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

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Abstract

Decarbonizing the global energy matrix through investments in renewable energy (RE) is considered a pathway to mitigate the effects of global climate change. Auctions have become an increasingly popular policy instrument for this purpose. In the last few years, auctions have been rapidly adopted by low- and middle-income countries due to their flexibility and several theoretical advantages to mitigate risks deriving from poor business environments. Previous research has used data from higher-income countries and two-way fixed effects models to estimate the effects of auctions on RE capacity, mostly with favorable results. However, none of these studies accounted for heterogeneous treatment effects across units to explore whether auctions are effective in countries with unstable business environments. Here we analyze if auctions can foster RE in countries facing macroeconomic instability or poor institutional quality. For this purpose, we have drawn from multiple publicly available databases to build a panel dataset covering 98 countries for the period 2000-2020. Our definition of RE includes solar, wind, and biomass sources. We show results for each RE source separately and all of them combined. We first cluster countries in terms of the quality of their business environment and then perform a differences-in-differences analysis considering staggered treatment adoption. Our results show that auctions positively affect RE capacity, but average treatment effects are higher for countries with better business environments. Thus, caution is needed in adopting this instrument, especially in countries exposed to macroeconomic or institutional instability. At the same time, dynamic treatment effects suggest that the policy needs time to show results.

Keywords: renewable energy, auctions, policy evaluation, difference-in-differences, causal inference

JEL codes: L94, Q42, Q48, Q54, Q58

1. Introduction

Energy systems account for the largest share of global anthropogenic greenhouse gas (GHG) emissions (Lamb et al., 2021). Around 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 will likely increase their energy-related GHG emissions (Henriques and Borowiecki, 2017). Low-carbon electricity systems predominantly based on renewables are therefore needed to keep temperatures below 1.5 degrees from pre-industrial levels (IPCC, 2022).

Many countries worldwide are fostering the decarbonization of their energy matrixes through renewable energy (RE) sources. This transition towards low-carbon energy systems has been supported by policies that attempt to create an enabling environment for investments in these kinds of technology (Jordan and Huitema, 2014). RE auctions are an example of such institutional innovation used to promote renewables. This policy has become increasingly popular in recent years, gradually replacing administratively-set incentives, such as feed-in-tariffs and RE tradable green certificates (Fitch-Roy et al., 2019; Grashof, 2021). RE auctions synthesize elements from both price-based and quantity-based policies, ensuring fair remuneration for RE projects while avoiding excessive support costs (IRENA, 2015). As a result, even low and middle-income countries without a track record in RE policies have adopted auctions (IRENA, 2019; Viscidi and Yepez, 2019).

There is a growing body of literature that analyses 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 that they are an effective policy instrument (Bento et al., 2020; Bersalli et al., 2020; Jenner et al., 2013; Kilinc-Ata, 2016). However, most of these studies focus mainly on stable OECD or European economies. Despite the global optimism around auctions and their rapid adoption, whether they are an appropriate instrument for all countries remains an open question. RE projects tend to be capital intensive (Mazzucato and Semieniuk, 2018) and involve lengthy and somewhat uncertain payback periods, so 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, weak rule of law, ineffective contract enforcement, or recurrent political changes. Evaluating auctions in such contexts is relevant since most of the renewable potential is in low and middle-income countries, where we also expect a rise in the demand for electricity (Vanegas Cantarero, 2020).

Studies focusing on lower and middle-income countries are often based on a few case studies and qualitative assessments. For example, Winkler et al. (2018) and Bayer et al. (2018) use six and four country cases, respectively, and neither of them is conclusive regarding the effectiveness of tendering mechanisms. Those focusing on particular countries, such as Brazil

(Bayer, 2018) and India (Shrimali et al., 2016), also show inconclusive results regarding the effects of auctions. To the best of our knowledge, Bersalli et al. (2020) is the only large-scale quantitative study that uses data from OECD, European, and low and middle-income countries (particularly Latin American countries).

In terms of methodological choices, many of these quantitative studies rely on two-way-fixed-effects (TWFE) models to evaluate the effects of RE policies (see *Supplementary material 1* 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 countries have adopted auctions at different points in time, and it is unlikely that the effects of the policy are perfectly homogeneous across all countries in the sample.

Here we build on this body of literature by analyzing whether the effect of RE auctions varies according to the quality of the business environment in the countries that have adopted auctions. Our definition of business environment comprises both macroeconomic stability and the quality of institutions. For this purpose, we have drawn from multiple publicly available databases to build a panel dataset for 2000-2020, covering 98 countries with different macroeconomic and institutional profiles. In particular, we address the following research questions: 1) Does the quality of the business environment operate as a driver for the adoption of RE auctions? 2) Are RE auctions successful in promoting the deployment of RE in contexts of macroeconomic instability and poor institutional quality? 3) Does the effectiveness of auctions to promote investments in RE vary across different technologies (i.e., solar, wind, biomass)?

To the best of our knowledge, this is the first quantitative study that uses data from a large number of countries with varying macroeconomic and institutional conditions to explicitly analyze the effects RE auctions in different business environments. Furthermore, we make an empirical contribution by using two novel differences-in-differences 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 to the more traditional TWFE approach.

The remainder of this paper is structured as follows: in section 2, we conceptually describe how the effects of auctions might vary depending on the quality of the business environment. In section 3, we describe the data sources and methods used in the paper. In section 4, we show the results of our empirical analysis, which are discussed in section 5. Policy implications and further research opportunities are presented in the final section.

2. Auctions as a mechanism to promote renewable energy

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 against each other to supply those volumes. According to 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 21, 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 to OECD or European countries. This section explores some theoretical aspects of RE auctions to understand their main advantages and disadvantages in unstable business environments.

2.1 The promise of auctions for countries in weak business environments.

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, 2015). The actual marginal costs of the energy produced are only partially known by the government, leading to a potential overcompensation of costs (especially for mature technologies). Auctions promote competition and encourage price discovery, thus reducing public expenses to remunerate RE (Maurer and Barroso, 2011). Tendering schemes also allow better control of the volumes provided (del Río, 2017). Therefore, countries with limited public budgets might benefit from auctions as they can be cost-effective for procuring RE.

A second argument relates to risk mitigation, both to the government and private investors. Auction winners sign a legally binding agreement (usually a long-term contract) that specifies both the quantity to supply and the price received. This provides more robust warranties to investors against sudden policy changes (IRENA, 2017). Enforcement issues, potential penalties, and conflict settlement are more explicit 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 pre-qualifications usually improve the instrument's effectiveness (Matthäus, 2020).

Finally, tendering systems allow for a flexible design and can be easily adapted to different contexts. For example, auctions may include secondary goals such as employment generation or value chain development (through local content requirements), the deployment of a specific RE technology (through technology-specific auctions), or actor diversity (i.e., a special regime for smaller actors) (Steinhilber and Roselund, 2016). As such, auctions can be designed to address multiple socioeconomic and environmental challenges simultaneously. This is especially attractive for developing countries that may need to adopt broader criteria in policy design.

2.2 Potential disadvantages of auctions in weak business environments.

Depending on the macroeconomic and institutional setting in which auctions are held, they could be less effective in deploying RE or even lead to non-desirable outcomes. The first relates to non-competitive settings 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 in their electricity markets, such as dismantling public monopolies, unbundling production and distribution, and fostering the entry of international power producers. However, these reforms had different success rates, not always increasing competition or reducing electricity prices (Nagayama, 2007; Zhang et al., 2008).

A second critique relates to transaction costs (del Río and Linares, 2014). Hidden transaction costs may outperform savings for governments while restricting the chance of bidding only to big firms (which are the ones 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). Moreover, the excessive efforts to create attractive financial conditions for private investors in developing countries may increase market concentration and create tensions with local communities (Sovacool et al., 2019).

The third potential disadvantage comes from high corruption levels and an overall lack of trust in the government. The literature on public procurement systems indicates that we tend to observe lower quality in the procured goods or contracted infrastructure in contexts with high levels of corruption (Dastidar and Mukherjee, 2014). Furthermore, high corruption can lead to overpricing (Arozamena and Weinschelbaum, 2009; Finocchiaro Castro et al., 2014). Without a minimum level of trust in the government and public institutions, investors might fear that payment conditions are arbitrarily modified or their contracts are unilaterally terminated.

The fourth critique is related to underbidding and the winner's course. Competitive pressures might force bidders to offer prices that barely cover marginal costs, and this may be particularly relevant with a high number of bidders (Hong and Shum, 2002). Bidders may manage low price-cost margins in high-income economies that are usually stable. However, sudden exchange or interest rate changes in unstable environments can severely affect bidders' projected revenues and thus lead 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.

Despite the instrument's popularity and the increasing number of adopters from low and middle-income countries, given the arguments presented in this section, it is yet unclear from a theoretical standpoint if auctions are an effective instrument for fostering RE capacity in countries with unfavorable business environments. This is what we will explore in this paper. In the following sections, we present the data and methods used for this purpose.

