Market-pull policies to promote renewable energy: a quantitative assessment of tendering implementation

Nuno Bento[1,*], *Mattia Borello*[2] *and Gianfranco Gianfrate*[3]

[1] Instituto Universitário de Lisboa (ISCTE-IUL), DINAMIA'CET, Av.das Forças Armadas, 1649-026 Lisboa, Portugal. * Corresponding author: Phone: (+351) 91 641 60 87, Fax: (+351) 21794 00 42. Nuno.Bento@iscte.pt

[2] Bocconi University, Via Roberto Sarfatti 25, 20136 Milan, Italy. Phone: (+39) 0258361, Mattia.Borello@studbocconi.it

[3] EDHEC Business School, 393 Promenade des Anglais 393, BP3116, 06202 Nice Cedex 3, France. Gianfranco.Gianfrate@edhec.edu

Abstract

Policymakers ideally select the support mechanism that better foments renewable energy production at the lowest cost to comply with international climate agreements. Currently, tendering is the fastest rising scheme. Yet a quantitative assessment of its performance in the literature is missing. We assess the effect of the introduction of auctions in accelerating the addition of renewable capacity through three econometric models: fixed-effects multivariate regression, statistical matching and synthetic control. The dataset includes 20 developed countries, spanning from 2004 to 2014, and both macroeconomic and policy drivers. Results show that tendering has the strongest effects to promote net renewable capacity comparing to other mechanisms like feed-in tariffs. Countries implementing tendering on average have a higher addition of net capacity of renewables in the order of 1000-2000 MW annually. The positive effect of tenders is clearer when analyzing with synthetic controls the case of Italy: while tendering enhances the deployment of renewables, policy instability jeopardizes the sustainability of tendering's impact.

Keywords: policy assessment; synthetic control; investment; tendering; renewable energy.

1. Introduction

Governments have been supporting the deployment of renewable energy (RE) as a way to tackle climate change and reinforce energy security. In fact, renewables are more expensive than fossil fuels in most cases because the negative externalities associated with the burn of fossil fuels largely remain absent from the prices. Therefore the government need to support RE to become competitive in the market. In 2017, renewable energy accounted for 14.3% of the total primary energy demand (IEA, 2018). Even though this share is constantly increasing, it is doing so at a modest rate due to the persistent and significant growth in energy demand. A faster deployment rate is needed to limit global warming to 1.5ºC (IEA, 2018).

There is a growing literature on the most efficient policy, or the right "policy mix" (e.g., Del Rio and Bleda, 2012). While the qualitative literature (e.g., Gan *et al.*, 2007) argues for a positive correlation between regulation and RE deployment, the quantitative studies (i.e. panel data analysis on country level) display more ambiguous results. Marques and Fuinhas (2012) argue for the effectiveness of policies in strengthening the use of renewables. Popp *et al.* (2011) do not find a significant impact of policies on wind generation, and Aguirre and Ibikunle (2014) find a negative relationship between fiscal/financial incentives and deployment of renewable energies. When comparing the different instruments, Johnstone *et al.* (2010) find that feed-in tariffs (FiTs) are helpful for the development of less mature technologies, and Zhao *et al.* (2013) posits that FiTs are the only policy that encourages the development of renewable energy sources. Kilinc-Ata (2016) observes a positive relationship between RE deployment and FiTs or tendering. There is still a debate in the literature about the impact of the policies intended to support the investment in renewable capacity.

Auctions in particular are the object of a growing debate (e.g., Del Rio, 2017). On the one hand, proponents point to their advantages in terms of effectiveness (e.g., European Commission, 2014). On the other hand, opponents argue about their risk to undermine the benefits of existing supporting mechanisms namely in terms of the effects in competition (Butler and Neuhoff, 2008) or in cost reductions (Grau, 2014). Recent assessments show that tendering may increase the effectiveness and efficiency of support depending on the circumstances (e.g., Winkler et al., 2018). Winkler et al.

(2018) has taken a first step in this purpose by performing a preliminary quantitative analysis on a limited number (eight) countries. However, there is a lack of a more systemic assessment of the tendering performance.

This paper aims to fill this gap by performing a cross-country quantitative analysis of the effect of both the introduction and implementation of auctions. It performs a comparative assessment of the policies supporting RE investment over time, with a focus on the introduction of tendering and the conditions of its implementation. For that we use a data set comprising a large and representative sample of 20 countries. The novelty of our approach consists on the study of this new dataset with the combination of three different econometric models: multivariate fixed effects regression, matching estimation, and synthetic controls. In particular, synthetic controls create a counterfactual group that controls for external factors, such as technology cost reductions, and cross-country differences, such as resource endowment, to provide more accurate effects of the policy instruments.

Our interest lies in the supporting policies aimed at directly increasing the share of energy generation from renewable energy sources. We therefore proceed to analyse the different factors affecting renewables deployment in order to identify which are the most effective measures the individual countries can adopt and which are the "external" factors that are not under the countries' control but still impact investors' decisions. Since tendering has been overcoming feed-in tariffs as primary support mechanism not only in Europe (CEER, 2018) but also worldwide (IRENA, 2015), and given the previous calls for a systematic quantitative assessment of the tendering performance (e.g., Winkler et al., 2018), this paper aims to evaluate the most recent evidence on tendering as an instrument to promote the increase of renewable energy capacity.

The work is organized as follows. Section 2 reviews the literature on support mechanisms—particularly tendering—of renewable energy projects. Section 3 discusses the determinants of the investment in renewable energy in the literature. Section 4 presents the empirical research, namely the data and the econometric models which produce the results presented in Section 5. Section 6 analyzes the robustness of the models and the hypothesis. Finally, Section 7 concludes by discussing the main results and their implications.

2. Renewable energy investment

2.1. Barriers specific to renewable energy projects

The investment in renewable energy falls into the broader category of infrastructure investment, and therefore is subject to the general barriers pertaining to this asset class. These are related to the features of infrastructure projects, such as high upfront capital requirements, long asset life, inelastic demand for services and prevalence of fixed costs. Apart from these generic risks of infrastructure investment, there are other specific issues to which renewables projects are subject. Table 1 provides an overview of the typical factors used by Standard & Poor's (2007) to determine the rating of infrastructure projects, along with the risks more specific to RE projects.

Table 1. Factors accounted for in infrastructure projects rating: common risks and specific risks to renewable energy projects

Common risks to infrastructure projects	**Project-level Risks**	Contractual foundation Technology, construction and operations Resource availability Competitive-market exposure Counterparty risk Cash-flow risk and debt repayment structure
	Transactional Structure	Special-purpose entities vs. multi-purpose entities Cash management Risk to cash flow of insolvency of related parties
	Sovereign Risk	Local currency risk Willingness and ability of sovereign governments to service its obligations
	Business and Legal Institutional Risk	Commercial laws Property rights risk
	Credit Enhancement	Extent of coverage of insurance policies Timeliness of payment on claims
Specific risks to renewable energy projects	**Market failures**	Degree of internalization of externalities (environmental, knowledge) Low market competition
	Policy barriers	Unstable policy commitment Regulatory access to the market
	Informational barriers	Develop resources (e.g. staff training) timely Availability of basic infrastructures (e.g. transmission)
	Financial barriers	Higher perceived risk and cost of capital

		Variable revenues while fixed costs
	Socio-cultural barriers	Social perception of the projects

Source: "Common risks" adapted from Standard & Poor's (2007); "Specific risks" own elaboration. See text for more details.

Renewable energy projects have some peculiar features that can add specific risks on top of those detailed above for traditional infrastructures. We group them into five groups: market failures; domestic policy barriers, domestic market and informational barriers, general financial barriers and socio-cultural barriers.

Market failures create an allocation of resources that, if not corrected by policy measures, is not efficient. Specifically externalities impact RE development and tilt energy production towards fossil fuels, as often consumers do not bear the full cost of carbon emissions (associated with the combustion of the latter) which provokes global warming. Sen and Ganguli (2017) point out: (i) under-priced environmental impacts, since costs for greenhouse gas emissions are not correctly incorporated in commodity prices; (ii) underinvestment of R&D programs, as initiators cannot benefit from exclusive property rights; (iii) lack of competition in the energy sector (both production and transmission/distribution) as monopolies within a given area tend to be more cost effective; and (iv) too high initial investment cost.

Supporting policies can become a source of problems if not adopted with consistency. Standard & Poor's (2010) has quantified that *longevity risk*, meaning certainty of enforcement of related policies, is the most significant risk for low-carbon investments. Investors are particularly concerned about the comparatively short time frame of regulations compared to the long-term commitments of their investment (De Jager et al., 2011). History has proved them right, as demonstrated by the sudden and sometimes retroactive policy changes in a handful of developed markets, including Italy and Spain, to which has followed a contraction in installations, mainly in the wind power sector (REN21, 2017). Policies can be a barrier also in countries where the regulatory system is designed around near-monopoly providers, preventing new players to enter into the market (Sen and Ganguli, 2017).

Lack of basic infrastructures and of local competences can delay investments. These informational barriers are important factors, which need time to be addressed, and can make projects more expensive or even not economically viable. Especially in developing countries like India, the inadequacy of the transmission grid can be a huge problem since potential wind sites are often located in remote locations, far from the main consumption centres (Proparco, 2010). Furthermore, being RE site specific (unlike fossil fuels), the availability of detailed datasets (e.g. irradiation data for solar) is fundamental for the success of the projects (Sen and Ganguli, 2017).

