choose the ones that are significant in the Poisson models[8] (explained in Section 4.2), as they suggest that those variables influence the decision to adopt auctions.

5. Results

5.1. The effect of auctions over the share of RE in total system capacity

This article examined the effectiveness of auctions for promoting RE investments under different business environments. In Fig. 3, we plot the coefficients of the effects of auctions for our three models and three specifications. The estimates for the entire sample and the subsamples of countries with high-quality and low-quality business environments are shown. All the coefficients are expressed as the increase in the share of RE over total system capacity (additional percentual points, p.p.) caused by adopting auctions.

The first group of estimations is calculated over the whole sample, with 98 countries. Overall, we find that the adoption of auctions has a positive effect on the share of RE capacity in the energy matrix. For the full sample, the results range from 1 to 2.90 p.p., all significant at least at the 10% level. Previous papers have found even smaller effect sizes; for

[4] This concept is equivalent to the average treatment effect on the treated from the canonical 2 × 2 DiD.

[5] Given the nature of our research setting, we have multiple groups of small size, and the overlapping condition is weak (see *Appendix F*). For these cases, the authors suggest the outcome regression approach (Callaway and Sant'Anna, 2021, p. 13). This estimation procedure requires accurately modeling the expectation of the outcome evolution for the control group.

[6] However, as we mentioned above, the author recognizes that this approach is less stringent than CS.

[7] The base period is "the period immediately before observations in a particular group become treated" (Callaway and Sant'Anna, 2022b).

[8] In the TWFE and the 2SDID, we will interact the 2000 level of those variables with a time trend variable, which is the approach used by Hoynes and Schanzenbach (2009). For the CS model, the variables are included at their baseline level.

