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The Effect of Feed-in Tariffs on the Deployment of Renewable Energies

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O Efeito das Tarifas Feed-in na Implementação de Energias Renováveis

Margarida Ramalho Almeida Oliveira

Sumário

Este estudo pretende avaliar a relação entre as tarifas feed-in e o desenvolvimento das energias renováveis. Selecionamos uma amostra de 28 países da UE cobrindo o período de 1990-2017. Para analisar os dados, adotamos uma abordagem de dados em painel realizando uma estimativa de efeitos aleatórios. Entre as diversas variáveis explicativas, os valores de tarifas feed-in discriminadas pelos diferentes tipos de tecnologia são definidos como as variáveis de interesse em explicar a parcela da capacidade elétrica gerada a partir de uma fonte renovável não hídrica. Os resultados sugerem que, das diferentes tecnologias em análise, apenas o Vento e os Resíduos impactam variável dependente, aliados à parcela da eletricidade gerada a partir de uma fonte de combustível nuclear e fóssil e dos preços das fontes tradicionais de energia. As conclusões anteriores são robustas para os países membros da OCDE e também para os países onde a tarifa feed-in é aplicada a pelo menos uma das tecnologias em análise.

Códigos JEL H23, Q42, Q48, Q58.

Palavras-chave: Energias renováveis, tarifas feed-in, geração de capacidade de electricidade, efeitos aleatórios.

The Effect of Feed-in Tariffs on the Deployment of Renewable Energies

Margarida Ramalho Almeida Oliveira

Abstract

This study intends to evaluate the relationship between the use of feed-in tariffs and the deployment of renewable energies. We collected a sample of 28 EU countries for the period 1990-2017. Following a panel data approach, we performed a random effects estimation. Among the several explanatory variables, feed-in tariffs, discriminated by different renewable energies' technologies, are defined as the variables of interest in explaining the share of the electricity capacity generated by non-hydro renewable sources. The results suggest that only Wind and Waste impact the dependent variable allied to the share of electricity produced from both nuclear and fossil fuel sources and the prices of traditional energy sources. The previous findings are robust for OECD member countries and also for countries where feed-in tariffs are applied at least once in the period considered.

JEL Codes: H23, Q42, Q48, Q58.

Keywords: Renewable energies, feed-in tariffs, electricity capacity generation, random effects.

Contents

List of Abbreviations

CEM - Clean Energy Ministerial

CO2 - Carbon dioxide emissions *per capita*

Cov - Covariance

CPI - Consumer price index

dFossilShare - First differences of FossilShare

dNuclearShare - First differences of NuclearShare

dRenew - First differences of Renew

EIA - Energy Information Administration

Electpc - Electricity consumption *per capita*

EU - European Union

FDI - Foreign direct investment

FGLS - Feasible generalized least squares model

FiT - Feed-in tariffs

FossilShare - Importance of fossil fuels to total electricity capacity generation

GDPpc - Gross domestic product *per capita*

gGDPpc - Gross domestic product *per capita* growth rate

IEA - International Energy Agency

ImpDep - Energy imports dependency rate

IPS - Im-Pesaran-Sin test

IRENA - International Renewable Energy Agency

kWh - Killowatt-hour

MWh - Megawhatt-hour

NuclearShare - Importance of nuclear to total electricity capacity generation

OECD - Organisation for Economic Co-operation and Development

OLS - Ordinary least squares

p.p. - percentuage points

RE - Renewable energy

REN21 - The Renewable Energy Policy Network for the 21st Century

Renew - Importance of non-hydro renewable to total electricity capacity generation

ROI - Return on investment

RPO - Renewable purchase obligations

Solar PV - Solar photovoltaic

TFEU - Treaty on the Functioning of the European Union

TGC - Tradable green certificates

UK - United Kingdom

UN - United Nations

US - United States

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1 Introduction

Are feed-in tariffs (FiT) effective on the deployment of renewable energies (RE)? In this study we investigate how the application of FiT influences the share of electricity capacity generated from a non-hydro source, for the period 1990-2017 regarding the 28 EU countries. Policy instruments play an important role on RE adoption due to the environmental-related consequences of fossil fuels, the countries' dependence on foreign suppliers, and also due to the heavy barriers to participants in the energy market. Among the available instruments, feed-in tariffs appear to be the one contributing the most for RE deployment. For this analysis, we collected data concerning the application of FiT discriminated by RE technologies, namely wind, solar PV, geothermal, waste-to-energy, biomass and marine, being this our main contribution to the literature since most of the authors we studied perform the analysis considering all the technology types combined into a single measure – they ignored the fact that FiT may have different incidences on each technology type which may influence the final outcome. To complement our analysis, we also consider a set of explanatory variables grouped in smaller subchapters (substitute energy variables, economic variables, security variables and environmental variables), that, according to their rationale, are considered to play a major role when approaching renewable energies capacity. We then perform a panel data evaluation through the estimation of a random effects model.