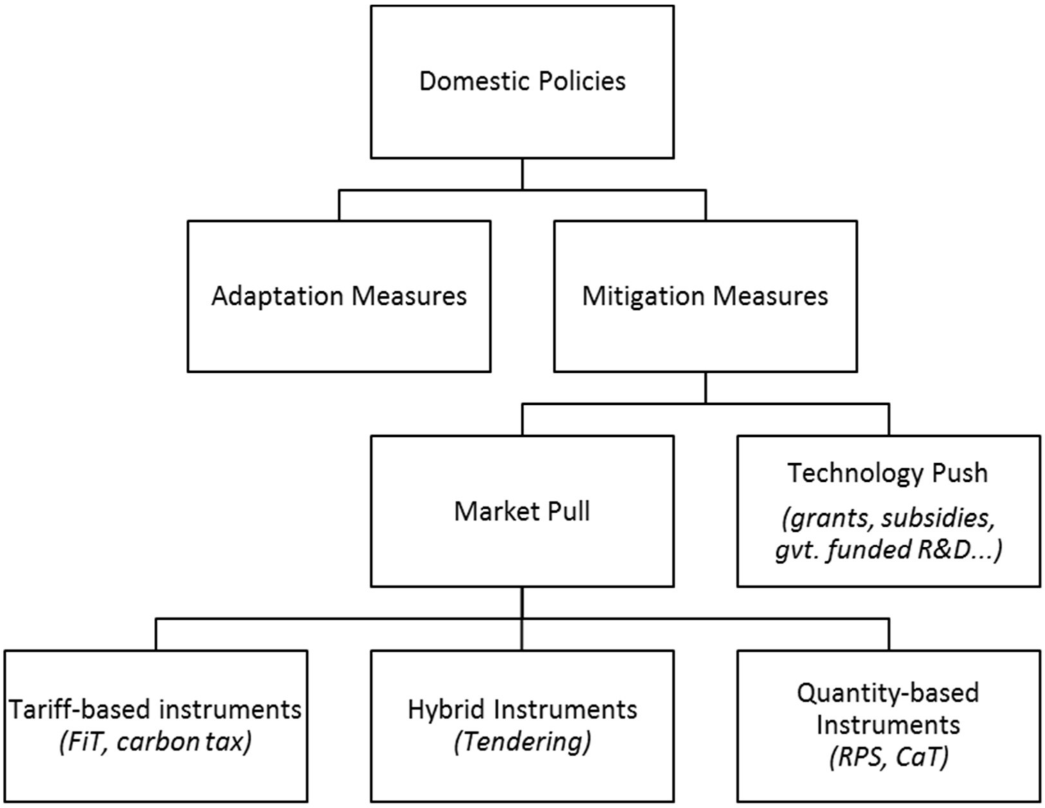
Financial barriers arise from the cost and revenues profile of investments in RE capacity. Firstly, cost of capital can be significantly higher for RE projects, as they are perceived as riskier than traditional power generation projects, due mainly to: (i) higher proportion of fixed cost (which are often also paid upfront) with respect to variable costs; (ii) lack of track record of more recent technologies; and iii) declining costs over time (e.g. average module prices of solar photovoltaics reduced 65% in France between 2013 and 2018 (IRENA, 2019)). Secondly, while the costs of generating electricity are mostly fixed, the revenues from selling it on the free market are variable and tied to current prices, making financial viability of the projects uncertain and leading to cost-based competition.

Socio-cultural barriers may arise from the inadequate attention towards the climate change issue or from the social consequences of some projects (Sen and Ganguli, 2017). For example, social acceptance plays an important role, as recently shown from the ruling to overturn the installation of 14 wind turbines in Scout Moor (which would have created the biggest wind farm in England) due to its potential "significant adverse effect" on the landscape and views (Department for Communities and Local Government, 2017).

2.2. Support mechanisms to renewable energy investments

Domestic policies are necessary to overcome the barriers specific to the investments in RE capacity in order to meet the targets set by international agreements. These policies are typically divided into two main categories: adaptation and mitigation (see Figure 1). Adaptation measures are directed to stimulate "practical steps to protect countries and communities from the likely disruption and damage that will result from effects of climate change" (UNFCCC, 2015). They address the consequences of climate change and not the economic issues to respect the international agreements in order to avoid climate change, and as so, they are not part of our empirical analysis. On the other hand, mitigation measures directly address the economic and investment activity meant to reduce CO_2 emissions, namely in electricity generation by increasing the share of RE.

Figure 1. Domestic Policies breakdown



Sources: adapted from UNFCCC (2015), Burer and Wustenhagen (2009), IRENA (2015).

Mitigation measures can be further divided in *technology-push* and *market-pull* policies (Burer and Wustenhagen, 2009). Technology-push policies, such as government funded R&D, are deployed with the objective of increasing the technology "supply". Market-pull policies, such as Feed-in Tariffs (FiTs), have the goal of increasing the "demand" of the same technologies (Rickerson *et al.*, 2012). Both are necessary, since innovation is fundamental in providing new technologies and making existing technologies more marketable as they often cannot compete on the market without policy support.

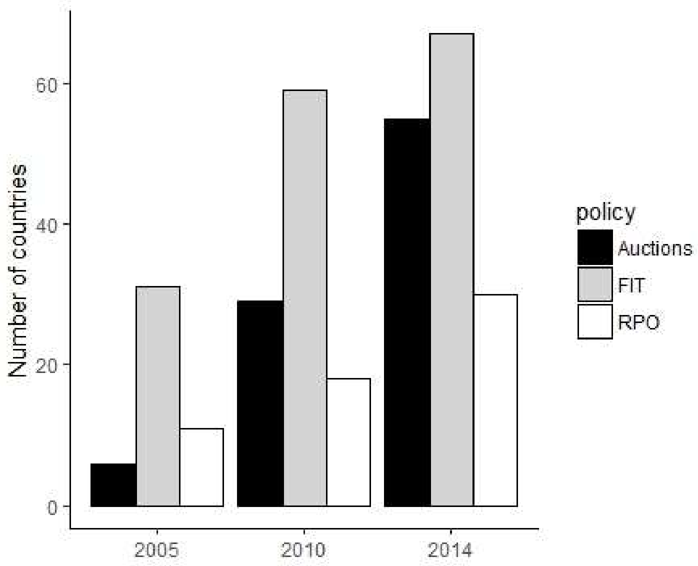
Technology push aims to compensate the so-called knowledge market failures (Dechezlepretre and Popp, 2015) in the early stages of research and production of a technology (e.g., new types of bioreactors for producing bio-energy from biological waste treatment (Sepehri and Sarrafzadeh, 2018)). At this point, the knowledge and experience gains have a public nature that can spill-over to other producers, preventing the innovator from getting the full benefits from them. The government can develop several instruments, such as tax incentives, grants and public funded R&D, to compensate for the insufficient incentives.

Market-Pull policies are important for technologies entering into a wider commercialization. They can themselves be divided into *tariff-based* instruments and *quantity-based instruments* (IRENA, 2015). Tariff-based instruments provide economic incentives for electricity production from RE sources, through subsidies or payments for the energy generated (e.g. FiTs, carbon taxes). Feed-in Tariffs (FiTs), for example, are policies designed to guarantee a certain price for a fixed amount of time for electricity generated from RE sources (Couture and Gagnon, 2009). Even though FiTs have effectively promoted RE deployment (e.g. Jenner *et al.*, 2013) and are a very popular support scheme (REN21, 2017), increasing concerns have been raised on the consequences of over dependency on incentives and lack of trust in the continuation of the policy (Antonelli and Desideri, 2014).

Quantity-based instruments instead provide direct control over the amount of renewable capacity installed or energy produced (e.g. Renewable Portfolio Standards or Obligations (RPSs or RPOs), cap and trade systems (CaT)). For example, Renewable Portfolio Standards (RPSs) are a policy requiring that a certain percentage of electricity generated by utilities comes from renewable sources. This creates price competition among the technologies that can promote innovation and lower the cost of renewable energy. RPSs are usually enforced through a credit trading mechanism, i.e., each MWh of electricity generated through an eligible RE source is accounted in the form of renewable energy credits (RECs). These RECs can either be traded or simply used to control the producer’s compliance with the RPS’s requirements. The main problem with this instrument is the unpredictable impact on the cost of compliance (Kilinc-Ata, 2016).

A new category of policies emerged, the so-called *hybrid instruments* or auction-based policies (commonly called “tendering”), that combine features of both tariff-based and quantity-based instruments in an attempt to remedy to the downsides of both schemes. Tendering refers to “a procurement mechanism by which renewable energy supply or capacity is competitively solicited from sellers, who offer bids at the lowest price they would be willing to accept” (REN21, 2017). These auctions can be classified according to their technology focus in: (i) technology-neutral, where different projects using different technologies compete among themselves; (ii) technology-specific, where different projects using the same technologies compete among themselves; and (iii) project specific, where bidders compete for a particular project selected by the government. In recent years auctions have been the fastest rising mechanism worldwide, as shown by Figure 2.