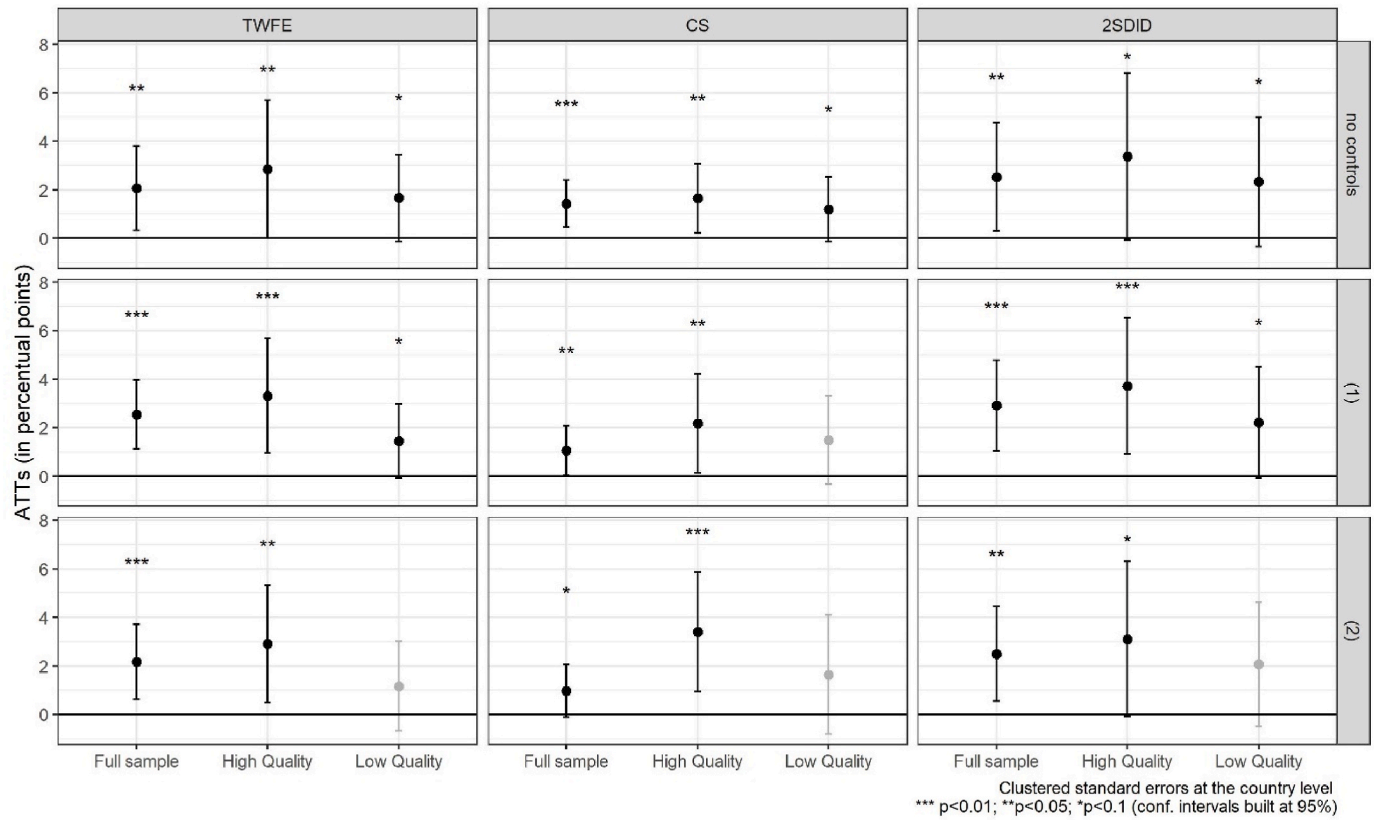

Fig. 3. Average treatment effects (ATT) of auctions on RE as share of total installed capacity. Point estimates from all three models (TWFE, CS, and 2SDID) are shown with 95% confidence intervals. Grayed-out point estimates indicate that the coefficient is not statistically significant ($p > 0.10$). Rows indicate different model specifications: *"no controls"* assumes that the parallel-trends assumption is fulfilled unconditionally; *"controls (1)"* include as covariates feed-in policies, GPD per capita (in 2015 USD), oil rents, the share of electricity produced through fossil sources, CO_2 emissions, net imports of electricity and the natural endowment for solar, wind and biomass; and *"controls (2)"* additionally controls for inflation, FDI, and the rule of law.

instance, Kilinc-Ata (2016), [9] found an effect of approximately 0.7% for tendering mechanisms.

We then conduct the subsample analysis, dividing countries according to the quality of their business environment. Countries that are stable from a macroeconomic perspective and have high-quality institutions are considered high-quality. In contrast, countries with some degree of macrolevel instability and less stable institutions belong to the low-quality group. *Appendix E* presents the complete list of countries and their classifications.

There are two main aspects to highlight from the subsample analysis. The first is that, in every model specification, the results are significant at least at the 10% level for countries in the high-quality group. The same is not true for countries in the low-quality group, however, for which we find significant results only for some model specifications. The second aspect relates to the size of the coefficients: the effects are always more significant for countries in the high-quality group. In specifications that include all the control variables, the estimations range from 2.90 to 3.40 percentual points for countries in the high-quality group, whereas estimations for the low-quality countries range from 1.17 to 2. Auctions have consistently been more effective for the period under analysis in countries with a more stable business environment. The reasons behind these results will be discussed in the next section.

Given that the results may be affected by how countries were classified into the two groups, we use an alternative approach to categorize the quality of countries' business environments as a robustness check. This is explained in *Appendix D*. The results of this alternative procedure are presented in *Appendix G* and do not differ substantially from the main analysis.

5.2. The effect of auctions for each RE technology

Our second research question asks whether the results differ substantially according to the type of renewable technology. In Fig. 4, we present the results disaggregated by RE technology. Our models do not have an indicator to account for technology neutrality or specificity of auctions. Therefore, the results are primarily exploratory and should be treated with caution. We change the outcome variable in each case to study the share of each specific technology over total system capacity (reasonably, we expect lower results in absolute terms).

Here, the results are less conclusive; nevertheless, we can identify some general trends. We find significant results in some models for wind technologies in the high-quality group. Wind power has had a considerable uptake in Europe, both onshore and offshore (IRENA, 2019, p. 10). In contrast, we find significant results for solar and biomass in the low-quality group. Countries in Africa and Southeast Asia have prioritized solar projects (del Río and Kiefer, 2021; IRENA, 2019, pp. 11–12). Biomass is behind wind and solar technologies in terms of the volumes auctioned. Still, countries in South and Central America and Southeast Asia are seeking to exploit their biomass potential. In contrast, European countries have disincentivized crop biomass due to potential land-use changes and food-energy competition (Scarlat et al., 2018).