Our results suggest that while FiT applied to Wind is contributing positively to the deployment of RE, Waste is unexpectedly influencing it in a negative way. We believe that the rationale to justify this odd outcome lies on the relationship between the effectiveness and efficiency of the different RE technologies and the amount of incentive that is being attributed to each one of them. Regarding the remaining technologies, FiT seem to not produce any effect on the share of electricity capacity generated from a non-hydro source taking into account the years and countries under analysis. In what concerns the control explanatory variables, we found that the share of electricity produced from both nuclear and fossil fuel sources and the prices of traditional energy sources present significant results with the expected sign. To complement our analysis, we perform several robustness test and we conclude that the previous findings are robust for OECD member countries and also for countries where feed-in tariffs are applied at least once in the period considered.

The remainder of the study is organized in the following way: in chapter 2 we present a brief context of RE outlook and respective policy instruments; in chapter 3 we present the literature review; in chapter 4 we describe the variables and the empirical approach used in the study; in chapter 5 we present and discuss our results from the main regression; in chapter 6 we realize diverse robustness tests; and in the last chapter 7 we conclude our study.

2 The Context

The energy market is a platform that allows participants to exchange energy, being defined as a commodity market since energy production is included in the primary economic sector. According to the World Energy Outlook (IEA, 2020), electricity represents a rising share of energy services and, with world population tending to increase throughout the years – 8.6 billion people by 2030 and 11.2 billion by 2050 (UN, 2019) –, its consumption will also become larger. IRENA (2019) advocates that the effect of this increasing demand is the escalating emission of CO_2 to the atmosphere, once the main sources for electricity production are the hydrocarbon-related ones. In the light of growing environmental concerns, RE have assumed an important role in the energy market in two main ways: they decrease countries' energy dependence from the fossil fuel-based supplier countries; and they contribute to mitigate climate changes by providing clean energy from non-finite resources (REN21, 2020). Following this reasoning, the upfront capital investment needed to start producing this kind of energy, specifically in terms of storage as well as distribution networks, is a barrier to entry in the market – IRENA and CEM (2015) complement this argument by stating that there are also institutional and administrative barriers preventing the entry in the clean energy market. This way and considering that RE deployment is recent in the energy market, they become less competitive than the non-renewable types of energy (prices are an example as explained by Haas *et al.* (2011)). Their market share, although slowly growing, is still small, and they are not able to attain their full potential.

Due to their importance and considering the difficulties exemplified above, Government policy instruments appear as an attempt to support the investment and deployment of renewable electricity generation, such as offshore wind farms, solar panel plants, among others. The three categories where these mechanisms can be included are the quantity-based instruments, the tariff-based instruments and the hybrid ones (IRENA and CEM, 2015). It is essential to notice that although several mechanisms can be considered, we rely our description on the most relevant for each group.

The first group of incentives operates by setting an obligation on the electricity suppliers in a way that a specific quantity of the electricity they distribute must be generated from a renewable source. Renewable urchase Obligation (RPO) and Tradable Green Certificates (TGC) are two examples of this mechanisms on which the renewable electricity generators eligible for the incentive will earn a certificate for each MWh of clean energy produced (Passey *et al.*, 2014). Then, electricity suppliers (wholesalers, distribution companies or retailers) will purchase this renewable electricity with its associated certificates. One of their main advantages is that they represent an efficient approach to meet the target of RE market share since they set a mark directly on the quantities (Haas *et al.*, 2011). Furthermore, there is no risk of uncontrolled electricity growth because after the quota has been achieved there is no incentive to produce additional MWh. This last point may be ambiguous: although it is possible to control undesired overgrowth, there will be no room for RE deployment beyond this upper limit. Moreover, this is not the most suited mechanism if we pretend to invest in technological development and innovation once quotas and certificates have a cost-minimizing approach, discouraging the investment in more expensive RE technologies. There is also the risk of noncompliance of the target, translated into increased penalties for non-achievement of the quota obligations. (IRENA and CEM, 2015)