Figure 2. Number of countries with renewable energy policies by type



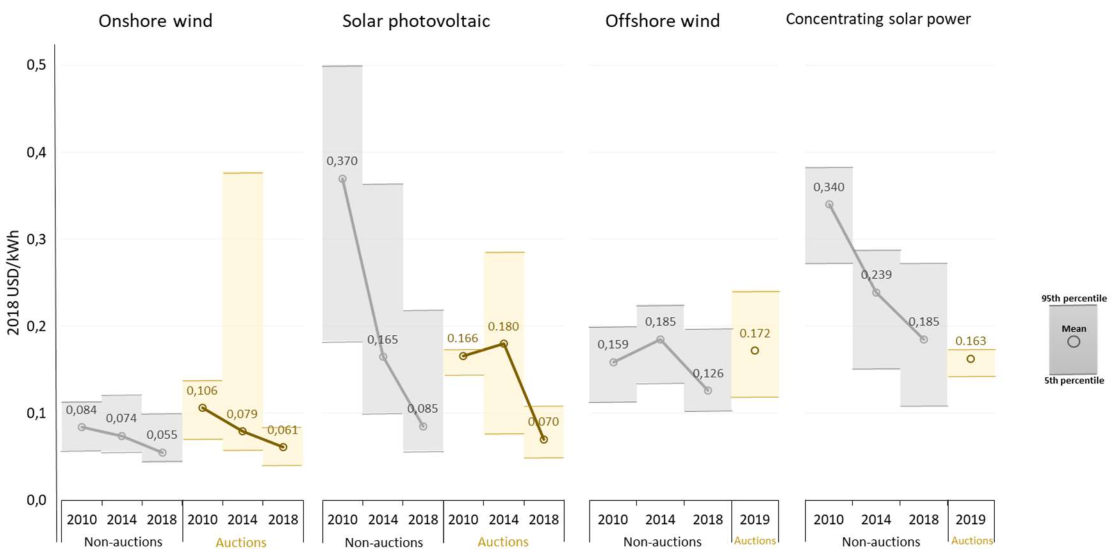
Source: IRENA (2015)

2.3. Impacts of tendering on renewable energy investments

To understand how tendering effectively promote the investment in RE capacity, by addressing the specific barriers discussed in Section 2.1., several arguments have been risen in the literature about its strengths and weaknesses.

Several strengths are attributed to tendering. First and foremost, by setting the quantity in advance, auctions can be more effective than traditional price instruments to address market failures (IRENA, 2015). Theoretically, well-designed auctions are also efficient by selecting the projects with the lowest production costs (Winkler et al., 2018). Tendering fosters competition among different technologies that can lower RE prices over time, improving dynamic efficiency (Verbruggen & Lauber, 2012). Figure 3 shows that tendering has been at least as efficient as other instruments in bringing down levelized costs of energy (LCOE) for onshore wind, solar photovoltaic, offshore wind and concentrating solar power in the past decade. BNEF (2015) argues that a shift from FiTs or RPS schemes to tendering lowers on average RE project tariffs by 30%. In addition, tenders are a flexible instrument, which can adapt to different jurisdictions with disparate energy sector's structure and maturity. Tenders allow to overcome the information asymmetry between regulators and RE project developers. Often policymakers do not possess the knowledge required to set the support levels at an adequate level, leading to too high or too low tariffs (Del Rio and Linares, 2014). Tendering instead, if carried out competitively and transparently, can be an effective mean of price discovery (Winkler et al., 2018). This was the case in Germany, where the first renewable energy auction held in 2015 revealed a solar PV project development cost higher than the FiT in place at the time. Finally, tendering can offer greater regulatory certainty for investors, since the result of an auction typically is the signing of a bilateral contract in which each party's commitments and liabilities are clearly stated, contributing to mitigate policy and financial risks (e.g., Verbruggen and Lauber, 2012).

Figure 3. Global weighted average LCOE and percentile ranges for auctioned and non-auctioned projects on CSP, solar PV, onshore and offshore wind, 2010-2019



Source: IRENA, 2019.

Some weaknesses have also been pointed to tendering, as well. Transaction costs might be too large compared to the potential profits, thus discouraging potential bidders. This could especially hit smaller size projects, showing that tendering is particularly suitable for large-scale RE projects despite the benefits of smaller-scale and distributed RE generation (Grau, 2014).[1] On the other hand, complexity requires higher structuring costs for the regulator. These costs are nevertheless mostly linked to the learning with the initial design of the policy, and can therefore be amortized over subsequent auctions. Moreover, aggressive bidding may lead to project delays and underperformance (Winkler et al., 2018). The introduction of auctions creates additional risks, such as of penalties for non-realization and delays, that can increase financial costs. This would explain why in some cases FiT was found more efficient and resulting in larger deployment (e.g. Grau, 2014). However, these risks could be mitigated through an adequate contractual structure incorporating penalties and by evaluating bids on parameters other than the sole price (Del Rio and Linares, 2014).

[1] Generation of electricity from dispersed, small-scale systems close to the point of consumption (*e.g.* rooftop solar PV).

Therefore, the literature is unclear about the impact of tendering on promoting RE investments. It has assessed the performance of tendering relative to other instruments in more abstract and qualitative manner (e.g., Batlle et al., 2012) or more focused on individual cases (e.g., Haufe and Ehrhart, 2018). Some studies suggest the superiority of auctions may change from case to case (e.g., Winkler, 2018). There are examples of very efficiently designed schemes turned out to be ineffective (Pollitt, 2010). The implementation is also very important as policy instability and retroactivity change undermine the confidence of investors (Tiedemann et al, 2016). However, there is a lack of a systemic, cross-country comparative assessment of the tendering performance. Winkler et al. (2018) take a first step by analyzing empirical evidence for eight countries. This paper aims to fill this gap by performing a more systematic quantitative assessment of the effect of auctions introduction and implementation.

3. Determinants of the investment in renewable energy

New energy needs are often supplied to with traditional energy solutions, as they are typically cheaper and more rapidly implementable (Kilinc-Ata, 2016). Hence, a strong change in the incentive schemes is required to increase the use of renewable energy. Economic and finance literature already provides a guidance on the factors that affect the investment decision in favour to renewable energy. This section systematizes the previous literature by identifying eight factors that could determine the investment in new capacity of renewable energy, discussing their role to foster or hinder the investment in cleaner energy generation. Following the discussion in section 2, we group the factors into three types, encompassing socioeconomic-related aspects, country-specific features, and regarding institutional/political incentives.

3.1 Socioeconomic factors

Macroeconomic variables influence the behaviour of investors, especially in high capital intensive projects such as investments in renewable energies. Some of these socioeconomic factors contribute to foster the investment (e.g., welfare, population, strength of financial markets, cost of fossil energy sources (incumbent)), others have a negative effect (e.g., interest rates). We analyse next the impact of each one of these factors.

3.1.1 Welfare

Economic activity increases demand for energy and subsequently investment in the energy sector. Wealthier countries can also afford the costs of RE deployment and incentivize it with more ease. However, academic literature is torn on the welfare effect on renewable energy investment. Dong (2012) and Shrimali and Kneifel (2011) maintain that they are uncorrelated, while Aguirre and Ibikunle (2014), Carley (2009) and Chang *et al.* (2009) advocate for a positive relationship between the two. There is also no consensus of which proxy of welfare should be used: Aguirre and Ibikunle (2014) use GDP per capita, Marques *et al.* (2010) use GDP and Eyraud *et al.* (2013) use both. Thus welfare variables such as GDP should have a positive or no effect in the RE investment.

3.1.2 Population and human capital

Population can be representative of more than sheer size, as its growth can point to energy needs not always captured in GDP growth. However, new energy needs could be supplied with both fossil fuels and RE. Following general investment theory (Baldacci *et al.*, 2009), we still expect a population growth to positively affect RE deployment.

Human capital is essential for successful RE deployment. Education can also increase attention on the global warming issue. Thus the investment in RE should be positively correlated with the Human Development Index (HDI), yearly computed by the United Nations, which encompasses life expectancy, education and per capita income indicators.

3.1.3 Interest rates

Interest rates are theoretically the result of the equilibrium between demand and supply for funding. They have a negative effect in RE projects, which are usually financed through project finance structures comprising a higher level of debt compared with normal corporate financing (Eyraud *et al.*, 2013). In addition, project finance loans have a tenor in the life of the project which can go up to 30 years. Thus they will be more exposed to long-term interest rates rather than to the fluctuations of short-term interest rates (Eyraud *et al.*, 2013).

3.1.4 Strength of financial markets

Investors need properly functioning capital markets throughout the lifetime of technologies (De Jager et al., 2011). Business angels provide the first equity when demonstrations start; Venture Capital (VC) and Private Equity (PE) help overcoming the "valley of death" in the transition to market; and corporate finance, project finance and public markets assist market expansion and the full deployment of the technology (Grubb, 2004). Furthermore, the credit granted through project finance depends also on both the availability of funds and the strength of the banks' balance sheet. Thus the investment in RE should have a positive correlation with compounded indicators like the Financial Development Index (FDI) which encompass depth (size and liquidity), access and (cost-related) efficiency for financial markets.

3.1.5 Cost of fossil energy sources

Once in operation, the marginal costs of electricity production using renewable energies are stable (given the high proportion of capital costs in final costs). This contrasts with the marginal costs of electricity produced from fossil fuels (oil, gas and coal) that are dominated by the raw materials costs which are volatile. Thus renewables can shield the countries from the fluctuations in the costs of fossil fuels, particularly of oil (Awerbuch and Sauter, 2006). Moreover, an increase in fossil fuels prices—the incumbent technology—decreases the relative price of RE generation, hence making it more competitive (Popp, 2001). Thus the increase in the fossil fuel prices should have a positive effect in the RE investment.

3.2 Country-specific factors

A second group of variables relates to the circumstances that determine the RE investment. The energy economics literature typically considers two country-specific factors: energy dependency; and renewable potential.

3.2.1 Energy dependency

Fossil energy sources are concentrated in a limited number of areas while renewable energy sources are more widespread around the world (IRENA, 2019). By increasing the share of renewables in the national energy mix, countries can increase their energy security and create economic benefits (shielding themselves from fluctuations in energy supply and prices). Thus a high energy dependency (i.e. the ratio between net energy imports and total energy consumption) could therefore act as an impulse to develop locally generated clean energy sources (Kilinc-Ata, 2016).