3. Methods

3.1 Data and descriptive statistics

We built a database collecting information from publicly available data sources for 98 countries. Out of these, 70 implemented auctions between 2000-2020. We have compiled data from all 98 countries for this period to describe them regarding their RE energy policies and installed capacity, socioeconomic characteristics, natural endowment, and business environment.[1] In Table 1, we present 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 3.2). 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 since this is the most popular and widely adopted policy (Ferroukhi et al., 2018, p. 22), and it is the main policy gradually being replaced by auctions (REN 21, 2021, p. 79). For our outcome variable, we collected information from the IRENA on the capacity for solar, wind, and biomass technologies and expressed it as a share of the total installed capacity (detailed in section 3.1).

In our empirical analyses, we control for variables that characterize the countries in terms of their socioeconomic profiles and natural endowment. To capture economic growth and overall income level, we use GDP per capita from the World Bank. 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, CO2 emissions per capita, the share of electricity produced through fossil sources, and net electricity imports. 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 have included covariates related to the level of development (i.e., GDP or income) and the 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. We define macro-level stability 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). For price stability, we use the variable inflation from International Monetary Fund (IMF). We include dummies for debt and currency crises to reflect sustainable public finances and exchange rate

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

stability. These data come from Laeven and Valencia (2020) and Nguyen et al. (2021). Additionally, we use the IMF financial development index as a proxy for the long-term quality of the financial system. As for the 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).

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 supplementary material
Auctions	2058	0	1.0	0	0.2	0.4	2000-2020	Dummy	AUC3 = 1 if treatment is in place; AUC3 = 0 otherwise	See supplementary material
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.	Global Data Pack 2021 (REN 21) 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 US$	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 100m (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 & Valencia (2020) + Nguyen (2021)
Debt Crisis	1960	0	1.0	0	0.1	0.3	2000-2019	Dummy	debt_crisis = 1 if the country experienced a currency crisis in the specific year; debt_crisis = 0 otherwise	Laeven & Valencia (2020) + Nguyen (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)
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 uncon stitutional 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 0-100 to facilitiate the interpretation of the coefficient.
(3) The original index goes from -2.5 to 2.5, but it was rescaled from 0-100 to facilitiate the interpretation of the coefficient.
(4) For estimation purposes, these variables are included in its log form.

3.2 Outcome variables

There are different alternative measures for the incidence of renewable sources in the energy matrix (*Supplementary material 1*). 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 generation since the capacity reflects better 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 since these are the two most widely adopted RE sources. We also incorporate biomass, given its role in providing stable capacity to the system. We exclude hydropower sources due to reported negative environmental impacts (Rosenberg et al., 2000). We also use as outcome variables individual measures for the share of solar, wind, and biomass.

3.3 Treatment variables

For our empirical analyses, we consider the adoption of auctions as our treatment variable. In other words, countries that have implemented auctions between 2000-2020 are considered “treated,” and countries that have not implemented auctions during this time 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 is not running auctions regularly every year, the implementation of 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 in terms of the willingness of the authorities to promote RE (IRENA, 2015; Maurer and Barroso, 2011). *Supplementary material 2* details each country's treatment start and the sources used to code this variable.

In our sample, 70 out of the 98 countries have implemented auctions between 2000-2020 (i.e., “treated”) while 28 have not (i.e., “controls”)[2]. Figure 1 shows which countries are treated and which are controls. We include the length of the treatment for the treated units (i.e., the number of years from the first documented auction up to the end of the period).

[2] Originally, we collected data for 100 countries. However, UK and Ireland were excluded from the analysis since both countries had RE auctions programs during the 90s, before the start date of our analysis.

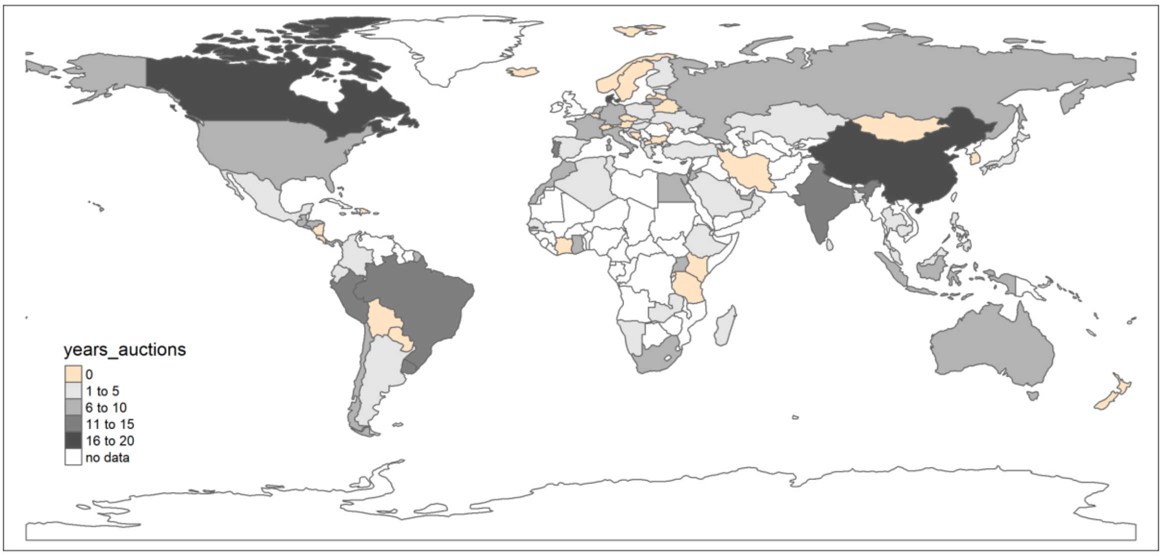

Figure 1. Countries selected in the sample and length of the treatment.

3.4 Checking self-selection

Because countries self-select into treatment, i.e., they choose if and when to implement auctions, this decision might be cofounded by other factors affecting RE deployment, thus biasing our estimates. Therefore, we start our empirical analyses by checking to what extent self-selection might be a concern, putting special emphasis on whether countries with specific institutional or macroeconomic features are more likely to adopt auctions. This first step will also contribute to answering our first research question, in which we ask whether the quality of the business environment is a driver for choosing auctions.

For this purpose, we follow an approach similar to Hoynes and Schanzenbach (2009) and run a Poisson regression of the following form:

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

z_i^{2020} is a count variable that reflects the total number of years since country i implemented its first auction. The variable takes the value 0 for non-adopters. We regress this on a set of pre-treatment variables to identify what characteristics help explain if and when countries chose to adopt auctions.

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 and if it already had feed-in policies in force at that time. ENE_i^{2000} is a group of variables reflecting the profile of the energy matrix in the year 2000. We include oil rents, the share of electricity generation from fossil fuels, emissions per capita, and net electricity imports. NAT_i includes variables that capture the natural endowment of the country. These variables are time-invariant, so the superscript '2000' is not included. ECO_i^{2000} is a vector of variables related to the macro-level instability in 2000 and INS_i^{2000} is a vector of variables that describe the institutional quality in 2000. ε_i is the error term, which we cluster using the World Bank income groups in the year 2000. For calculation purposes, we use the R package *mfx*, which allows us to recover marginal effects and calculate clustered standard errors (Fernihough and Henningsen, 2019).

3.5 Classifying countries according to their business environment

In this second step, we classify countries according to the quality of their business environment. For this purpose, we work with the four macroeconomic and six institutional variables related to the business environment and combine two tools: principal component analysis (PCA) and cluster analysis. We conduct these analyses using the sum of currency and debt crises for the time 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 over those scores using the k-medoids approach (Partitioning Around Medoids, PAM). This approach is more robust than the k-means, being less sensitive to outliers (Kaufman and Rousseeuw, 1990). 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 40 countries being classified as having a high-quality business environment and the remaining 58 as low-quality. The methodological details are presented in *Supplementary material 3*, and the list of countries classified in each group are shown in *Supplementary material 5*.

3.6 Econometric Analysis

To estimate the causal effects of auctions on the deployment of RE, we use a Differences-in-Differences (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:

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

With multiple time periods, not every unit might get the treatment simultaneously (what is known as 'differential timing'). The standard approach, in this case, is the two-way fixed effects model (TWFE), 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 that we will use in this paper.

Previous studies that analyse the effects of RE auctions have relied on TWFE for their empirical analyses (see *Supplementary material 1*). However, the estimation of the parameter β may be biased when treatment effects are heterogeneous across units. 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). Since 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 2x2 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 to 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 the weighting method 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 previous to treatment, we use the event-study plots (Callaway and Sant'Anna, 2022a), presented later in the paper (Figure 6).

The second DiD model we use follows a somewhat different estimation procedure. It is called two-stage DiD (hereafter 2SDID), developed by Gardner (2021). The intuition behind this method is that the untreated potential outcomes ($y_t^0|\ treated = 0$) decompose into group and time effects (Cunningham, 2021b). 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 $y_t^0|treated = 1$ by using untreated units. It has the advantage of simplicity and shows efficiency gains compared to CS when the parallel trend assumption holds (Borusyak et al., 2021). However, when the parallel trend assumption holds conditionally, 2SDID is less stringent and more parametric 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:

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

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

[4] This concept is equivalent to the average treatment effect on the treated from the canonical 2x2 DiD.