The second group of mechanisms (tariff-based ones) provide an economic incentive to the generation of renewable electricity in the form of subsidies. Their main goal is to scale up renewable electricity capacity – FiT are the best known example. FiT usually offer long-term contracts (often between 15 to 25 years) that guarantee a pre-determined price to be paid to the electricity generator (producer) according to the kWh fed into the electricity grid (Jenner *et al.*, 2013). These tariffs are usually differentiated by the source of renewable energy and by the size of the project as well. In other words, FiT work as an extra payment over the market price to help agents overcoming the higher upfront capital costs of installing the renewable energies' equipment (e.g., solar panels) – this will promote an attractive environment for RE deployment (Nicolini and Tavoni, 2017). The main advantage of this type of incentive is related with its long-term planning/commitment that contributes to increase the project stability and to provide a feeling of security for the investors (IRENA and CEM, 2015). Furthermore, its modeling is relatively simple and adaptable, being easily customised to different specific technologies. In some countries, FiT are funded through the electricity utility bills, which means that its associated costs are transferred to the consumers, representing no burden for the public budget (Haas *et al.*, 2011): if the tariff is not funded by the consumers through the electricity bills, its consistency may be dependent on the government budget stability (IRENA and CEM, 2015). Furthermore, the determination of the tariff awarded to project developers could be an obstacle representing one of the main challenges, and if bad implemented it can become very costly for the country.

Lastly, the hybrid instruments were created as an attempt to overcome both previous instruments' weakness (Haas *et al.*, 2011). Renewable energy auctions are a very good example where both quantities generated and price are set in advance through public bidding (IRENA and CEM, 2015). In the auctions, project developers submit a bid representing the price *per* unit (kW) of electricity at which they would be willing to move forward with the project. The different options are evaluated by the government, and they will be ranked according to several aspects, usually the price and the years of the contract (IRENA and CEM, 2015). The main positive points of auctions are that they are very easily adaptable to the countries specific characteristics and that they provide a long term guarantee by fixing the contract price during its length. On the other side, auctions involve high transaction and administrative costs which means that most of the times it is difficult for small/medium companies to be part of them. There are also risks resulting from the mechanism characteristics: if there is a small number of competitors the offers may be too high, and if the number of participants is too high underbidding is a possible scenario reflected in low financial returns (Lucas *et al.*, 2013).

3 Literature Review

Renewable energies' sources have emerged as a sustainable solution to the fossil-fuel environmental related consequences. However there are still many barriers that prevent them from reaching their full potential, such as the projects' financing, administrative or institutional obstacles and increasing upfront investment costs needed for their implementation (regarding infrastructures and distribution networks). Governmental policy instruments appear as a way to mitigate these difficulties (IRENA and CEM, 2015).

In this chapter, the relationship between the policy instruments and the energy market is explored, by presenting the empirical evidence of existing research.

3.1 The Effect of Policy Instruments in the Renewable Energy Market

Several authors have tried to model and analyze the need for policy instruments in the energy market, namely in what concerns the renewable energy market. Table 3.1 presents a summary of the different empirical results that were found in previous research.

Butler and Neuhoff (2008) make a comparison between different support schemes' efficiency in fostering wind power development. The authors focus their analysis in two countries – Germany and United Kingdom (UK) – since these have always presented different policy directions in what concerns the promotion of renewable energy sources. During the last decades, Germany was in favor of FiT while in the UK the projects were delivered by a tendering system. Nowadays, while Germany still uses the same support scheme (although it suffered a design change), the UK replaced the auctions by a quota system, namely the RPO. To evaluate the performance of both policies, the authors conducted surveys among project developers of wind power. They start their analysis by hypothesizing that although FiT appear to be more efficient in fostering RE deployment this was achieved at a higher cost. When comparing the results of the survey with their initial idea, the authors verify that renewable obligations are not necessarily cheaper than FiT, and that in terms of capacity installed deployment is comparatively higher where the FiT are employed (in this case, Germany).

Blazquez *et al.* (2018) study the behaviour of five policy instruments under different market conditions, analyzing the impact of price volatility and uncertainty of the related investments. For this examination, the authors collected data from 2006 until 2013 on Spanish onshore wind power. The five policy instruments (contract-for-difference FiT, floor FiT, FiT with both floor and cap prices, feed-in premium and investment credit) are evaluated in three dimensions: the cost of the policy, their speed of adoption and whether or not they achieve large deployment of renewables. One of the main results concerns the fact that none of the previously mentioned policies can achieve simultaneously the following three goals: low costs, high speed of adoption and large deployment of renewables. There is an implicit trade-off among the different instruments: while the FiT in general grant a larger deployment of renewables at a very high cost, the investment credit is the cheapest solution although it is also the one that yields the lower success ratio. Thus, the decision of what policy to adopt depends on the goals of the government and not on the policy design just by itself.