3.2.2 Renewable potential

Natural resources are unevenly distributed (IRENA, 2019). Factors such as hours of solar exposition, water and wind supply, wave and tidal power, all constitute a country's renewables potential, and they vary across regions and states. Some studies use as a proxy of renewables potential the geographic area of each nation (Marques *et al.,* 2010). This would mean that for the time frame considered we deem the potential to be time invariant. This issue has been debated by Carley (2009), who esteems the potential of renewable sources to be invariant for 9 years. Thus renewable potential should impact little on the investment in RE in the short-run.

3.3 Political factors

Finally, the implementation of incentive mechanisms can spur the investment in RE as discussed in the energy economics and policy literature. This concerns in particular the adoption of market-pull policies. Such policies are important to accelerate the growth of emergent technologies (Burer and Wustenhagen, 2009), comprising: tariff-based instruments (e.g., feed-in-tariffs (FiTs), carbon taxes (C_T)); quantitative-based instruments (e.g., renewable portfolio standards (RPSs); tradable renewable energy certificates (RECs), cap and trade schemes (CaT)); and auction-based policies or "tendering". A comparison between the different types of support mechanisms is provided in Section 2.2. Recent studies already suggest the superiority of the change to auctions in specific conditions of context (Winkler, 2018) and stability (Tiedemann et al, 2016). Thus the investment in RE should increase with the existence of incentive mechanisms.

3.4 Synthesis and hypothesis

The economics, finance and management literature suggest a number of determinants for the investment in renewable energies that can be grouped in socioeconomic, country-specific and institutional factors. Given that this paper addresses the benefits with the change to an auction-based instrument, we focus on the factors that drive net capacity additions including the differences between countries in terms of resource endowment and environment stability, without considering specific investor and project characteristics. These drivers of the investment in RE will serve to test empirically the significance of the following explanations:

H1: The investment in RE depends more on socioeconomic and country-specific factors.

H2: The investment in RE depends more on the policy instruments.

H3: The investment in RE increase with the change to auction-based mechanisms.

The last hypothesis (H3) is the central one of this study. The other hypothesis H1 and H2 are mutual exclusive and serve to clearly distinguish the most important set of drivers that increase the investment in RE. Of course, drivers from different groups of factors can determine the investment. But this strategy helps to more clearly isolate (and compare) the positive effects that can be attributed to the change of the policy (to tendering) from the impacts of contextual variables.

Data sources, the selection of variables and the empirical approach are explained in the next section.

4. Empirical analysis of tendering efficacy

4.1. Data

To assess the effect of the introduction of tendering mechanism on renewables' deployment, we collect data for a sample of developed countries (all OECD members). Developed countries have had an important role in the introduction of renewable energy capacity. Our sample encompasses twenty countries in the period from 2004 to 2014: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Korea, Netherlands, New Zealand, Portugal, Spain, Sweden, Switzerland, United Kingdom and United States.[2]

Table 2 summarizes the different variables used for our analysis, providing detailed information for each one of them. Tables 3-4 show the descriptive statistics for all the variables and the correlation matrix for the independent variables, respectively.

[2] These are the OECD countries represented in the top 70 of the List of countries by electricity production from renewable sources (https://en.wikipedia.org/wiki/List_of_countries_by_electricity_production_from_renewable_sources last accessed in 4/7/2019). We removed the following countries from the sample because of their specificities: Norway (hydropower legacy, which represents 99% of electricity production), Chile (late arrival to OECD in 2010 in the middle of the surveyed period); Poland (small share of renewables in the mix 13,7% in 2016); Greece (financial crisis impact).

Table 2. Variable description and data sources

Variable	Abbreviation	Description	Source	Expected effect
Dependent Variable				
Yearly increase in net capacity of renewables	RE_CAP	Net capacity measured in MW; includes hydropower, wind power, solar photovoltaic, solar thermal, solid and liquid biofuels, biogases, geothermal, renewable municipal waste, tidal, wave and ocean motion	IEA	
Independent Variables				
Socioeconomic Factors				
Gross Domestic Product	GDP	GDP in current US $ billions	World Bank	Positive
Population	POP	Total population in millions	World Bank	Positive
Human Development Index	HDI	Composite statistic of life expectancy, education, and per capita income indicators	United Nations	Positive
Country's Long-Term Interest Rates	LT_IR	10-year government bond yields	OECD	Negative
Financial Development Index	FDI	Composite statistic of financial institutions and financial markets' development indicators	IMF	Positive
Brent Price	BRT	Oil price benchmark in US $ per barrel	BP Statistical Review of World Energy 2017	Positive
National Balancing Point Price	NBP	Natural gas price benchmark in US $ per million Btu	BP Statistical Review of World Energy 2017	Positive
Northwest Europe Marker Price	COAL	Coal price benchmark in US $ per tonne	BP Statistical Review of World Energy 2017	Positive
Country Specific Factors				

Energy Dependency	EN_IMP	Net energy imports as a % of energy consumption	World Bank	Positive

Political Factors

Feed-in Tariffs	FiT	Dummy	REN21 reports, IEA Global Renewable Energy policies and *measures database*	Positive
Renewable Portfolio Standards	RPS	Dummy	REN21 reports, IEA Global Renewable Energy policies and *measures database*	Positive
Tradable Renewable Energy Certificates	REC	Dummy	REN21 reports, IEA Global Renewable Energy policies and *measures database*	Positive
Tendering	TDR	Dummy	REN21 reports, AURES reports	Positive
Carbon Tax	C_T	Dummy	Carbon Pricing Watch 2016 by World Bank and Ecofys	Positive
Cap and Trade Schemes	CaT	Dummy	Carbon Pricing Watch 2016 by World Bank and Ecofys	Positive

Table 3. Descriptive statistics

Variable	Observations	Mean	Std. Deviation	Minimum	Maximum
RE_CAP	220	1,542.25	2,551.01	-318.00	17,326.00
GDP	220	1,990.89	3,248.68	103.91	17,393.10
POP	220	46.74	67.84	4.07	318.56
HDI	220	0.89	0.03	0.79	0.94
LT_IR	220	3.64	1.51	0.52	10.55
FDI	220	0.79	0.09	0.56	1.00
BRT	220	81.75	24.23	38.27	111.67

NBP	220	7.76	2.06	4.46	10.79
COAL	220	87.95	24.93	60.54	147.67
EN_IMP	220	36.31	56.59	-192.02	93.98
FiT	220	0.74	0.44	0.00	1.00
RPS	220	0.42	0.49	0.00	1.00
REC	220	0.67	0.47	0.00	1.00
TDR	220	0.33	0.47	0.00	1.00
C_T	220	0.25	0.43	0.00	1.00
CaT	220	0.71	0.45	0.00	1.00

Table 4. Independent Variables Correlation Matrix, All Countries, 2004-2014

	GDP	POP	HDI	LT_IR	FDI	BRT	NBP	COAL	EN_IMP	FiT	RPS	REC	TDR	C_T	CaT
GDP	1.00														
POP	0.99	1.00													
HDI	0.17	0.10	1.00												
LT_IR	-0.19	-0.17	-0.35	1.00											
FDI	0.31	0.32	0.31	-0.19	1.00										
BRT	0.06	0.01	0.33	-0.22	-0.09	1.00									
NBP	0.04	0.01	0.22	-0.16	-0.08	0.83	1.00								
COAL	0.03	0.00	0.10	0.13	-0.04	0.58	0.55	1.00							
EN_IMP	0.00	0.05	-0.52	-0.09	-0.25	-0.01	0.00	0.00	1.00						
FiT	0.23	0.24	-0.03	-0.20	0.26	0.08	0.04	0.03	0.06	1.00					
RPS	0.36	0.37	0.02	-0.01	0.20	0.04	0.04	-0.01	-0.17	-0.20	1.00				
REC	0.17	0.15	0.19	-0.17	-0.04	0.05	0.04	-0.01	-0.07	-0.15	0.28	1.00			
TDR	0.23	0.22	-0.03	0.08	-0.05	0.15	0.11	0.03	-0.06	0.33	0.13	0.08	1.00		
C_T	-0.18	-0.22	0.24	-0.19	-0.12	0.17	0.12	0.01	-0.28	-0.01	0.06	0.22	0.17	1.00	
CaT	-0.07	-0.12	-0.02	-0.18	-0.25	0.41	0.32	0.14	0.34	-0.04	-0.18	0.16	0.08	0.09	1.00

4.2. Models

To assess the effect of the introduction of auctions and of the conditions of its implementation, we take a novel approach based on the combination of econometrical analysis. The first step is a multivariate regression with the objective of testing the relationship between tendering and the addition of renewable energy capacity, taking into account other policy instruments and external factors. In order to detect a possible causality between tendering and renewables' deployment, we further implement two different estimation techniques: statistical matching and synthetic control (more details next). These two models also test for country-specific conditions while controlling for external factors (e.g., technology cost decrease over time).

4.2.1. *Multivariate Regression*

We perform a multivariate regression with fixed effects in order to control for unobserved country heterogeneity (e.g., resource endowment). Our general specification is the following:

$$y_{it} = a_i + \sum_{1}^{k} \beta_k * X_{it,k} + \varepsilon_{i,k}$$

where y_{it} is the amount of net capacity of renewable energy added in year *t* in country *i*, a_i is the intercept,, X_i is a matrix of the explanatory variables described in Table 2, *β* is the coefficient matrix to be estimated, and $\varepsilon_{i,k}$is the error term. We are therefore testing the following model:

$$RE\_CAP = f(Socioeconomic\ Factors, Country - Specific\ Factors, Political\ Factors)$$

Where:

$$Socioeconomic\ Factors = (GDP, POP, HDI, LT\_IR, FDI, BRT, NBP, COAL)$$

$$Country - Specific\ Factors = (EN\_IMP)$$

$$Political\ Factors = (FiT, RPS, REC, TDR, C\_T, CaT)$$

and *f* is a linear function.