[5] Given the nature of our research setting, we have multiple groups of small size, and the overlapping condition is weak (see *Supplementary material 4*). 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.

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

In this case β^{2s} recovers the true ATT. For the empirical estimation, we use the R package *did2s* developed by Butts et al. (2021). Observations are weighted by the size of their group cohort to keep coherence with the CS group aggregation (see *Supplementary material 4*).

3.7 Inclusion of covariates

We need to 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 both 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 CO2 emissions); import dependency (net imports of electricity); and natural endowment for solar, wind and biomass.

(iii) *Controls (2)*: we include 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 the countries with high-quality business environments (*high_qual*) and only the countries with low-quality business environments (*low-qual*). This allows us to estimate the average effect of RE auctions and to analyze if these effects vary depending on countries' business environments. Lastly, to analyse 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 while others are not. The TWFE and 2SDID models rule out time-invariant variables. On the other hand, the CS package (2022a) requires explicitly 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

[6] However, as we mentioned before in the paper, the author recognizes that this approach is less stringent and more parametric than CS.

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

set of covariates in both stages of the regression. As for the macro-level and institutional variables in controls (2), we choose the ones that are significant in the Poisson models[8], as they suggest that those specific variables influence the decision to adopt auctions.

A summary of the methodology presented in this section is shown in Figure 2.

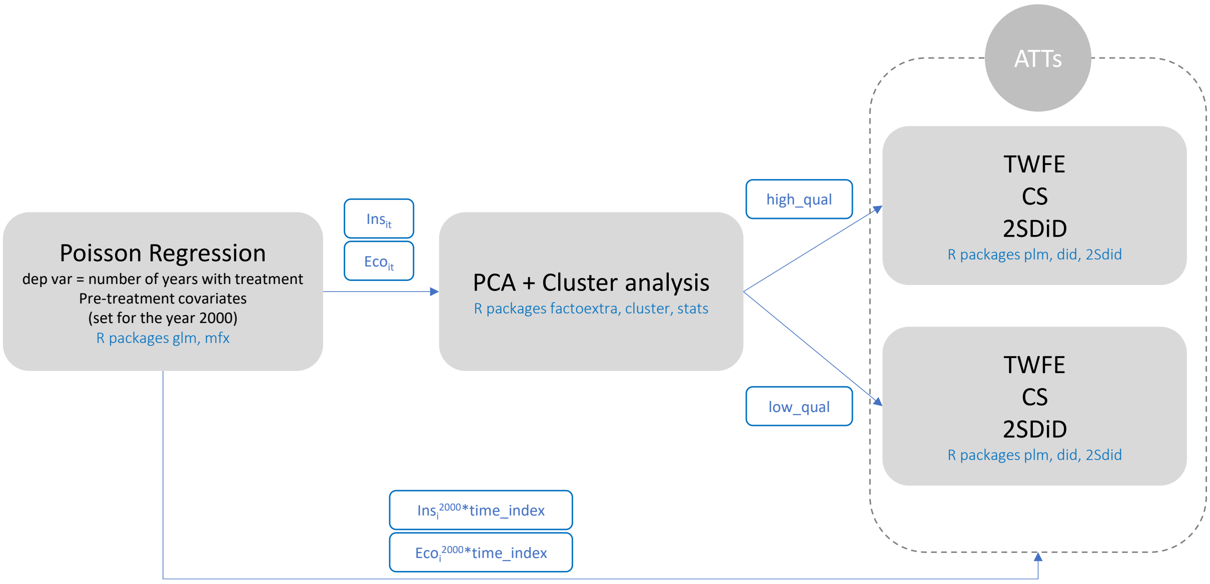

Figure 2. Summary of the methodology. We use Poisson regression to explain the influence of institutional (Ins_{it}) and macroeconomic (Eco_{it}) variables in adopting auctions. Then, we use both sets of variables (Ins_{it} and Eco_{it}) to classify countries according to the quality of their business environment. Finally, we calculate the average treatment effects of adopting auctions through three different methodologies (TWFE, CS and DID).

[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.

4. Results

4.1 The role of the business environment in the adoption of auctions

The first step of our methodology is to check for self-selection issues and, simultaneously, explore to what extent the quality of the business environment determines the adoption of auctions. Table 2 summarizes the results for various specifications of Poisson regressions. In each specification, we gradually added different groups of covariates (as defined in section 3). The six variables from the Worldwide Governance Indicators database included in the vector INS_i^{2000} were added separately to avoid multicollinearity. All of the results in Table 2 are expressed in average marginal effects, reflecting 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, we found results consistently significant across models for FDI and inflation. The positive sign for FDI indicates that a more developed financial infrastructure lowers the cost of capital to fund RE projects. The negative sign for inflation is expected, considering how unpredictable costs and income become in inflationary contexts.

Rule of law is the only significant variable from the institutional setting. According to Kaufmann et al. (2010, p. 4), 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 is contrary to intuition, given that healthier democratic institutions are typically associated with higher adoption of environmental policies (Stadelmann and Castro, 2014). 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 areas, auctions may help to reduce functionaries' discretion for handling procurement projects (Baldi et al., 2016).

Although these coefficients are statistically significant, their size is too small to support that institutional or macro-level variables consistently affect the decision to adopt auctions. For instance, if we take the values of FDI and Inflation in Model 6, 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 around 1 point explains a change of 0.093 years in the length of the treatment.

Table 2. Results. Determinants of treatment adoption (Poisson models).

	Dep. Var.: Lenght of Treatment (# of years with auctions in the period 2000-2020)									
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**
Share of Wind, Solar and Biomass	0.127*	0.123*	0.216***	0.162**	0.175*	0.228***	0.222**	0.226*	0.176***	0.183*
	(0.074)	*(0.066)*	*(0.061)*	*(0.081)*	*(0.099)*	*(0.068)*	*(0.109)*	*(0.124)*	*(0.062)*	*(0.095)*
Feed-in policies	3.100**	2.912**	2.579	2.113	2.006	1.889	1.497	1.684	2.032	2.308
	(1.288)	*(1.355)*	*(1.642)*	*(1.417)*	*(1.346)*	*(1.701)*	*(1.095)*	*(1.286)*	*(1.609)*	*(1.545)*
share fo electricity from fossil sources		0.002	-0.016	-0.008	-0.01	-0.016	-0.014	-0.017	-0.011	-0.013
		(0.023)	*(0.018)*	*(0.020)*	*(0.017)*	*(0.015)*	*(0.016)*	*(0.012)*	*(0.021)*	*(0.015)*
Oil rents		-0.015	-0.072***	-0.047**	-0.058**	-0.081***	-0.073**	-0.060**	-0.048***	-0.084*
		(0.030)	*(0.022)*	*(0.021)*	*(0.029)*	*(0.026)*	*(0.036)*	*(0.027)*	*(0.016)*	*(0.051)*
CO2 emissions per capita		0.124	0.776*	0.268	0.356*	0.471	0.499	0.427*	0.345*	0.424*
		(0.271)	*(0.403)*	*(0.182)*	*(0.190)*	*(0.296)*	*(0.308)*	*(0.229)*	*(0.198)*	*(0.225)*
Net imports of electricity		-0.002	-0.008	-0.01	-0.008	-0.011	-0.01	-0.006	-0.007	-0.008
		(0.051)	*(0.044)*	*(0.048)*	*(0.045)*	*(0.044)*	*(0.048)*	*(0.044)*	*(0.050)*	*(0.046)*
Solar potential			1.286***	1.223**	1.229**	1.225***	1.173**	1.207***	1.199**	1.132**
			(0.339)	*(0.529)*	*(0.521)*	*(0.350)*	*(0.462)*	*(0.448)*	*(0.510)*	*(0.568)*
Wind potential			-0.049	0.006	0.04	0.460*	0.146	0.258	0.07	0.111
			(0.351)	*(0.229)*	*(0.219)*	*(0.235)*	*(0.209)*	*(0.224)*	*(0.172)*	*(0.196)*
Biomass potential			-0.006***	-0.004***	-0.004***	-0.005**	-0.004***	-0.004***	-0.004***	-0.003
			(0.001)	*(0.001)*	*(0.001)*	*(0.002)*	*(0.001)*	*(0.002)*	*(0.001)*	*(0.002)*
FDI				0.043***	0.048***	0.104***	0.080***	0.074**	0.047***	0.056***
				(0.005)	*(0.010)*	*(0.016)*	*(0.026)*	*(0.029)*	*(0.008)*	*(0.020)*
Inflation				-0.055**	-0.058**	-0.070***	-0.064**	-0.061**	-0.055**	-0.056**
				(0.025)	*(0.027)*	*(0.023)*	*(0.028)*	*(0.028)*	*(0.022)*	*(0.024)*
Currency crisis				4.082	4.27	6.467*	4.828	4.627	4.07	4.598
				(3.203)	*(3.356)*	*(3.914)*	*(3.655)*	*(3.488)*	*(3.080)*	*(3.544)*
Debt crisis				0.509	0.464	-0.334	0.023	0.114	0.421	0.237
				(1.958)	*(1.939)*	*(1.943)*	*(1.905)*	*(1.940)*	*(1.986)*	*(1.928)*
Regulatory quality					-0.015					
					(0.026)					
Rule of Law						-0.093***				
						(0.025)				
Government effectiveness							-0.06			
							(0.041)			
Control of corruption								-0.052		
								(0.047)		
Political Stability and No Violence									-0.015	
									(0.016)	
Voice and Accountability										-0.039
										(0.057)
Num. obs.	98	98	98	98	98	98	98	98	98	98
Deviance	424.877	423.926	394.86	372.567	372.187	350.487	366.545	366.139	371.731	367.648
AIC	676.424	683.474	660.408	646.115	647.735	626.034	642.093	641.686	647.279	643.196

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

(Standard errors)

Errors clustered by Income Group Year 2000 (WB)

These results have implications for the identification strategy since the small size of the coefficients indicates that the quality of the business environment has only a marginal influence in the choice for RE auctions. Thus, based on these observed variables, we cannot conclude that there are substantial and systematic differences between countries that affect their decision to adopt auctions early on. Nonetheless, as explained in the methods section, despite the small size of the coefficients, we still include the variables FDI, Inflation, and 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.