[9] The rest of the papers that assess the effectiveness of auctions from a quantitative perspective use different dependent variables, hindering results comparisons.

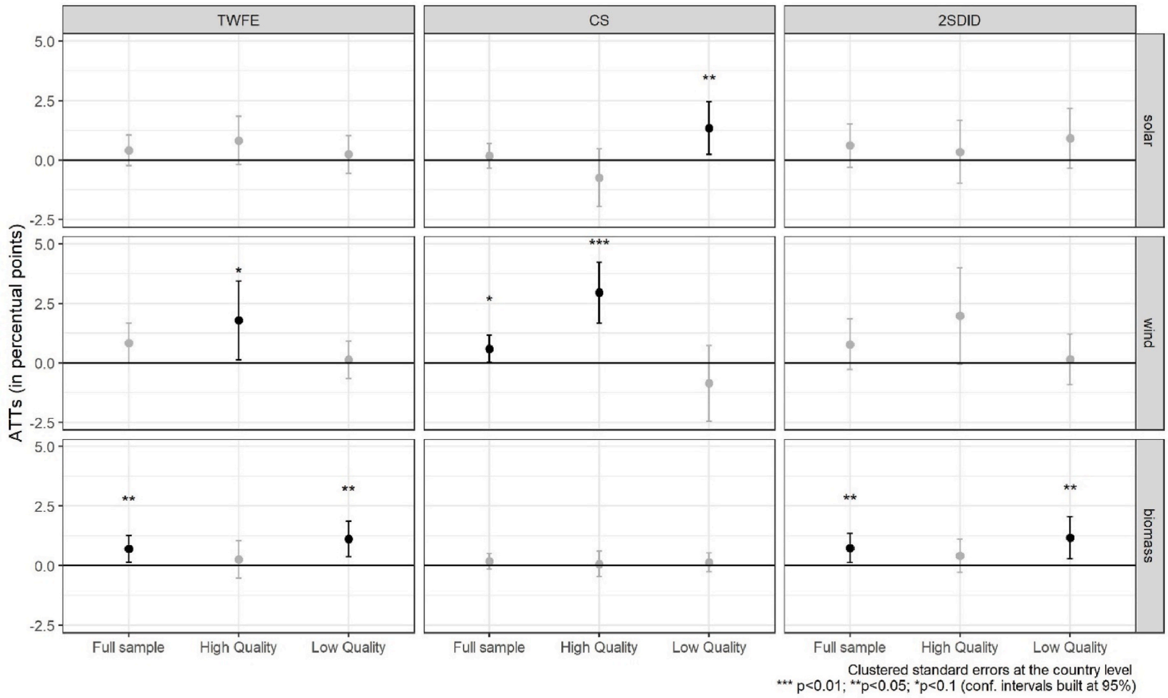

Fig. 4. Average treatment effects (ATT) of auctions by RE technology. Point estimates from all three models are shown with 95% confidence intervals. Grayed-out point estimates indicate that the coefficient is not statistically significant (p > 0.10). Rows indicate the effects disaggregated by RE technology. In all models, we use the covariates from "controls (2)."

6. Discussion

In terms of the aggregated effects, we observe an increase in the share of RE capacity due to auctions. The effect size for the whole sample ranges from 1 to 2.9 p.p. and is higher for countries with stable business environments. Despite its small size in absolute terms, this is still promising compared with the evidence for other policy instruments from the literature. For feed-in tariffs, the evidence is mixed: Kilinc-Ata (2016) found a positive effect of approximately 2.8 p.p. over the ratio of RE capacity, whereas Aguirre and Ibikunle (2014), Bento et al. (2020), and Popp et al. (2011) found no significant effects. Romano et al. (2017) even found a negative impact of feed-in tariffs. While these traditional policies have been drivers of RE, they have reached a saturation point; countries are now exploring new instruments, especially considering that policy accumulation does not necessarily lead to better outcomes (Zhao et al., 2013).