4.2.2. *Matching Estimation*

In order to determine a possible causality between tendering and renewables' deployment, i.e., a causal treatment effect, we apply matching estimation. This method permits to control for external developments such as technology cost reductions. Formally, given a population of $i=1,\ldots, N$ individuals, and a binary treatment represented by a treatment indicator D_i that takes the value one if individual i receives treatment and zero otherwise, we are interested in computing the treatment effect τ_i

on a variable of interest Y. Defining the potential outcomes for each individual i as $Y_i(D_i)$, τ_i will be equal to:

$$\tau_i = Y_i(1) - Y_i(0)$$

In our specific case, the population is composed by the i=20 countries in our dataset, the treatment D is tendering, and the variable of interest Y is the addition in net capacity of renewables. If τ_i was found to be positive across all countries, this would solve our quest for causality. The fundamental problem is that at a given time only one of the two potential outcomes can be observed for each individual country, making it impossible to estimate the individual treatment effect τ_i. Matching estimation allows the creation among the nonparticipants of a *control group*, composed by individuals similar to the participants in relevant pre-treatment characteristics X (our independent variables), and compare the differences in outcomes between the participants and the control group, which can then be attributed to treatment.

The effect of the treatment on the variable Y is usually quantified as the average treatment effect (ATE) and the average treatment effect on the treated (ATT). Formally:

$$\tau_{ATE} = E(\tau) = E[Y(1) - Y(0)]$$

$$\tau_{ATT} = E(\tau|D = 1) = E[Y(1)|D = 1] - E[Y(0)|D = 1]$$

The ATE represents the difference in expected outcomes after participation and nonparticipation. However, the ATE can sometimes be misleading as it includes the effect on individuals for whom the treatment was not designed. The solution to this is the ATT, which represents the difference in expected outcome with and without treatment for those who actually were subject to the treatment. We will proceed to estimate both parameters in order to assess the effect of tendering on net renewable capacity addition, and we will do it using two of the most popular matching techniques: the propensity score matching (PSM) and the nearest neighbour matching (NNM).

PSM relies on the idea of solving the curse of dimensionality by using the relevant characteristics X to compute the probability that an individual will enrol in the treatment (Rubin and Rosembaum, 1983); this value $p(X)$, such that:

$$p(X) = P(D = 1|X) = E[D|X] \in [0,1]$$

is the so-called *propensity score*. By attributing a propensity score to each individual, we obtain the distribution of $p(X)$ which helps us to individuate the common support area, i.e. the overlap between the PS distribution in the two groups. The sample will then be restricted to the individuals that fall in the common support area.

Using the propensity score we can then compute our average treatment effect (ATE) and the average treatment effect on the treated (ATT) as:

$$\tau_{ATE}^{PSM} = E\{E[Y(1)|D = 1, p(X)] - E[Y(0)|D = 0, p(X)]\}$$

$$\tau_{ATT}^{PSM} = E\{E[Y(1)|D = 1, p(X)] - E[Y(0)|D = 0, p(X)]|D = 1\}$$

We can see that the propensity score acts weighting the mean difference in outcomes over the common support, giving a higher weight to individuals with a higher *p(X)*.

NNM works by imputing the missing potential outcome $Y_i(1)$ or $Y_i(0)$ by using average outcomes for individuals with "similar" values for the covariates that have received the other treatment level (Abadie and Imbens, 2002): hence, since both treated and control units are matched, matching is carried out with replacement, so that every unit can be used as match more than once. "Similarity" is accounted for by using a weighted function of the covariates for each individual. Formally, the distance between $x_i \in X$ and $x_j \in X$, two vectors of covariates for individuals i and j, is parametrized by the vector norm:

$$\|x_i - x_j\|_S = \{(x_i - x_j)' S^{-1} (x_i - x_j)\}^{1/2}$$

where S is a given symmetric, positive definite matrix. By default, Stata set S to be the Mahalanobis scaling matrix, in which weights are based on the inverse of the covariates' variance-covariance matrix. We can then rank each individual in terms of "distance" based on the norm, and call $j_m(i)$ the index of the unit that is the m^{th} closest to individual i. We then set the desired number of matches M (in our analysis we will use M=1) and denote with $J_M(i)$ the set of indices for the first M matches for unit i:

$$J_M(i) = \{j_1(i), \dots, j_M(i)\}$$

At this point, we can obtain an estimate for all the unobserved potential outcomes, by using the following estimates:

$$Y_i^{NNM}(0)\begin{cases} Y_i(0) & if\ D_i = 0 \\ \frac{1}{M}\sum_{j\epsilon J_M(i)} Y_j(1) & if\ D_i = 1 \end{cases}$$

$$Y_i^{NNM}(1)\begin{cases} \frac{1}{M}\sum_{j\epsilon J_M(i)} Y_j(0) & if\ D_i = 0 \\ Y_i(1) & if\ D_i = 1 \end{cases}$$

Using these estimates, we can compute our ATE and ATT as:

$$\tau_{ATE}^{NNM} = E[Y(1) - Y(0)] = \frac{1}{N}\sum_{i=1}^{N}(Y_i^{NNM}(1) - Y_i^{NNM}(0))$$

and

$$\tau_{ATT}^{NNM} = E[Y(1)|D = 1] - E[Y(0)|D = 1] = \frac{1}{N_1}\sum_{D_i=1}(Y_i(1) - Y_i^{NNM}(0))$$

with N_1=# of treated individuals, since if $D_i=1$, then $Y_i^{NNM}(1)=Y_i(1)$.

As a first step in the implementation of matching estimation, we individuate three groups of covariates on which we will match separately, in order to control for three different categories of covariates - namely, policy (X_{policy}), socio-economical/country-specific ($X_{se/cs}$), and size(X_{size}). They include:

- X_{policy}: Year, FiT, RPS, RECs, C_T, CaT

- $X_{se/cs}$: Year, HDI, LT_IR, FDI, EN_IMP

- X_{size}: Year, GDP, POP.

The variable Year is used in each set of covariates in order to avoid a selection bias due to the use of panel data. Furthermore, implementing NNM require an exact match for the variable Year and a number of matches M=1.

4.2.3. Synthetic Control

Synthetic control enables cross-country comparisons of the effect of auctions introduction. It provides a systematic methodology to construct control groups which can be compared against for counterfactual analysis. The proof of causality would be to obtain for an individual *i* that:

$$\tau_i = Y_i(1) - Y_i(0) \neq 0$$

or, by making variables dependent on time as well:

$$\tau_{it} = Y_{it}(1) - Y_{it}(0) \neq 0$$

but this is not feasible due to the possibility of observing only one of the two potential outcomes at any given time. Instead of reverting to estimate average treatment effects, synthetic control (SC) solves this issue by estimating the unobserved potential outcome for a treated individual i following the implementation of the treatment (Abadie *et al.*, 2010; Abadie & Imbens, 2016).

Given a treated individual i and a control group of $j = 1, \dots, J$ untreated individuals, SC estimates $Y_{it}(0)$ for any $t>T_0$, where T_0 (with $1<T_0<T$) is the period in which the treatment begins, by creating a synthetic untreated individual i as a weighted average of the untreated individuals from the control group. We suppose $Y_{it}(0)$ is given by a factor model, such that:

$$Y_{it}(0) = \delta_t + \theta_t Z_i + \lambda_t \mu_i + \varepsilon_{it}$$

where δ_t is an unknown common factor with constant factor loadings across units, Z_i is a (*r* x 1) vector of observed covariates (not affected by the treatment), θ_t is a (1 x *r*) vector of unknown parameters, λ_t is a (1 x *F*) vector of unobserved common factors, μ_i is an (*F* x 1) vector of unknown factor loadings, and the error terms ε_{it} are unobserved transitory shocks at the region level with zero mean.

We also consider a (J x 1) vector of weights $W = (w_1, \dots, w_j)'$, with J being the number of untreated individuals, such that $w_j \geq 0$ for $j = 1, \dots, J$ and $w_1 + \dots + w_J = 1$. Each particular value of the vector W represents a potential synthetic control, which means a weighted average of untreated individuals. The value of the outcome variable for each synthetic control indexed by W is:

$$\sum_{j=1}^{J} w_j Y_{jt}(0) = \delta_t + \theta_t \sum_{j=1}^{J} w_j Z_j + \lambda_t \sum_{j=1}^{J} w_j \mu_j + \sum_{j=1}^{J} w_j \varepsilon_{jt}$$

In a similar fashion to the method employed with the NNM, we look for the W^* that minimizes the distance:

$$\|X_i - X_J W\|_S = \{(X_i - X_J W)' S^{-1} (X_i - X_J W)\}^{1/2}$$

where S is a (*k* x *k*) symmetric and positive definite matrix, X_i is a (*k* x 1) vector of pre-treatment characteristics for the treated individual and X_J is a (*k* x *J*) matrix containing the same variables for the untreated individuals; the characteristics taken into account can include covariates as well as pre-treatment values for the outcome of interest Y. Abadie *et al.* (2010), choose S such that the mean squared prediction error of the outcome variable is minimized for the pre-treatment period (*i.e.* the resulting synthetic control individual approximates the trajectory of the outcome variable of the treated individual in the pre-treatment period). They also show that, if the number of pre-treatment period is large compared to the size of the transitory shocks, for $t \leq T_0$, $Y_{it}(0) - \sum_{j=1}^{J} w_j^* Y_{jt} \cong 0$. This result suggests using as estimator of τ_{it}, for $t > T_0$:

$$\tau_{it}^{SC} = Y_{it}(1) - \sum_{j=1}^{J} w_j^* Y_{jt}$$

The need for a sufficiently long pre-treatment and post-treatment period compels us to focus on countries which implemented tendering at a mid or late stage of our time frame: therefore, we apply SC to Italy (which implemented tendering in 2010).