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

sss The main objective of this article is to analyse the effectiveness of auctions to promote RE investments under different business environments. In Figure 3, we plot the coefficients of the effects of auctions for our three models and three specifications. The estimates are shown for the entire sample and for the sub-samples of countries with high-quality and low-quality business environments. All the coefficients in the table 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 10%. Previous papers have found even smaller effect sizes: for instance, Kilinc-Ata (2016)[9] found an effect of around 0.7% for tendering mechanisms.

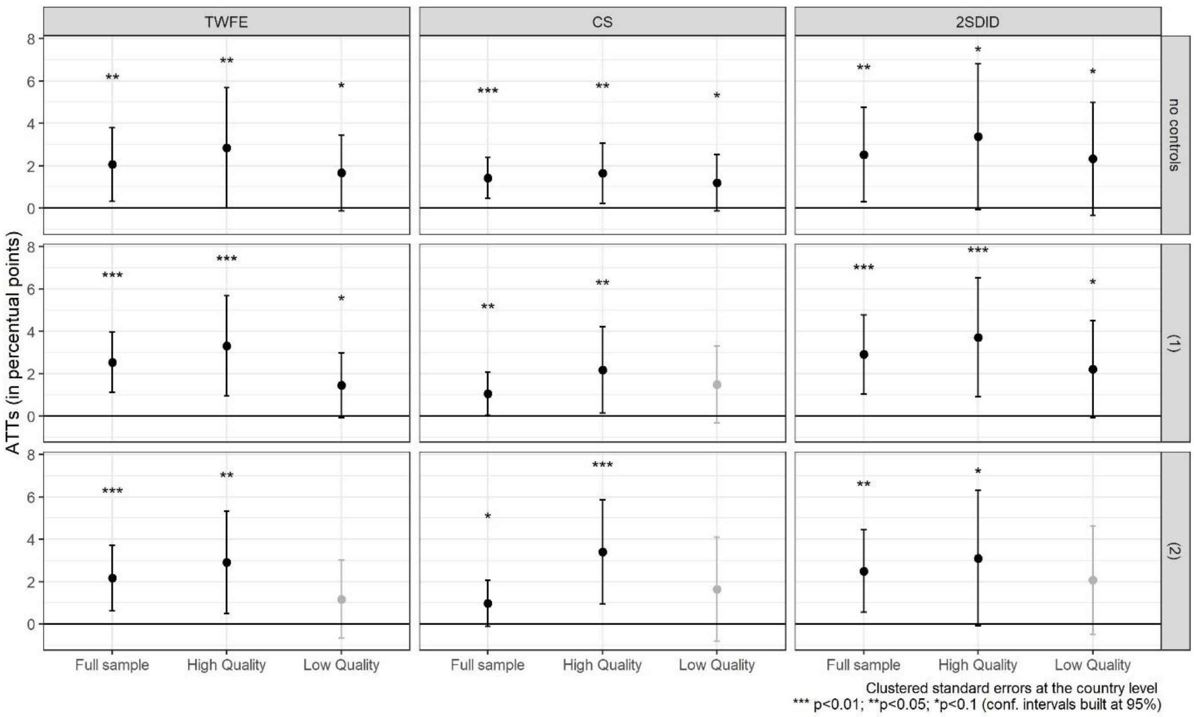

Figure 3. Average treatment effects (ATT) of auctions on RE as share of total installed capacity. Point estimates from all three models (TWFE, CS, and 2SDID) are shown with 95% confidence intervals. Grayed out point estimates indicate that the coefficient is not statistically significant (p > 0.10). Rows indicate different model specifications: *'no controls'* assumes that the parallel-trends assumptions is fulfilled unconditionally*; 'controls (1)'* include as covariates feed-in policies, GPD per capita (in 2015 USD), oil rents, share of electricity produced through fossil sources, CO2 emissions, net imports of electricity and the natural endowment for solar, wind and biomass; *'controls (2)'* additionally controls for inflation, FDI and rule of law.

Then, we move to the subsample analysis, dividing countries according to the quality of their business environment. Countries that are stable from a macroeconomic perspective and show high-quality institutions fall under the 'high-quality' category. In contrast, countries with some

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

degree of macro-level instability and poorer institutions belong to the 'low-quality' group. In *Supplementary material 5*, we present the complete list of countries and how they are classified.

There are two main aspects to highlight from the subsample analysis. The first point is that, in every model specification, the results are significant at least at 10% for countries in the high-quality group. The same is not true for countries in the low-quality group, for which we find significant results only for some model specifications. The second aspect is related to the size of the coefficients: the effects are always greater in magnitude 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, while in the case of low-quality countries, it ranges from 1.17 to 2. For the period under analysis, auctions have consistently been more effective in countries with a more stable business environment. The reasons behind these results will be discussed in the next section.

Bearing in mind 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 *Supplementary material 3*. The results of this alternative procedure are presented in *Supplementary material 6* and do not differ substantially from the main analysis.

4.3 The effect of auctions for each RE technology

In our third research question, we ask if there are substantial differences in the results according to the type of renewable technology. In Figure 4, we present results disaggregated by RE technology. We do not have an indicator in our models to account for technology neutrality or specificity of auctions. Therefore, the results are primarily exploratory and should be taken 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, but 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). On the other hand, we find significant results for solar and biomass in the low-quality group. Africa and South East 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 South East Asia are trying to exploit their biomass potential. On the contrary, European countries have disincentivized crop biomass due to potential land-use changes and food-energy competition (Scarlat et al., 2018).

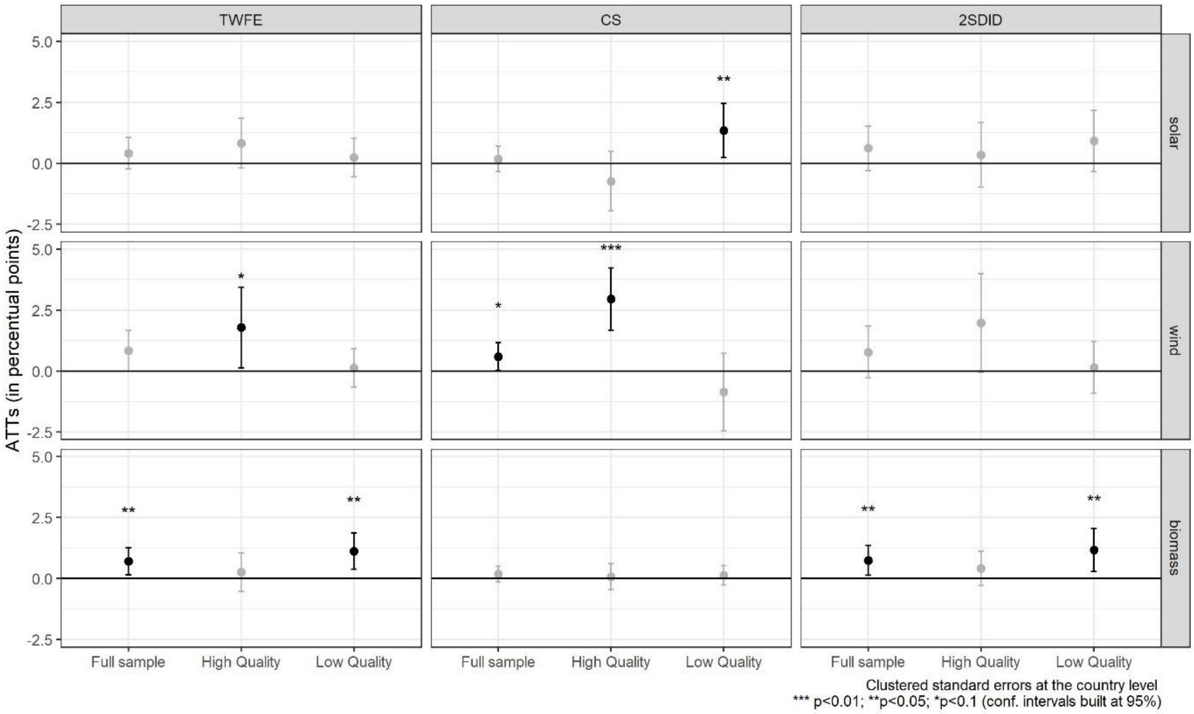

Figure 4. Average treatment effects (ATT) of auctions by RE technology. Point estimates from all three models are shown with 95% confidence intervals. Grayed out point estimates indicate that the coefficient is not statistically significant (p > 0.10). Rows indicate the effects disaggregated by RE technology.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

5. Discussion

When we look at 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 to the evidence for other policy instruments from the literature. For feed-in-tariffs, the evidence is mixed: Kilinc-Ata (2016) finds a positive effect of around 2.8 p.p. over the ratio of RE capacity, while Aguirre and Ibikunle (2014), Bento (2020) and Popp et al. (2011) do not find significant effects. We even see a negative impact of feed-in-tariffs in Romano et al. (2017). While these traditional policies have been drivers for the promotion of RE, they have reached a saturation point in which countries are exploring new instruments, especially considering that policy accumulation does not necessarily lead to better results (Zhao et al., 2013).