Despite the fast adoption rate of RE auctions in low and middle-income countries and some potential advantages in contexts with

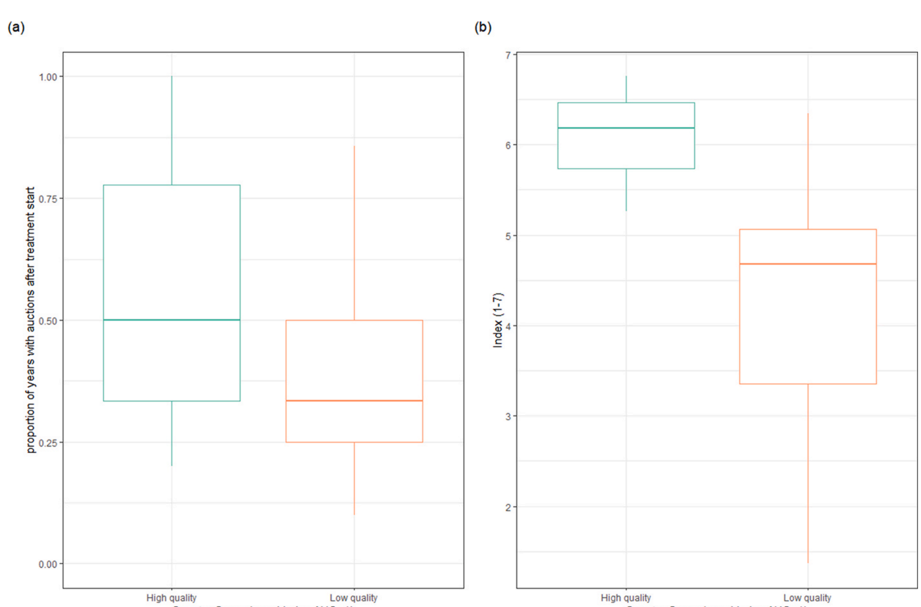

Fig. 5. Panel (a). Frequency of auctions. The proportion of years in which countries have effectively launched auctions after implementing the first one (for countries that have adopted auctions before 2019). **Panel (b). Perceived quality of infrastructure.** In your country, how reliable is the electricity supply (lack of interruptions and lack of voltage fluctuations)? [1 = extremely unreliable; 7 = extremely reliable] (World Economic Forum Global Competitiveness Index).