The pool of donors for synthetic Italy is composed by the ten countries in our sample which did not implement tendering in the time frame considered, which are: Austria, Finland, Germany, Korea, Netherlands, New Zealand, Spain, Sweden, Switzerland and United Kingdom.

5. Empirical results

The findings of the multivariate regression are presented in Table 5. We report both the global regression including all the variables at the same time, and two partial regressions that isolate Political Factors from Socioeconomic Factors and Country-Specific Factors.

Table 5. Global and partial regressions

Variable	Global Regression	Socioeconomic & Country-Specific	Political
RE_CAP			
Socioeconomic			
GDP	1.33	0.99	
	(2.71)***	(1.93)*	
POP	164.98	146.88	
	(1.83)*	(1.52)	
HDI	2516.18	1701.72	
	(0.87)	(0.06)	
LT_IR	-152.34	-22.66	
	(-1.22)	(-0.18)	
FDI	997.54	2134.74	
	(0.28)	(0.58)	
BRT	137.03	99.98	
	(1.88)*	(1.28)	
NBP	-510.00	-428.48	
	(-1.60)	(-1.24)	
COAL	-1.69	-10.14	
	(-0.09)	(-0.53)	
Country-Specific			
EN_IMP	29.76	26.83	
	(2.47)**	(2.08)**	
Political			
FiT	344.62		359.43
	(0.86)		(0.82)
RPS	592.39		301.78
	(1.01)		(0.51)
REC	-879.71		-696.64
	(-0.94)		(-0.70)
TDR	2172.42		1233.43
	(4.83)***		(2.63)***
C_T	1197.58		947.42
	(2.57)**		(1.92)*
CaT	387.04		1102.22
	(0.89)		(2.36)**
Constant	-43994.74	-16803.24	204.26
	(-1.52)	(-0.61)	(0.17)
Year Controls	YES	YES	YES
R^2	42.04% (within)	29.39% (within)	24.67% (within)

Annual data over 2004-2014; fixed-effects estimation; t-statistics in parenthesis; *** (**,*) indicates significance at the 1% (5%, 10%) level.

The global regression explains a high share (42%) of the variation in net RE capacity during the period surveyed. Among the socioeconomic factors, only GDP is positively associated with addition of renewable energy capacity in both regressions (while population is only moderately positively associated with dependent variable in the global regression), confirming that absolute size (in economic or demographic sense) is an important factor in renewables deployment. This is consistent with previous works (e.g. Marques et al, 2010) which used geographical size as proxy for resource potential. Contrary to the initial expectations, the coefficients of HDI, FDI, and NBP are not significant and negative. Oil price appears to have a positive effect on RE capacity addition (although the statistical significance is moderate), as expected: higher oil prices turn renewable electricity more competitive relative to other modes of power generation (oil, natural gas, etc.), attracting investments in renewable energy capacity.

Energy dependency appears to be significant in both model specifications, suggesting that the quest for energy security leads to renewables deployment. Finally, looking at the last group of variables on policies, which is also the most relevant for our study, we can see that both carbon pricing schemes are significant (even though cap and trade systems only in the partial regression), while FiTs, RPS and RECs do not show significance in our model. However, we observe that tendering has strong statistical significance (1% level). At this stage, we can support the view that tendering mechanisms are on average associated with the increase in renewables' investments but we are unable to claim – on the sole basis of this result - for a causal relationship. The coefficient of the Tendering dummy implies that having a national tendering scheme in place is associated with about 1200-2200 MW of renewables installed capacity per country annually.

The findings from the matching estimation are reported in Table 6. We show the results of matching on each category of covariates with both PSM and NNM.

Table 6. Statistical matching results[3]

		X_{policy}	$X_{se/cs}$	X_{size}
PSM	***ATE***	794.79	935.97	-64.98
		(2.72)***	(2.24)**	(-0.22)
	ATT	1,112.01	1,115.01	282.79
		(3.26)***	(2.11)**	(0.70)
NNM	***ATE***	744.43	1,030.84	245.75
		(1.68)*	(1.81)*	(0.99)
	ATT	903.96	434.45	1,152.48
		(2.17)**	(0.89)	(3.14)***
Confirm		*Confirmed*	*Weakly-Confirmed*	*Weakly-Confirmed*

Using the matching estimation, the positive impact of tendering on addition in net capacity of renewables is generally confirmed. Especially encouraging is the result by matching with the policy covariates, that is strongly confirmed and is sign that given a similar set of policies, tendering implementation has a considerable positive effect on the addition of net capacity of renewables.

Finally, regarding the implementation of the synthetic control method, and since large sample inferential techniques are not well suited, placebo tests are used instead by applying the SC method to every potential control in the sample (Abadie et al. 2010; 2015). Therefore, we consider whether the prediction error - when considering the actual treated country - is “unusually” large relative to the distribution of prediction errors for the countries in the donor pool. This analysis rejects the null hypothesis when the post-intervention mean squared prediction error (MSPE) for the SC estimate is greater than the post-intervention MSPE for the placebo estimates (Abadie et al., 2015).

Figure 4 shows the treatment, black line, and all the donors that are used to build the synthetic treatment. Figure 5 shows the effect of the treatment, when controls are aggregated.

[3] Z-statistics in parenthesis; *** (**,*) indicates significant at the 1% (5%, 10%) level.