Despite its fast adoption rate in low and middle-income countries and some potential advantages in contexts with macroeconomic and institutional instability, our results show that RE auctions perform better in countries with stable business environments. What are the reasons behind these results? We present here four different lines of explanation.

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

The second reason is the absence of a schedule for auctions in some countries, which might lead to auctions running on a sporadic basis. According to Del Río and Kiefer (2021), European countries have shown a scheduling trend, which is not the case for other regions. Private actors might be reluctant to invest if they do not foresee consistent auction planning (Hochberg and Poudineh, 2018; IRENA, 2019). Figure 5 panel (a) shows the proportion of years in which countries effectively performed auctions after implementing the first one[10]. While the median for countries in the high-quality group is above 0.5, it is lower for the low-quality group.

Running auctions regularly is relevant because of dynamic effects. In Figure 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 units adopted the treatment (lags). The fact that these coefficients are close to zero and non-significant shows that the pre-testing of parallel trends assumption is fulfilled. Positive values represent leads

[10] Countries with less than two years into the treatment were excluded.

of the variable, showing the effects of the policy according to the length of exposure to the treatment. Here we see how average treatment effects grow over time. This implies that countries must capitalize on lessons from initial rounds and stick with the instrument to see consistent results (IRENA, 2015).

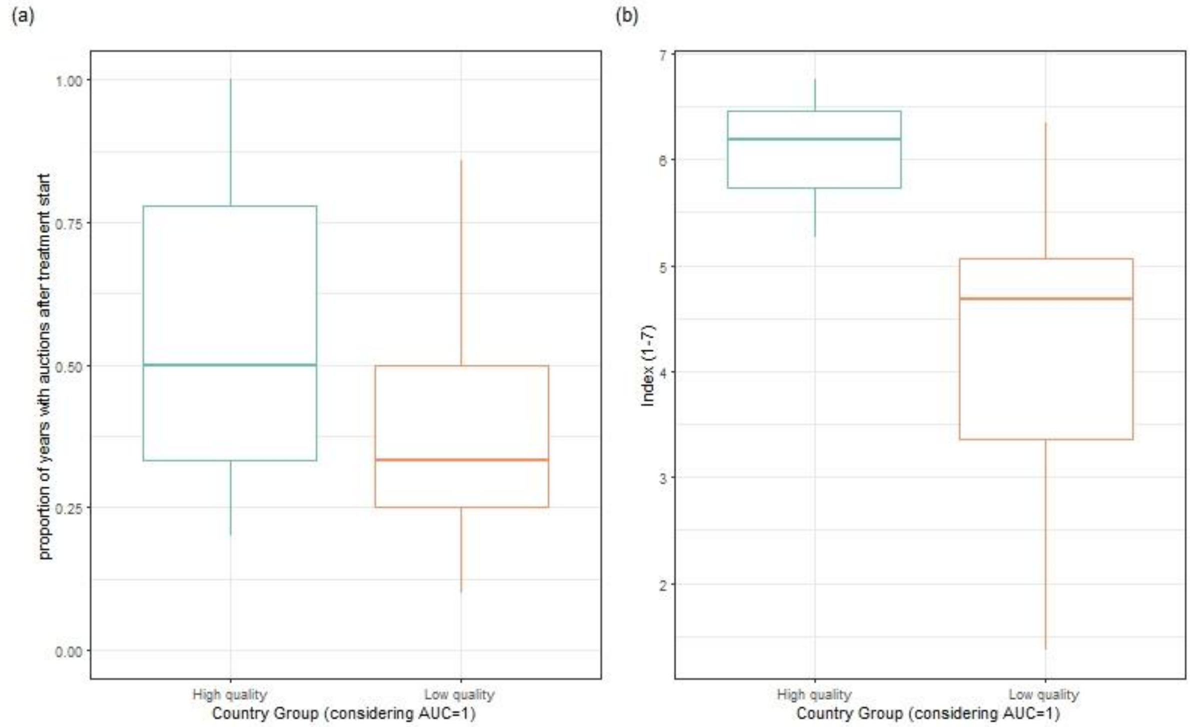

Figure 5. Panel (a). Frequency of auctions. Proportion of years in which countries have effectively launched auctions after implementing the first one (for countries that have adopted auctions before 2019). **Panel (b). Perceived quality of infrastructure.** In your country, how reliable is the electricity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

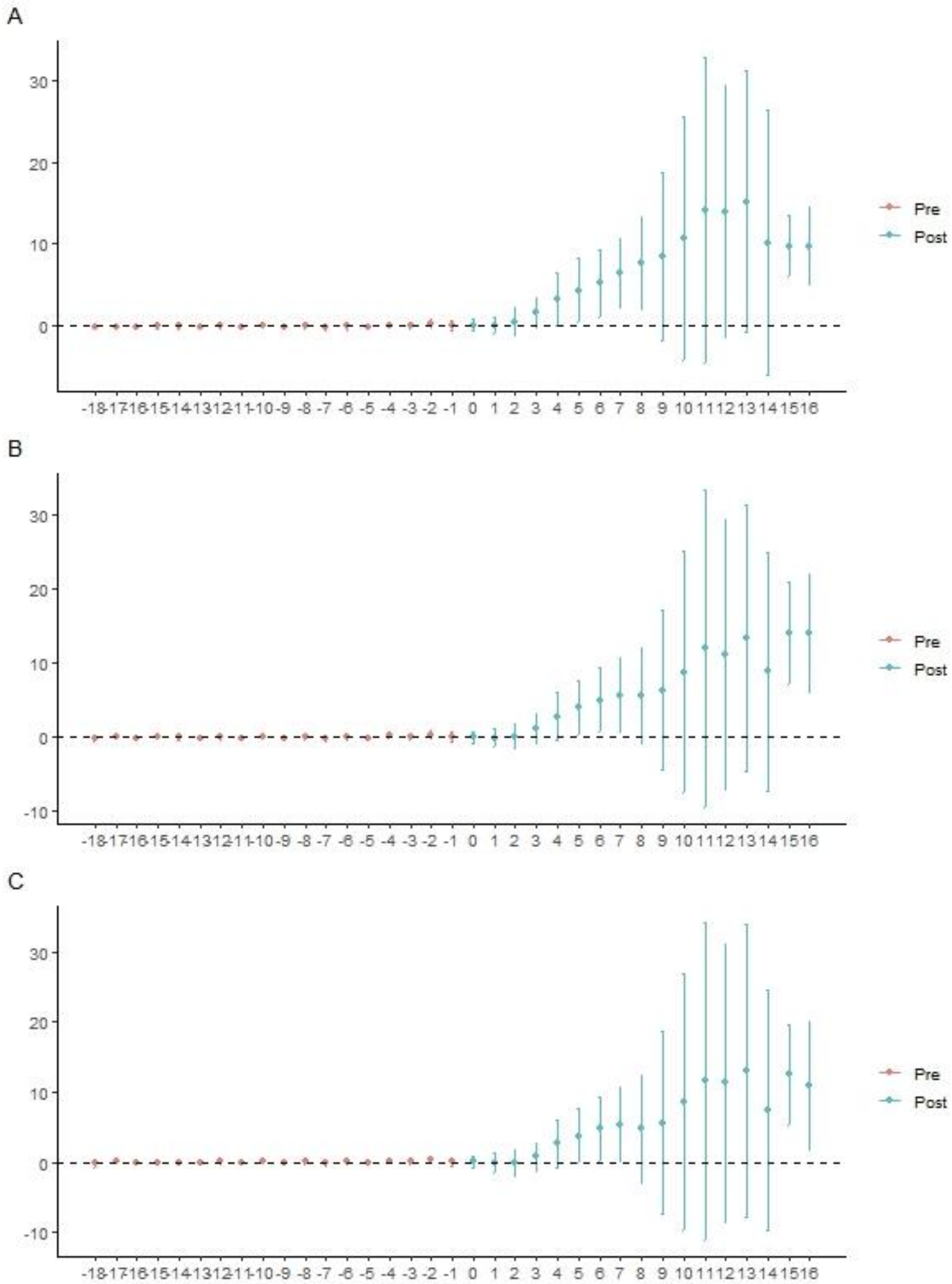

Figure 6. Event-study plot to test for pre-treatment parallel trends. This figure presents even-study plots for three scenarios of control variables as explained in Section 4.4: no controls in panel A, controls (1) in panel B, and controls (2) in panel C. In each case, we see that the parallel trend condition is fulfilled before treatment (period 0) since we don't see any significant coefficients.