Johnstone *et al.* (2010) evaluated the effect of renewable energy policies on technological innovation. The authors perform this analysis by evaluating the patent applications for each type of technology, since they appear as the most suitable proxy to reflect the innovative performance of each policy. Cross-country data from 25 OECD countries was selected, over the period 1979-2003. The authors found evidence of a strong influence of public policies on the development of new renewable energy technologies. When analyzing each type of source, results show that feed-in tariffs are needed to induce innovation on more expensive technologies, like solar power. However, when it comes to more cost-competitive technologies, as the wind power, there is no evidence that FiT induce additional innovation.

Haas *et al.* (2011) performed several case studies on different European countries, namely on the EU 27 member states, with the goal of analyzing the performance of several policies in encouraging the RE's deployment. For this analysis, the authors evaluate different types of promotion schemes as well as their properties. Furthermore, a member-state level analysis is conducted, considering historical evidence, with the goal of showing how the different policies have evolved through the years. They conclude that the effectiveness and efficiency of the policies is not related with the policy itself, but with its design and criteria implementation. Besides, FiT appear to be preferable to the quota-based tradable green certificates if well designed. Since FiT are easier to implement and to be revised, its administration costs are lower when compared to the tradable green certificates ones.

Jenner *et al.* (2013) performed an econometric analysis of the effectiveness of FiT on influencing renewable electricity capacity. The authors used a panel from 1992 to 2008 for 26 EU countries, concerning the technology-specific level of FiT, namely for solar PV and onshore wind capacity. On a first phase, they tested the impact of political and socioeconomic variables on the RE deployment, accessing whether FiT were effective. Afterwards, the authors chose a fixed-effects regression model controlling for unobserved country-level characteristics that could influence policy implementation. On a third phase, they attempt to construct a statistical indicator for FiT strength, considering market and policy design characteristics to better capture RE policies' effectiveness. This instrument reflects the return of investment (ROI) for RE installations. With this analysis, the authors conclude that the tariffs have been influencing capacity development of solar photovoltaic in Europe. However, when it comes to onshore wind power, there is no robust evidence that support this hypothesis. Besides, the interaction between market characteristics and policy design features is more significant for the RE development than the tariff just by itself.

Smith and Urpelainen (2013) studied the effect of FiT on renewable electricity generation. To perform this analysis, the authors used data from Johnstone *et al.* (2010) for 1979-2005 concerning 26 industrialized countries. On a first stage, the authors opted for using aggregate data on renewable electricity generation because it is difficult to compare countries that have differentiated access do the several natural resources. On a second stage, they disaggregated the data to possibly highlight differences in the distinct types of energy. An econometric regression was used to evaluate the percentage change in a country's RE share, based on variables such as previous deployment of tariffs and their use by neighbour countries. The authors found that FiT represent an efficient way to increase renewable electricity generation. Furthermore, they discovered that countries that had imposed FiT in the past are more likely to use them in the future.

Marques and Fuinhas (2012) try to verify whether public policies contribute to the deployment of RE. In addition, the authors evaluate the impact of the policies' measure both as a whole and disaggregated. To support this analysis, a panel data regression was made, considering data for the period 1990-2007 across 23 EU countries, using the share of RE to total energy supply as the dependent variable – the used measure represents the replacement of the traditional sources by the renewable ones. Results show that until 2012 quotas' obligations, tradable certificates, among others, had not yet produced the expected effect. On the contrary, evidence points to FiT as an effective incentive to the deployment of RE.

Nicolini and Tavoni (2017) adopted a cross-country approach focusing on the five largest European countries (Spain, Italy, France, Germany and United Kingdom) in order to study policy effectiveness in promoting renewable electricity from 2000 until 2010. For this examination, the authors collected data related to five different technologies, namely bioenergy, geothermal, hydropower, solar photovoltaic and wind power, disaggregating it for the different policy instruments (FiT and quotas). Their results reveal that there is a positive relationship between the subsidies and the production of incentivized energy as well as the installed capacity – the first represents a short-term perspective and the second a long-run one. Regarding the performance of each policy instrument, FiT shows itself more efficient in promoting RE production, at least in the short-run. In what concerns the long-run view, namely the installed capacity, no conclusion is addressed.