Figure 4. Treatment and donors

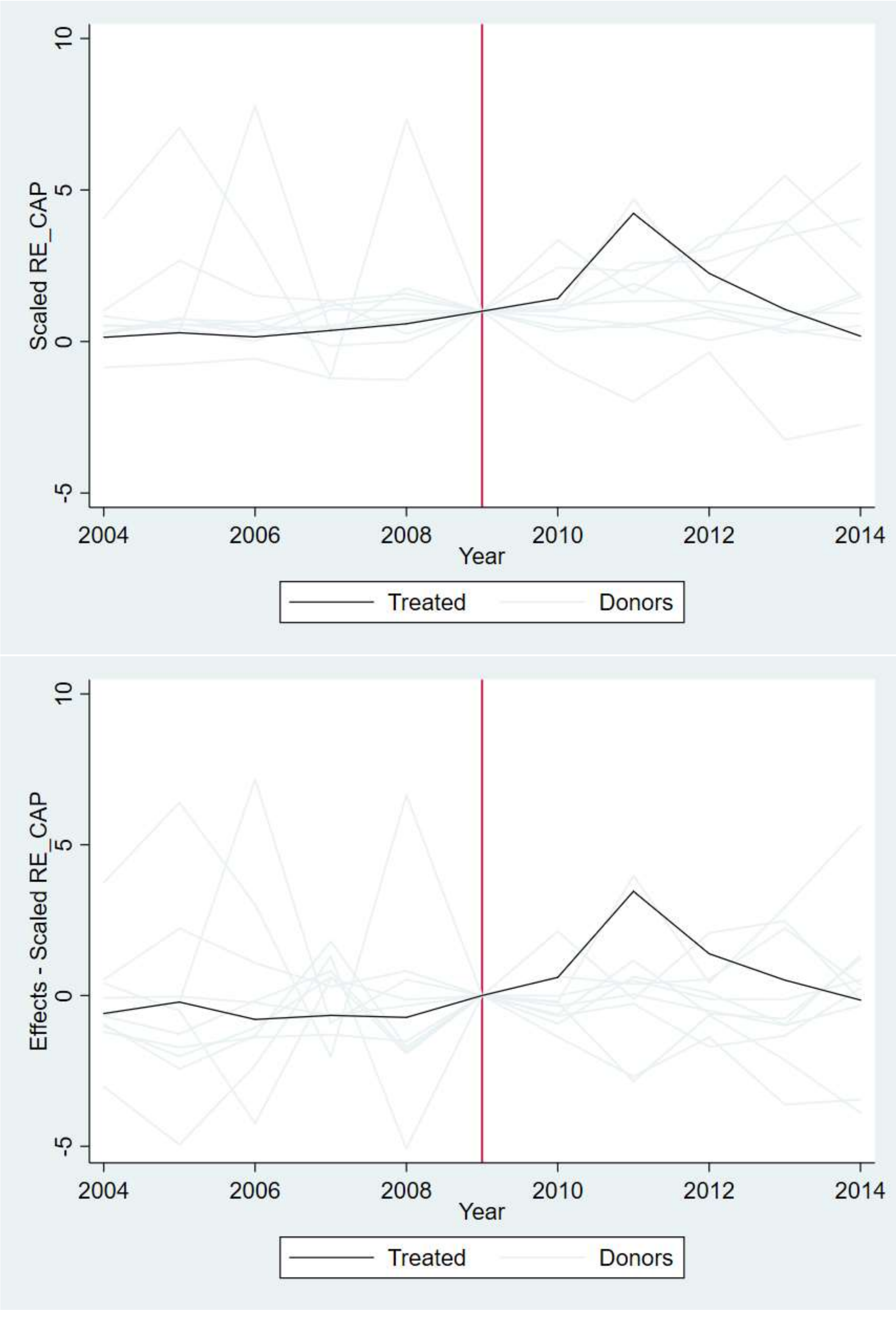


Figure 5. Treatment effect

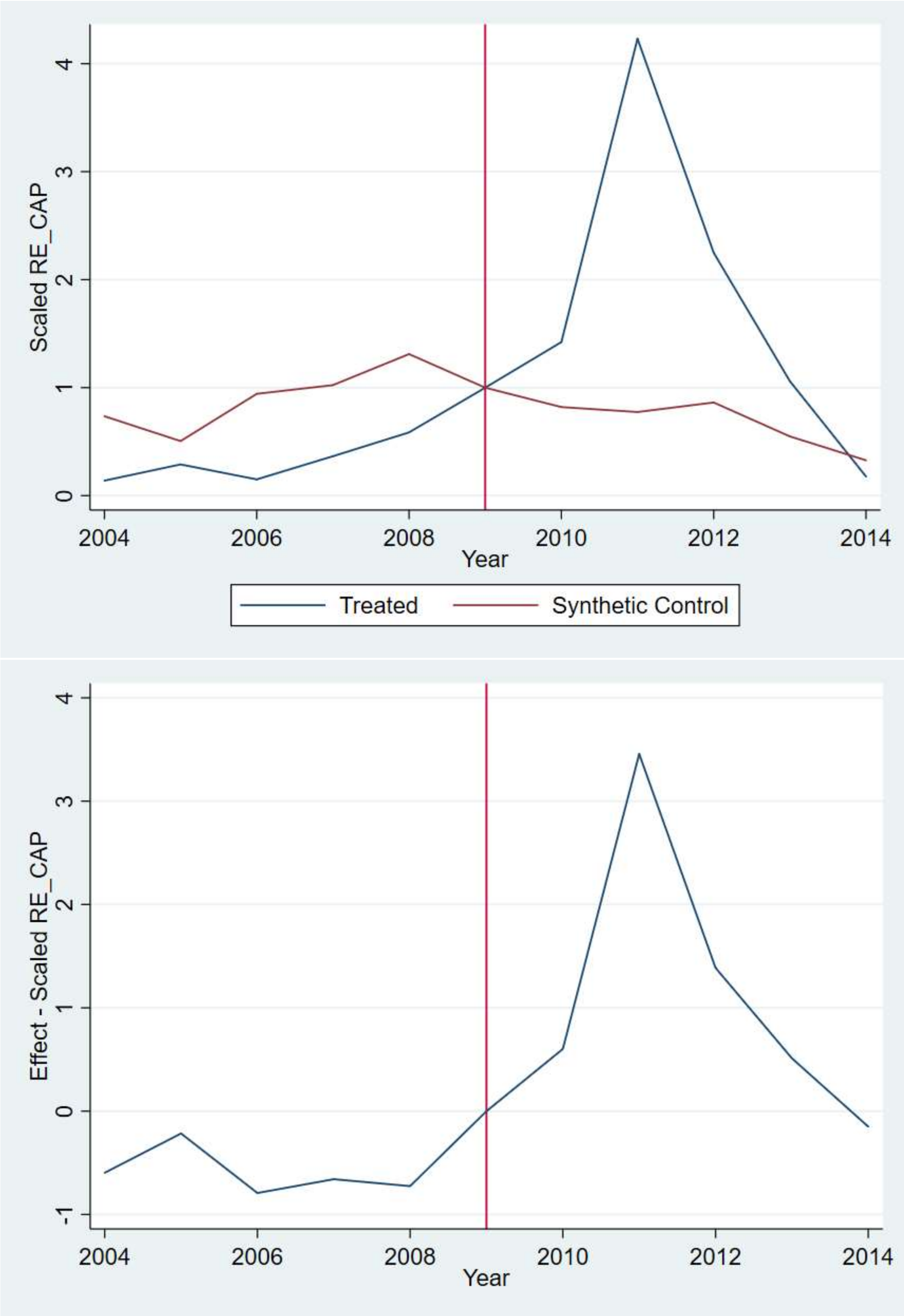


Table 7 and 8 summarizes the results of our analysis on Italy. The root mean squared error is equal to 2521.117 (not shown), while Table 8 reports (third column) the robustness check: the p-value is calculated on the basis of all placebo tests distribution, thus showing that there is a statistically significant effect.

Table 7. Synthetic Control method: the Italian case

	Italy	
Weights	Germany (37.5%) Spain (62.5%)	
Predictors Balance	**Actual**	**Synthetic**
GDP(log)	7.626	7.524
POP(log)	4.066	4.029
HDI	.862	.868
LT_IR	4.22	4.20
FDI	0.79	0.82
EN_IMP	82.98	70.92
FiT	0.83	1.00
C_T	0.00	0.00
CaT	0.83	0.83

Table 8. Synthetic Control method: robustness

t, τ^{SC}	Effect	P-vals	P-vals std.
2010	.6017612	.6	.2
2011	3.456613	.1	0
2012	1.386734	.2	0
2013	.5115796	.9	.5
2014	-.1504204	.9	.7
Total τ^{SC}	5,806		
Average τ^{SC}	1,161		

The introduction of tendering appears to have had a positive bringing an additional 6000 MW circa installed capacity in Italy (Table 7). However, the implementation of tendering lead to contrasting results in the two cases. Figure 4 shows the added capacity for synthetic Italy overcomes the value for actual Italy in 2014.

According to the model, tendering had a negative effect on new installations in those two years. In fact, there was a strong policy change in Italy marked by a substantial cut in RE subsidies starting from 2012, including the cancellation of FiTs on solar PVs in 2013 (the so-called "conto energia") (Tiedemann et al., 2016). These policy changes have undermined investors' confidence in the stability of the regulatory framework (Mahalingam and Reiner, 2016). The shift in investors' mood is obviously not captured by the model in creating the synthetic control; the countries composing synthetic Italy did not underwent a similar scale-back in RE support policies, as reflected by a more stable addition in capacity in the same years.[4]

Therefore, the implementation conditions are very important. Even though the analysis show that tendering can have a positive impact on net RE investment, policy instability can crowd out the benefits with the introduction of auctions, as shown in the case of Italy.

6. Hypothesis analysis

The three different econometric models provide consistent and convergent results about the benefits of tendering. Despite the limitations of the analysis, the results show clear responses to the hypotheses. Hypothesis 1 stated that contextual variables, socioeconomic and country-specific factors, are the main drivers of the investment in RE. Even though the OLS model shows that the partial model with socioeconomic and country-specific factors explains a slightly higher share of the variance in the net additions of RE, their associated variables display a much lower coefficient than the political factors (policy). Furthermore, the analysis with the matching estimator reveals that policy instruments have a stronger effect, thus rejecting H1.

Under Hypothesis 2, the existence of policy instruments are the main determinants of the investment in RE. Conversely to H1, the results support this

[4] Moreover, FiTs are aimed at a broader range of recipients, and their cancellation might have had a deep effect on the addition of small-scale/distributed capacity, which is not the policy target of tendering.

hypothesis, particularly in the analysis with the matching estimator. Therefore, the data shows that the political factor linked to the implementation of policy instruments increase the RE capacity.

Finally, Hypothesis 3 suggests that the change to an auction-based mechanism increases the investment in RE. The OLS model clearly shows the superiority of tendering in relation to the other instruments. This result is further confirmed by the application of the synthetic control model which shows that the change to tendering in average has a positive effect in the amount of RE capacity added each year. This corroborates the European Union's policy that is prompting member states to implement auctions (European Commission, 2014). Nonetheless, the conditions of tendering implementation are just as important to incentivize new capacity additions as the downturn in the investments following a major change in the auctions regime in Italy shows.

7. Conclusion and policy implications

Tendering is the fastest rising mechanism to support the increase of electricity generation from renewable sources in the past two decades. So far the literature gives an unclear picture about the advantages of tendering in comparison with other instruments. The current debate is controversial with some authors assessing the effects of switching to auctions in terms of improved effectiveness, while others considering it would rise financial risks and costs. Recent assessments show that tendering may increase the effectiveness and efficiency of support depending on the circumstances, however no systematic cross-country analysis has yet been done. This paper performs a comparative analysis of the policies supporting RE investment over time, providing in particular a quantitative assessment for the effect of the introduction of tendering and of the conditions of its implementation.

An innovative econometric approach combined three different models (multivariate fixed effects regression, matching estimation, and synthetic controls) to evaluate the data from a representative sample of countries. Synthetic controls in particular create a counterfactual group that controls for external factors (e.g., technology cost reductions) and cross-country differences (e.g., resource endowment).

Our empirical analysis confirms the advantages of tendering over other support mechanisms in promoting the investment in cleaner, renewable capacity. The model with fixed effects shows evidence that tendering has a positive effect in net additions of RE capacity. This effect is significant and higher than of the other instruments like feed-in-tariffs. The matching estimator confirmed the superiority of tendering over other mechanisms on the countries surveyed, during the period under analysis. The results also indicate good performance of auctions to deal with financial and socio-cultural barriers to RE investments. Finally, synthetic controls revealed benefits of switching to tendering but these are contingent on other factors such as policy stability. The three approaches lead to estimates of additional renewable capacity installed in the order of 1000-2000 MW per country per year.

The analyses still have some limitations. Data was only available for the period up to 2014. However, this already includes the beginning of recovery from the financial crisis (e.g., Italy). In the future it would be possible to perform analysis including more countries, over a longer period. On the other hand, we were only able to assess the average effects of the mechanisms in the net addition of RE capacity. In practice, tendering performance might be different by technology. These limitations are however unlikely to affect the meaningfulness and the direction of the results.