The third factor is that auction programs can still fail in the construction phase despite high realization rates. Setting up the physical and administrative infrastructure takes time and money for auction winners. If financial or macroeconomic conditions change in the mid-time, this could bring unexpected delays and even early project termination (Gephart et al., 2017). Inefficiencies and delays have been frequently reported in different 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 is due to design flaws. Many countries include additional features that do not always contribute to the success of tendering schemes. For instance, in developing countries, we have seen a trend toward including Local Content Requirements (LCR). In such cases, auctions are considered both a RE policy and a means to promote local development (del Río and Kiefer, 2021). However, if these requirements are too stringent, or if there are no complementary measures to build local value chains, the effectiveness of the auction program could be severely affected. Delays due to a mismatch between LCR schemes and local capacities have been reported in Brazil, South Africa, and Indonesia (del Río, 2017; Dobrotkova et al., 2018; IRENA, 2013).

6. Conclusion

Auction mechanisms bring the promise to promote investments in RE while capping support costs. Accordingly, many low and middle-income countries have 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. In this paper, we presented a quantitative evaluation of RE auctions, exploring if the effectiveness of this policy in fostering RE capacity varies according to the quality of the business environment (defined as a combination of macro-level stability and institutional quality).

We make an important empirical contribution by considering heterogeneous treatment effects and staggered policy adoption. TWFE models, which have been 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 and compare the results to the more standard TWFE approach.

Overall, our analysis shows that auctions contribute to increasing the share of RE over total system capacity. However, the adoption of this policy should be taken with caution. Despite the prevailing optimism, the results still look modest for countries where the business environment is not optimal. This need for caution around RE auctions has already been pointed out in previous qualitative case studies (Cassetta et al., 2017; Grashof et al., 2020; Winkler et al., 2018).

The findings in this paper have three main policy implications. The first one is related to how governments in countries with unstable business environments manage uncertainty. Auctions 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 to mitigate risks and bring confidence to investors. One possible way is to engage 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, 2019, 2018). Another option is to include de-contracting auctions in which companies can bid for a fine and cancel the project (IRENA, 2017). This could provide additional safeguards against changes in the business environment.

A second policy implication is related to the frequency with which countries launch RE auctions. In countries with weak business environments, significant RE capacity increases will only occur if investors foresee the government’s willingness to keep 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 fine-tune the design features. Different analyses show 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 resources endowment. This is especially true for developing countries where public budgets are usually limited. For instance, we saw that auctions contribute to increasing the share of biomass energy in countries with a low-quality business environment (Figure 4). Biopower projects have higher initial investments and operational costs (FAO, 2020). Nevertheless, auctions could be suitable for fostering this technology in countries with a biomass surplus. Investments in biomass-based electricity foster cascading use of waste from agricultural and agro-industrial production and provide a low-carbon reserve capacity for the system (Johansson et al., 2019).

A critical assessment of the effectiveness RE auction mechanisms is needed since they are gradually becoming the dominant RE policy choice worldwide. Our work has limitations, though. The first one is the size of the cohorts of adoption. Even when we focus on aggregated measures, having such small groups widens confidence intervals and reduces estimation quality (especially in the CS methodology). The second limitation is related to treatment irreversibility. The DiD approaches we applied here 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 is policy stringency: pricing mechanisms, penalties, and physical or financial requirements are critical features to safeguard the instrument's effectiveness. Our definition of the treatment 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 to discover nuances or specificities for each RE source that could contribute to improving auction design.

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Supplementary material 1. Systematization of the literature.

Paper	Period	Geographical Scope	Outcome variable	Methods	Control for Institutional or macro-level instability	Include AUC	Subsampling
Shrimali and Kniefel (2011)	1991–2007	50 US States	RE capacity / Total net generation (%)	TWFE	N	N	-
Gan and Smith (2011)	1994-2003	26 OECD countries	RE supply (per cápita)	TWFE	N	N	-
Marques and Fuinhas (2012)	1990-2007	23 EU countries	RE over total primary energy supply (%)	PCSE, RE, TWFE	N	N	-
Dong (2012)	2005-2009	53 countries	Wind cumulative and total capacity	OLS, TWFE, RE	N	N	-
Jenner et al. (2013)	1992–2008	26 EU countries	RE annual added capacity	FE	N	Y (+/-)	-
Zhao et al (2013)	1980-2010	122 countries	RE over total electricity generation (%)	OLS, PPML	N	N	Developed / Developing / Emerging countries
Aguirre and Ibikunle (2014)	1990-2010	38 countries (all EU, rest of OECD countries and Brazil, Russia, India, China and SA)	RE over total primary energy supply (%)	FEVD, PCSE	N	N	-
Flora et al (2014)	1998-2011	18 European countries	RE unused output to maximum possible output (%)	OLS, RE, FE, AR(1)	N	N	-
Omri (2015)	1990-2011	64 countries	RE consumption	Pooled, TWFE, RE diff-GMM, sys-GMM	N	N	High / Middle / Low Income countries
Sisodia and Soares (2015)	1995-2011	European Union (EU-27)	RE Investments (solar and wind)	OLS	N	N	-
Polzin et al (2015)	2000-2011	30 countries (mostly OECD)	RE annual added capacity	OLS, TWFE, RE	N	N	-
Kilinc-Ata (2016)	1990–2008	27 EU countries and 50 US states	RE capacity over total capacity (%)	TWFE	N	Y (+)	-
Cadoret and Padovano (2016)	2004-2011	26 European countries	RE in gross energy consumption (%)	LSDV (1st stage) + OLS (2nd stage)	Y (corruption)	N	-
Sisodia et al (2016)	1995-2011	27 European countries	RE Investments (solar and wind)	OLS	Y (regulatory quality)	N	EU 27 / EU-15 / EU-11
Romano et al (2017)	2004-2013	56 countries	RE generation over total net electricity generation (%)	OLS, RE, FE	N	N	Developed / Developing countries
Upton and Snyder (2017)	1990-2013	49 US States	RE supply (per cápita)	SC	N	N	-
Ramalho et al. (2018)	1971-2004	193 countries	RE contribution to electricity output (in GWh)	Multinomial fractional Logit	Y (democratization)	N	-
Sequeira and Santos (2018)	1998-2017	Between 100 and 126 countries (meta-analysis)	RE in gross energy consumption (%)	Multinomial fractional Probit	Y (democratization)	N	-
Liu et al (2019)	2000-2015	29 countries (all EU, rest of OECD, Kyoto Protocol signees + India and China)	RE total installed capacity	RE, FE	N	N	-
Damette and Marques (2019)	1990-2012	24 Eropean countries	RE share over total energy production (%)	Fully Modified OLS Dynamic OLS	N	N	-
Bento et al. (2020)	2004-2014	20 OECD countries	RE capacity yearly increase	OLS, PSM, SC	N	Y (+)	-
Marques et al (2010)	1990-2006	24 EU countries	RE contribution to energy supply (%)	OLS, FE, RE, FEVD	N	N	-
Bersalli et al. (2020)	1995-2015	20 Latin american countries and 30 European countries	RE added capacity	FE, RE	N	Y (+)	European / Latin American countries
Uzar (2020)	1990-2015	32 Countries	RE consumption	ARDL	Y (institutional quality)	N	-
Kersey (2021)	2000-2018	31 Caribbean islands	RE cumulative capacity	TWFE	N	N	-
Abban and hasan (2021)	2007-2017	60 countries	RE added capacity	sys-GMM	N	N	Developed / Developing countries

TWFE = two-way fixed effects; **FE** = fixed effects; **RE** = random effects; **OLS** = Ordinary least squared; **SC** = Synthetic Control; **LSDV** = Least Square Dummy Variable;
PPML = Poisson pseudo-maximum likelihood; **diff-GMM** = difference generalized method of moments; **sys-GMM** = system generalized method of moments;
PCSE = Panel Corrected Standard Error; **FEVD =** Fixed Effects Vector Decomposition; **PSM** = Propensity Score Matching
AR (1) = Autorregressive model of order 1; **ARDL** = Autoregressive distributed lag model

Supplementary material 2. Start year of the auction program by country.