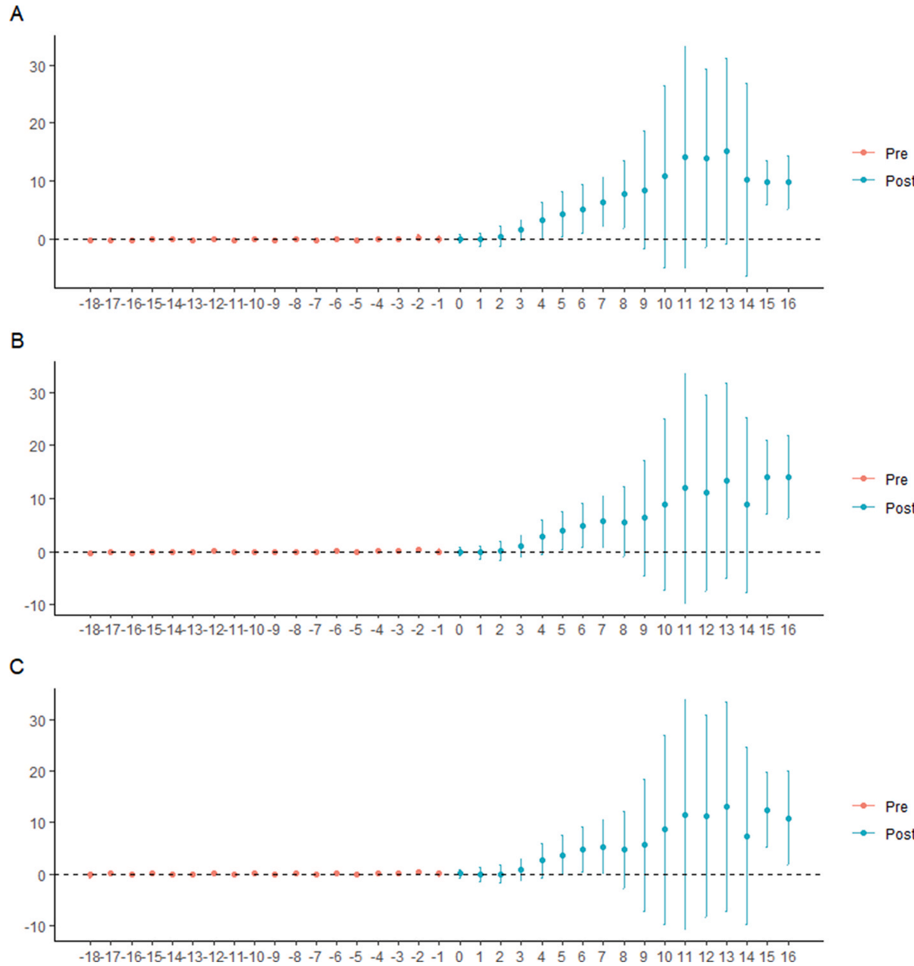

Fig. 6. Event-study plot to test for parallel pretreatment trends. This figure presents event-study plots for three scenarios of control variables as explained in Section 4.4: no controls in panel A, controls (1) in panel B, and controls (2) in panel C. In each case, the parallel trend condition is fulfilled before treatment (period 0) because we do not see any significant coefficients.

macroeconomic and institutional instability, our results show better outcomes in countries with stable business environments. What are the reasons for these results? We present four different lines of explanation.

The quality of infrastructure is the first factor that could undermine the effectiveness of auctions. As we see in Fig. 5 panel (b), the perception of infrastructure quality is more favorable in countries in the high-quality group. Private investors may be discouraged from participating in auctions if they anticipate difficulty accessing energy grids (del Río and Linares, 2014; Gephart et al., 2017). Even when they do participate in auctions, the administrative failure to provide expeditious access to the networks results in construction delays and higher implementation costs (del Río, 2017; del Río and Kiefer, 2021).

The second reason for the variable effect of RE auctions is the absence of an auction schedule in some countries, which might lead to auctions taking place sporadically. According to del Río and Kiefer (2021), European countries have tended to schedule their auctions, which is not the case for other regions. As a result, private actors might be reluctant to invest if they do not foresee consistent auction planning (Hochberg and Poudineh, 2018; IRENA, 2019). Fig. 5 panel (a) shows the proportion of years in which countries effectively performed subsequent auctions after implementing the first one[10]. While the median for countries in the high-quality group is above 0.5, it is lower in the case of the low-quality group.

Running auctions regularly is relevant because of dynamic effects. In Fig. 6, we present event-study plots. These plots show the effect size (y-axis) according to the length of the treatment (in the x-axis). Negative values represent the periods before the units adopted the treatment (lags). The fact that these coefficients are close to zero and nonsignificant indicates that the pretesting of the parallel-trends assumption is fulfilled. Positive values represent the variable's leads, showing the policy's effects according to the length of exposure to the treatment. It is evident that the average treatment effects grow over time. This implies that countries must capitalize on lessons from the initial rounds and stick with the instrument to see consistent results (IRENA and CEM, 2015).

The third factor is that auction programs can still fail in construction despite high realization rates. For auction winners, setting up the physical and administrative infrastructure requires time and money. If financial or macroeconomic conditions change in the middle of the construction process, this could result in unexpected delays or early project termination (Gephart et al., 2017). Inefficiencies and delays have been frequently reported in countries such as Peru, Brazil, China, and India (del Río and Kiefer, 2022; del Río and Linares, 2014; Kreiss et al., 2017).

A fourth reason auctions perform worse in countries with unstable business environments relates to design flaws. Many countries include additional features that do not always contribute to the success of tendering schemes. For instance, there has been a trend toward including Local Content Requirements (LCR) in developing countries. In such cases, auctions are considered both an RE policy and a means to

[10] Countries with <2 years into the treatment were excluded.

promote local development (del Río and Kiefer, 2021). However, excessively stringent requirements or a lack of complementary measures to build local value chains could severely undermine the effectiveness of the auction program. Such delays due to mismatches between LCR schemes and local capacities have been reported in Brazil, South Africa, and Indonesia (del Río, 2017; Dobrotkova et al., 2018; IRENA, 2013).