Two main policy implications derive from the results. Firstly, as shown by Italy's example, tendering is not a panacea for the transition to a low-carbon economy, as it can be effective only if investors trust the regulatory system in place. Here lies a lesson for policymakers, who have to design a portfolio of support schemes that is attractive for investors as well as sustainable in the long run: infrastructure investors have a time horizon that is lengthier than any legislature and lose confidence quickly in the political framework of a country. Secondly, tendering alone cannot substitute all the other RE support policies: they are specifically devised for the creation of large RE generation projects. This might be a challenge for new technologies in the early years of formation for which the size of the projects is typically smaller. In these cases, policies should gradually move from price-based mechanisms (e.g., FiT) to auctions as the new technologies mature and their markets develop. More research is therefore needed to check whether tendering may be useful to encourage more granular, distributed generation (e.g. small solar PV) featuring important environmental and electricity system benefits.

Funding sources

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

References

Abadie, A., Diamond, A., Hainmueller, J., 2015. Comparative politics and the synthetic control method. Am. J. Political Sci. 59(2), 495-510.

Abadie, A., Imbens, G.W., 2016. Matching on the estimated propensity score. Econometrica 84(2), 781-807.

Abadie, A., Diamond, A., Hainmueller, J., 2010. Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. J. Am. Stat. Assoc. 105(490), 493–505.

Aguirre, M., Ibikunle, G., 2014. Determinants of renewable energy growth: A global sample analysis. Energ. Policy 69, 374–384.

Antonelli, M., Desideri, U., 2014. The doping effect of Italian feed-in tariffs on the PV market. Energ. Policy 67, 583–594.

Awerbuch, S., Sauter, R., 2006. Exploiting the oil-GDP effect to support renewables deployment. Energ. Policy 34(17), 2805–2819.

Baldacci, E. et al., 2008. Social Spending, Human Capital, and Growth in Developing Countries. World Dev. 36(8), 1317–1341.

BNEF 2015. Global trends in renewable energy investment 2015. Bloomberg New Energy Finance, UNEP-Frankfurt School. http://fs-unep-centre.org/publications/global-trends-renewable-energy-investment-2015

Burer, M.J., Wüstenhagen, R., 2009. Which renewable energy policy is a venture capitalist's best friend? Empirical evidence from a survey of international cleantech investors. Energ. Policy 37(12), 4997–5006.

Butler, L., Neuhoff, K., 2008. Comparison of feed-in tariff, quota and auction mechanisms to support wind power development. Renew Energ 33(8), 1854-1867.

Cárdenas Rodríguez, M., Haščič, I., Johnstone, N., Silva, J., Ferey, A., 2014. Inducing private finance for renewable energy projects: Evidence from micro-data (No. 67). OECD Publishing.

Carley, S., 2009. State renewable energy electricity policies: An empirical evaluation of effectiveness. Energ. Policy 37(8), 3071–3081.

CEER 2018. Tendering procedures for RES in Europe: State of play and first lessons learnt, CEER Public Document C17-SD-60-03, Council of Europeans Energy Regulators, 18 June, Brussels.

Chang, T.H., Huang, C.M., Lee, M.C., 2009. Threshold effect of the economic growth rate on the renewable energy development from a change in energy price: Evidence from OECD countries. Energ. Policy 37(12), 5796–5802.

Couture, T. Gagnon, Y., 2010. An analysis of feed-in tariff remuneration models: Implications for renewable energy investment. Energ. Policy 38(2), 955–965.

De Jager, D. et al., 2011. Financing renewable energy in the European energy market. Final report by Ecofys, Fraunhofer ISI, TU Vienna EEG and Ernst &Young, Ecofys, Utrecht.

Dechezleprêtre, A., Popp, D., 2015. Fiscal and regulatory instruments for clean technology development in the European Union. ESRC Centre for Climate Change Economics and Policy, Grantham Research Institute on Climate Change and the Environment Policy Paper, (July).

Del Rio, P., 2017. Designing auctions for renewable electricity support. Best practices from around the world. Energ. Sust Dev. 41, 1-13.

Del Rio, P. Bleda, M., 2012. Comparing the innovation effects of support schemes for renewable electricity technologies: A function of innovation approach. Energ. Policy 50, 272–282.

Del Rio, P., Linares, P., 2014. Back to the future? Rethinking auctions for renewable electricity support. Renew. Sust. Energ. Rev. 35, 42-56.

Department for Communities and Local Government, 2017. Decision letter: land at Scout Moor Wind Farm, Rossendale Lancashire. (Ref.APP/B2355/V/15/3139740).

Dong, C.G., 2012. Feed-in tariff vs. renewable portfolio standard: An empirical test of their relative effectiveness in promoting wind capacity development. Energ. Policy 42, 476–485.

Eyraud, L., Clements, B. Wane, A., 2013. Green investment: Trends and determinants. Energ. Policy 60, 852–865.

European Commission, 2014. Guidelines on State Aid for Environmental Protection and Energy 2014-2020. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52014XC0628%2801%29

Gan, L., Eskeland, G.S. Kolshus, H.H., 2007. Green electricity market development: Lessons from Europe and the US. Energ. Policy 35(1), 144–155.

Grau, T., 2014. Comparison of feed-in tariffs and tenders to remunerate solar power generation. Discussion Paper 1363, DIW Berlin https://www.diw.de/documents/publikationen/73/diw_01.c.437464.de/dp1363.pdf

Grubb, M., 2004. Technology Innovation and Climate Change Policy: An Overview of Issues and Options. Keio Econ. Stud. 41(2), 103–132.

IEA, 2008. World Energy Outlook 2018. IEA/OECD, Paris.

IEA, 2015. Energy and Climate Change. World Energy Outlook Special Briefing for COP21, OECD/IEA, Paris.

IRENA, 2019. Renewable Power Generation Costs in 2018, International Renewable Energy Agency, Abu Dhabi.

IRENA, 2015. Renewable Energy Auctions: a Guide to Design. Working Paper. IRENA.

Jenner, S., Groba, F. Indvik, J., 2013. Assessing the strength and effectiveness of renewable electricity feed-in tariffs in European Union countries. Energ. Policy 52, 385–401.

Johnstone, N., Haščič, I. Popp, D., 2010. Renewable energy policies and technological innovation: Evidence based on patent counts. Environ. Res. Econ. 45(1), 133–155.

Kilinc-Ata, N., 2016. The evaluation of renewable energy policies across EU countries and US states: An econometric approach. Energy for Sustain. Dev. 31, 83–90.

Mahalingam, A., Reiner, D., 2016. Energy subsidies at times of economic crisis: A comparative study and scenario analysis of Italy and Spain. EPRG Working Paper 1603, Cambridge Working Paper in Economics 1608, https://doi.org/10.17863/CAM.5753

Marques, A.C., Fuinhas, J.A., Pires Manso, J.R., 2010. Motivations driving renewable energy in European countries: A panel data approach. Energ. Policy 38(11), 6877–6885.

Muller, S., Brown, A., Ölz, S., 2011. Policy Considerations for Deploying Renewables. Renew. Energ., p. 72.

Popp, D., 2001. Induced Innovation and Energy Prices. National Bureau of Economic Research Working Paper, 8284.

Popp, D., 2015. Using Scientific Publications to Evaluate Government R&D Spending: The Case of Energy. CESifo Working Paper Series.

Popp, D., Hascic, I., Medhi, N., 2011. Technology and the diffusion of renewable energy. Energ. Econ., 33(4), 648–662.

Proparco, 2010. Private Equity and Clean Energy: How to Boost Investments in Emerging Markets?. Agence Française de Développement, 29 p.

REN21, 2017. Renewables 2017 Global Status Report, REN21 Secretariat, Paris, France.

Rickerson, W. et al., 2012. Feed-in tariffs as a policy instrument for promoting renewable energies and green economies in developing countries. UNEP.

Sen, S. Ganguly, S., 2017. Opportunities, barriers and issues with renewable energy development – A discussion. Renew. Sustain. Energ. Rev. 69, 1170–1181.

Sepehri, A., Sarrafzadeh, M.H., 2018. Effect of nitrifiers community on fouling mitigation and nitrification efficiency in a membrane bioreactor. Chem. Eng. Process. 128, 10-18.

Shrimali, G., Kniefel, J., 2011. Are government policies effective in promoting deployment of renewable electricity resources?. Energ. Policy 39(9), 4726–4741.

Standard & Poor’s, 2010. Presale information: Kortis Capital Ltd. Tech. Report

Standard & Poor's, 2007. Standard & Poor's Project Finance Transactions Ratings Criteria: Reference Guide. Standard & Poor's Ratings Services, McGraw Hill Financial.

Tiedemann et al., 2016. Auctions for Renewable Energy Support in Italy: Instruments and lessons learnt. Report D4.1-IT, March 2016

<http://auresproject.eu/publications/auctions-renewable-energy-support-in-italy-instruments-and-lessons-learnt>

UNFCCC, 2015. Glossary of climate change acronyms. United Nations Framework Convention on Climate Change.

Verbruggen, A., Lauber, V., 2012. Assessing the performance of renewable electricity support instruments. Energ Policy 45, 635-644.

Winkler, J., Magosch, M., Ragwitz, M., 2018. Effectiveness and efficiency of auctions for supporting renewable electricity–What can we learn from recent experiences. Renew Energ 119, 473-489.

World Bank, 2018. Doing Business 218 - Reforming to Create Jobs. Washington. https://www.doingbusiness.org/content/dam/doingBusiness/media/Annual-Reports/English/DB2018-Full-Report.pdf

Zhao, Y., Tang, K.K. Wang, L., 2013. Do renewable electricity policies promote renewable electricity generation? Evidence from panel data. Energ. Policy 62, 887–897.