Country	ISO	Treatment start	Sources
Estonia	EST	2020	AURES II
Ukraine	UKR	2020	Del Río and Kiefer (2021)
Croatia	HRV	2019	AURES II - Del Río and Kiefer (2021)
Hungary	HUN	2019	AURES II - Del Río and Kiefer (2021)
Slovakia	SVK	2019	AURES II
Colombia	COL	2019	Matthäus (2020) - Del Río and Kiefer (2021)
Bahrain	BHR	2019	Matthäus (2020) - IRENA (2019)
Cambodia	KHM	2019	Del Río and Kiefer (2021)
Ecuador	ECU	2019	Del Río and Kiefer (2021)
Finland	FIN	2018	AURES II
Luxembourg	LUX	2018	AURES II - Del Río and Kiefer (2021)
Senegal	SEN	2018	Matthäus (2020) - Del Río and Kiefer (2021)
Kuwait	KWT	2018	Matthäus (2020) - IRENA (2019)
Oman	OMN	2018	Matthäus (2020) - IRENA (2019)
Qatar	QAT	2018	Matthäus (2020) - IRENA (2019)
Albania	ALB	2018	Matthäus (2020) - Del Río and Kiefer (2021) - IRENA (2019)
Kazakhstan	KAZ	2018	Matthäus (2020) - Del Río and Kiefer (2021) - IRENA (2019)
Philippines	PHL	2018	IRENA (2019)
Tunisia	TUN	2018	Del Río and Kiefer (2021) - IRENA (2019)
Madagascar	MDG	2018	Del Río and Kiefer (2021) - IRENA (2019)
Slovenia	SVN	2017	AURES II - Matthäus (2020)
Ethiopia	ETH	2017	Matthäus (2020) - Del Río and Kiefer (2021)
Saudi Arabia	SAU	2017	Matthäus (2020) - Del Río and Kiefer (2021) - Krueger (2018)
Turkey	TUR	2017	Matthäus (2020) - Del Río and Kiefer (2021)
Algeria	DZA	2017	Del Río and Kiefer (2021) - IRENA (2019)
Armenia	ARM	2017	Del Río and Kiefer (2021) - IRENA (2019)
Japan	JPN	2017	Del Río and Kiefer (2021) - IRENA (2019)
Israel	ISR	2017	Del Río and Kiefer (2021) - IRENA (2019)
Namibia	NAM	2017	Del Río and Kiefer (2021) - IRENA (2019)
Lebanon	LBN	2017	Del Río and Kiefer (2021) - IRENA (2019)
Bangladesh	BGD	2017	IRENA (2019)
Argentina	ARG	2016	Del Río and Kiefer (2021) - Viscidi and Yepez (2019)
Greece	GRC	2016	AURES II - Del Río and Kiefer (2021)
Poland	POL	2016	AURES II - Matthäus (2020) - Del Río and Kiefer (2021)
Spain	ESP	2016	AURES II - Del Río and Kiefer (2021)
Jamaica	JAM	2016	Del Río and Kiefer (2021) - Viscidi and Yepez (2019)
Mexico	MEX	2016	Matthäus (2020) - Del Río and Kiefer (2021) - Krueger (2018)
Zambia	ZMB	2016	Matthäus (2020) - Del Río and Kiefer (2021) - IRENA (2018)
Thailand	THA	2016	Del Río and Kiefer (2021) - IRENA (2019)
Sri Lanka	LKA	2016	Del Río and Kiefer (2021) - IRENA (2019)
Malaysia	MYS	2016	Del Río and Kiefer (2021)
Germany	DEU	2015	AURES II - Del Río and Kiefer (2021)
Chile	CHL	2015	Matthäus (2020) - Del Río and Kiefer (2021) - Viscidi and Yepez (2019)
Uganda	UGA	2015	Matthäus (2020) - Del Río and Kiefer (2021) - IRENA (2018)
Ghana	GHA	2015	Del Río and Kiefer (2021)
Egypt	EGY	2014	Del Río and Kiefer (2021)
Lithuania	LTU	2013	AURES II - Matthäus (2020)
El Salvador	SLV	2013	Matthäus (2020) - Del Río and Kiefer (2021)
Indonesia	IDN	2013	Del Río and Kiefer (2021)
Jordan	JOR	2013	Del Río and Kiefer (2021)
Russia Federation	RUS	2013	Del Río and Kiefer (2021)
France	FRA	2012	AURES II - Del Río and Kiefer (2021)
Italy	ITA	2012	AURES II - Del Río and Kiefer (2021)
Australia	AUS	2012	Matthäus (2020) - Del Río and Kiefer (2021)
United Arab Emirates	ARE	2012	Matthäus (2020) - Del Río and Kiefer (2021) - IRENA (2018)
Netherlands	NLD	2011	AURES II - Matthäus (2020) - Del Río and Kiefer (2021)
United States	USA	2011	Matthäus (2020) - Del Río and Kiefer (2021)
Panama	PAN	2011	Matthäus (2020) - Del Río and Kiefer (2021)
South Africa	ZAF	2011	Matthäus (2020) - Del Río and Kiefer (2021) - IRENA (2018)
Guatemala	GTM	2011	Matthäus (2020)
Honduras	HND	2011	IRENA (2013)
Morocco	MAR	2011	Del Río and Kiefer (2021) - Krueger (2018)
India	IND	2010	Del Río and Kiefer (2021) - Krueger (2018)
Peru	PER	2009	Del Río and Kiefer (2021) - Krueger (2018) - IRENA (2013)
Brazil	BRA	2007	Del Río and Kiefer (2021) - Krueger (2018) - Viscidi and Yepez (2019) - IRENA (2013)
Portugal	PRT	2006	AURES II - Matthäus (2020) - Del Río and Kiefer (2021)
Uruguay	URY	2006	Matthäus (2020) - Del Río and Kiefer (2021)
Denmark	DNK	2005	AURES II - Matthäus (2020) - Del Río and Kiefer (2021)
Canada	CAN	2005	Del Río and Kiefer (2021)
China	CHN	2003	Del Río and Kiefer (2021) - Matthäus (2020) - IRENA (2013)
Cyprus	CYP	0	
Costa Rica	CRI	0	
Bolivia	BOL	0	
Rwanda	RWA	0	
Tanzania	TZA	0	
Paraguay	PRY	0	
Austria	AUT	0	
Belgium	BEL	0	
Czechia	CZE	0	
Iceland	ISL	0	
Korea, Republic of	KOR	0	
Latvia	LVA	0	
Mauritius	MUS	0	
New Zealand	NZL	0	
Norway	NOR	0	
Sweden	SWE	0	
Switzerland	CHE	0	
Belarus	BLR	0	
Bosnia and Herzegovina	BIH	0	
Bulgaria	BGR	0	
Dominican Republic	DOM	0	
Iran, Islamic Republic of	IRN	0	
Macedonia	MKD	0	
Kenya	KEN	0	
Moldova, Republic of	MDA	0	
Mongolia	MNG	0	
Nicaragua	NIC	0	
Ivory Coast	CIV	0	
Ireland (*)	*IRL*	*Before 2000*	*Del Río and Kiefer (2021)*
United Kingdom (*)	*GBR*	*Before 2000*	*Del Río and Kiefer (2021)*

(*) Removed from the analysis

Sources:

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Supplementary material 3. Cluster and Principal Component Analysis (PCA).

As presented in Section 3, we use 10 variables to characterize the business environment (comprising macroeconomic stability and institutional quality). To classify countries according to the quality of their business environment, we combine two approaches: PCA and Cluster Analysis. Both methodologies belong to the field of unsupervised learning and have the goal of reducing the number of dimensions in a multivariate dataset. Cluster analysis finds specific groups within the data and classifies observations according to such groups. On the other hand, PCA identifies the main sources of variability within a dataset, helping to keep only a few components from a high-dimensional dataset.

We calculated averages for the period under analysis for the variables that belong to the vectors ECO_{it} and INS_{it} and standardized them (this implied dropping the panel feature of the data). Thus, the following variables took part in both analyses:

- The average Financial Development index (FDI) 2000-2019
- The average annual rates of inflation 2000-2020
- Number of currency crises 2000-2019
- Number of debt crises 2000-2019
- The average index of Regulatory Quality (rqe) 2000-2020
- The average index of Government Effectiveness (gee) 2000-2020
- The average index of Rule of Law (rle) 2000-2020
- The average index of Control of Corruption (cce) 2000-2020
- The average index of Political Stability and No Violence (pve) 2000-2020
- The average index of Voice and Accountability (vae) 2000-2020

We start with a **PCA Analysis.** The goal is to work with a more manageable number of components that explain most of the variability. We use the function 'princomp' from the R package stats.

As is seen in the following table, the first three components explain almost 87% of the variability in the data. Therefore, we are using these three components as the base for our analysis.