7. Conclusions and policy implications

Auction mechanisms promise to promote investments in RE at lower costs than conventional support mechanisms. Accordingly, many low and middle-income countries rapidly adopted this policy instrument in the last decade. Nevertheless, the effectiveness of tendering schemes has been mainly assessed in OECD or European countries, where the business environment is generally stable. This paper presented a quantitative evaluation of RE auctions, exploring whether the effectiveness of this policy in fostering RE capacity varies according to the quality of the business environment (defined as a combination of macrolevel stability and institutional quality).

We make an important empirical contribution by considering heterogeneous treatment effects and staggered policy adoption. TWFE models, widely used in the literature, may recover a biased ATT in the presence of heterogeneous treatment effects. To address this shortcoming, we use novel DiD methodologies to provide more robust results, which are then compared with the more standard TWFE approach.

Overall, our analysis finds that auctions contribute to increasing the share of RE over total system capacity. However, the adoption of this policy should be undertaken with caution. Despite the prevailing optimism, the results still appear to be modest for countries whose business environment is not optimal. Moreover, previous qualitative case studies have already suggested the need for caution in the case of RE auctions (Cassetta et al., 2017; Grashof et al., 2020; Winkler et al., 2018).

The findings in this paper have three main policy implications. The first relates to how governments in countries with unstable business environments manage uncertainty. Auction mechanisms can be designed to provide long-term contracts with safeguards against inflation or devaluation but cannot rule out every single source of risk. Additional measures to complement auction programs may help mitigate risks and instill confidence in investors. One possible way to achieve this is by engaging multilateral institutions. For example, the involvement of the World Bank in providing additional warranties in the Scaling Solar project in Africa or the RenovAR program in Argentina has shown promising results (The World Bank, 2018, 2019). Another option is to include decontracting auctions in which companies are permitted to bid for a fine and cancel the project (IRENA, 2017). This could provide additional safeguards against unexpected changes in the business environment.

A second policy implication involves the frequency with which countries launch RE auctions. In countries with weak business environments, significant RE capacity increases will only occur if investors anticipate the government's intention to maintain the policy in the long run. Moreover, our analysis showed dynamic treatment effects, implying that the impact of implementing auction programs increases gradually. Thus, there is a learning curve in which countries must learn from past mistakes and continually fine tune the design features. Various studies have shown that accuracy in design is critical for the success of tendering mechanisms (del Río, 2017; Matthäus, 2020; Winkler et al., 2018).

The third policy implication is that auction programs should consider countries' technological capabilities and natural resource endowment. This is key for developing countries where public budgets are typically limited. For instance, we saw that auctions contribute to increasing the share of biomass energy in countries with low-quality business environments (Fig. 4). Although biopower projects have higher initial investments and operational costs (FAO, 2020), auctions could be suitable for fostering this technology in countries with a biomass surplus. Investments in biomass-based electricity foster the cascading use of waste from agricultural and agroindustrial production and provide a low-carbon reserve capacity for the system (Johansson et al., 2019).

Because auctions are gradually becoming the dominant RE policy choice worldwide, a critical assessment of the effectiveness of RE auction mechanisms is needed. Nevertheless, our study has certain limitations. The first is the size of the cohorts of adoption. Even when we focus on aggregate measures, such small groups widen the confidence intervals and reduce estimation quality (especially in the CS methodology). The second limitation involves treatment irreversibility. The DiD approaches we applied in this study are designed for staggered adoption and do not consider treatments that switch on and off. Future models should consider the frequency of use and the learning effects implicit in auction mechanisms. A third point relates to policy stringency: pricing mechanisms, penalties, and physical or financial requirements are critical features for safeguarding the instrument's effectiveness; however, the definition of the treatment in this study does not include these features. Further research should consider them to account for the fact that some countries might be more rigorous in their policy design. Finally, differentiating the auctions by technology could help discover nuances or specificities for each RE source that could improve the design of auctions.

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CRediT authorship contribution statement

Pablo Mac Clay: Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft, Preparation. **Jan Börner:** Conceptualization, Supervision, Funding acquisition. **Jorge Sellare:** Conceptualization, Methodology, Writing – review & editing, Project administration, Supervision.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enpol.2023.113685.

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