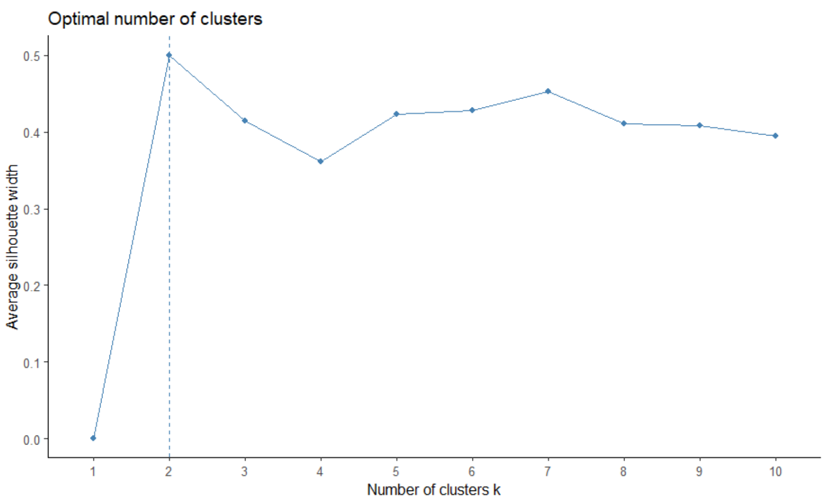
	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7	Comp.8	Comp.9	Comp.10
standard deviation	2.563	1.176	0.876	0.650	0.562	0.524	0.396	0.249	0.158	0.151
proportion of variance	0.657	0.138	0.077	0.042	0.032	0.027	0.016	0.006	0.002	0.002
cumulative proportion	0.657	0.795	0.872	0.914	0.946	0.973	0.989	0.995	0.998	1.000

We extract the scores for the first three components. Just for illustrative purposes, we present in the following table the first 10 components (out of the total 98).

n	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7	Comp.8	Comp.9	Comp.10
1	4.346	0.523	0.037	0.757	0.145	-0.310	0.302	-0.079	0.095	0.259
2	3.908	0.381	-0.255	-0.101	0.145	-0.140	-0.195	0.064	-0.201	-0.047
3	0.042	-1.184	0.571	0.656	0.690	0.592	-0.732	-0.358	-0.105	0.120
4	3.348	0.175	-0.107	0.123	-0.134	-0.225	-0.031	0.099	0.032	-0.184
5	4.384	0.477	-0.076	0.547	0.122	-0.212	0.206	0.033	0.092	0.066
6	2.589	0.084	-0.107	-0.265	-0.050	-0.329	-0.551	-0.138	0.044	0.193
7	0.769	-0.551	0.055	-0.451	-0.146	0.371	0.530	0.034	0.059	-0.212
8	2.368	-0.152	-0.218	0.066	-0.237	-0.052	-0.105	-0.093	0.034	-0.137
9	1.974	-0.142	-0.226	-0.739	-0.145	0.191	0.129	-0.363	-0.279	-0.110
10	4.570	0.512	-0.306	0.074	0.142	-0.293	-0.500	0.168	0.177	-0.078
...	...	...	...	...	...	...	...	...	...	...

We move to the cluster analysis by taking these first three scores. In this case, we use the partitioning around medoids (k-medoids) approach, which is less sensitive to noise and outliers than the traditional k-means approach, thus providing more robust results (Kassambara, 2017). The k-medoids approach search for representative data points within the data (called 'medoids'). The rest of the data points are assigned to each cluster according to its proximity to these medoids, using Euclidean or Manhattan distance measures (Kaufman and Rousseeuw, 1990). The representative data points are the center of the k-clusters.

For estimation purposes, we use the R packages factoextra (Kassambara and Mundt, 2020) and cluster (Maechler et al., 2022). Since the number of clusters needs to be pre-defined, we base our decision on the silhouette graph[11]. As shown by the following chart, the optimal number of clusters in our data is two:



With this analysis, we obtain two dissimilar groups in terms of the medians, as it is seen in the following table[12]:

[11] The silhouette is a measure of closeness of the datapoints within a cluster. A higher silhouette value reflects a better quality of the cluster analysis.
[12] The number of debt crisis and the number of currency crisis are treated as continuous variables for this purpose.

Variable	Low quality (n = 58)	High quality (n = 40)	p-value (1)
average rqe	-0.20 (0.44)	1.13 (0.43)	<0.001
average rle	-0.43 (0.40)	1.12 (0.54)	<0.001
average cce	-0.48 (0.37)	1.08 (0.72)	<0.001
average gee	-0.29 (0.37)	1.18 (0.52)	<0.001
average pve	-0.44 (0.55)	0.86 (0.47)	<0.001
average vae	-0.30 (0.59)	1.07 (0.59)	<0.001
average FDI	0.23 (0.14)	0.59 (0.21)	<0.001
average Inflation	6.1 (5.0)	2.1 (1.5)	<0.001
number of debt crisis	1.0 (6.4)	0.0 (0.5)	<0.001
number of currency crisis	0.0 (1.66)	0.0 (0.27)	0.002

Median (SD)

(1) Wilcox rank sum test

As presented in the following table, 68% in the high-quality group and 74% in the low-quality group adopted auctions during the period under analysis. This means that the control is reasonably large enough in both subsamples.

	performed_auctions		
group	N	Y	Total
High quality	13 (32%)	27 (68%)	40 (100%)
Low quality	15 (26%)	43 (74%)	58 (100%)
Total	28 (29%)	70 (71%)	98 (100%)

Alternative approach: Building an index based on PCA scores.

As a robustness check, we use an alternative approach to classify countries according to the quality of their business environment. We built an index using the same first three components we extracted in the cluster analysis. We used the amount of variance explained by each of the first three components to weight the scores for each observation:

$$\begin{aligned} instindex_i = Scores_{comp1i} \times \frac{var_{comp1}}{(var_{comp1} + var_{comp2} + var_{comp3})} \\ + Scores_{comp2i} \times \frac{var_{comp2}}{(var_{comp1} + var_{comp2} + var_{comp3})} \\ + Scores_{comp3i} \times \frac{var_{comp3}}{(var_{comp1} + var_{comp2} + var_{comp3})} \end{aligned}$$

The following table summarizes the main descriptive statistics for the index:

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-3.101	-1.629	-0.506	0.000	1.408	3.763

Finally, we used the mean as a cutoff point to create two groups: every observation with an index above the mean is considered 'high-quality', and every observation below the mean is considered 'low-quality'. As presented in the following table, with this new approach, we have 70% adopters in the high-quality group and 73% in the 'low-quality' group. This means we have enough control units in each case.

	performed_auctions		
Group	**N**	**Y**	**Total**
High quality	13 (30%)	30 (70%)	43 (100%)
Low quality	15 (27%)	40 (73%)	55 (100%)
Total	28 (29%)	70 (71%)	98 (100%)

Supplementary material 4. Adoption of the treatment. Cohort (G) composition.

G	n	percent
2003	1	1.4%
2005	2	2.9%
2006	2	2.9%
2007	1	1.4%
2009	1	1.4%
2010	1	1.4%
2011	7	10.0%
2012	4	5.7%
2013	5	7.1%
2014	1	1.4%
2015	4	5.7%
2016	10	14.3%
2017	11	15.7%
2018	11	15.7%
2019	7	10.0%
2020	2	2.9%
Treated	70	
Untreated (G=0)	28	

G = year in which the treatment starts

n = number of countries

Supplementary material 5. Classification of countries according to the stability of their business environment (PCA and cluster analysis).

	PCA and cluster analysis	
group	**Low quality**	**High quality**
countries	BHR, KWT, PAN, SAU, ALB, ARG, ARM, BLR, BIH, BRA, BGR, CHN, COL, DOM, ECU, GTM, IDN, IRN, JAM, JOR, KAZ, LBN, MKD, MEX, PRY, PER, RUS, THA, TUR, DZA, BGD, BOL, KHM, CIV, EGY, SLV, GHA, HND, IND, KEN, MDA, MNG, MAR, NIC, PHL, SEN, LKA, TZA, TUN, UKR, ZMB, ETH, MDG, RWA, UGA, NAM, ZAF, OMN	AUS, AUT, BEL, CAN, CHL, CYP, CZE, DNK, EST, FIN, FRA, DEU, GRC, HUN, ISL, ISR, ITA, JPN, JOR, LVA, LTU, LUC, MUS, NLD, NZL, NOR, POL, PRT, QAT, SVK, SVN, ESP, SWE, CHE, ARE, USA, URY, MYS, HRV, CRI

	Alternative PCA index	
group	**Low quality**	**High quality**
countries	BHR, KWT, PAN, SAU, ALB, ARG, ARM, BLR, BIH, BRA, BGR, CHN, COL, DOM, ECU, GTM, IDN, IRN, JAM, JOR, KAZ, LBN, MKD, MEX, PRY, PER, RUS, THA, TUR, DZA, BGD, BOL, KHM, CIV, EGY, SLV, GHA, HND, IND, KEN, MDA, MNG, MAR, NIC, PHL, SEN, LKA, TZA, TUN, UKR, ZMB, ETH, MDG, RWA, UGA	AUS, AUT, BEL, CAN, CHL, CYP, CZE, DNK, EST, FIN, FRA, DEU, GRC, HUN, ISL, ISR, ITA, JPN, JOR, LVA, LTU, LUC, MUS, NLD, NZL, NOR, POL, PRT, QAT, SVK, SVN, ESP, SWE, CHE, ARE, USA, URY, MYS, HRV, OMN, CRI, NAM, ZAF

Supplementary material 6. Results from an alternative subsampling procedure (based on an index using PCA scores)