Kilinc-Ata (2016) studies policies effectiveness in fostering the deployment of RE. The author uses data from 27 EU countries and 50 states from the US, performing a panel-data analysis for the period 1990-2008. The research conducted concerns four policies instruments, namely FiT, quotas, tenders and tax incentives. Also, the author included explanatory variables like thermal and nuclear energy (which represents a substitute energy source to the renewable ones) and energy imports (to provide an overview regarding the dependency of energy security). Results show that thermal energy sources do not have any effect on renewable electricity capacity generation. However, nuclear sources appear to influence negatively its deployment. This finding can be related with the fact that when energy demand increases consumers tend to opt for a more traditional energy solution since it is perceived as a cheaper option when compared to renewable energy sources. Regarding the policy analysis, the author found that FiT, tenders and tax incentives are statistically significant, having positive influence on the deployment of RE. The quota-based policies however revealed to have an non significant relationship with renewable electricity capacity, while FiT appear to be the one influencing it the most.

As one is able to infer grounded on the evidence presented, FiT's design is the most successful one since it appears to be the greatest contributor to RE market growth in most of the countries where they were imposed when compared to the other mechanisms. This way, we will focus our work on this policy instrument although trying to overcome the problems we consider to be present on previous research and also presenting more contributions which are not related to existing literature gaps, as follows. Most of the previously mentioned articles suffer from a general problem: the use of different technologies (such as geothermal, hydropower, solar PV, wind, biomass, marine and waste-to-energy) combined into a single measure. In these cases, it is not possible to take conclusions at technological-specific level, which can be problematic since each policy has different incidences on each technology type. To overcome this limitation, we chose to analyse the effect of FiT differentiated by technology. In addition, the set of explanatory variables used to explain the deployment of RE and their relationship with the policy instruments is most of the times limited and similar from article to article. We attempt to overcome this limitation by including in our analysis distinct variables that, according to its rationale and previous fundamental research regarding RE deployment (even if not related to the use of subsidies) are considered to be its main determinants. Similarly, most of the authors perform robustness tests by running different econometric approaches. We contribute to the existent work by performing several robustness exercises taking into consideration differences among specific subsamples, namely differences across the several European sub-regions. We also analyse how being a member of OECD influences our sample's results. Furthermore, we consider a more extended time period than most of the authors: more precisely 28 years.

Table 3.1: **Summary of Empirical Findings**

Authors	Periods	Samples	Empirical approach	Dependent variables	Independent variables	Main Results
Butler and Neuhoff (2008)	Period not mentioned	Germany and UK	Surveys	Not applicable	Not applicable	Obligations are not necessarily cheaper than FiT, and in terms of capacity installed, deployment is comparatively higher where the FiT are deployed.
Blazquez *et al.* (2018)	2006-2013	Spain	Cost analysis	Not applicable	Not applicable	While FiT in general grant a larger deployment of renewables at a very high cost, the investment credit is the cheapest solution although it is also the one that yields the lower success ratio. Thus, the decision of what policy to adopt depends on the goals of the government and not on the policy design just by itself
Johnstone *et al.* (2010)	1978-2003	25 OECD countries	Panel data model with fixed effects (Hsiao, 1986)	Patenting activity	Policy variables, specific Research and Development expenditures, growth of electricity consumption, electricity prices, total European Patent Office filings	Feed-in tariffs are needed to induce innovation on more expensive technologies, like solar power. Although, when it comes to more cost-competitive technologies, like the wind power, there is no evidence that feed-in tariffs induce additional innovation.
Haas *et al.* (2011)	Period not mentioned	27 EU countries	Historical evidence and case studies	Not applicable	Not applicable	Effectiveness and efficiency of the policies is not related with the policy itself, but with its design and criteria implementation. Within these results, the authors mention that FiT appears to be preferable to the quota-based tradable green certificates, if well designed.
Jenner *et al.* (2013)	1992-2008	26 EU countries	Panel data model with fixed effects	Annual added capacity	Nuclear share, oil share, natural gas share, coal share, GDP *per capita*, Net import ratio, total capacity and cost cap	FiT policies have driven solar PV development in the EU, however there is no robust evidence that FiT have driven wind power development. The interaction between the policy and other factors is more significant that the policy alone.
Smith and Urpelainen (2013)	1979-2005	26 industrialized countries	Panel data model with fixed effects (Johnstone *et al.*, 2010)	Change in Renewable share generation	Mean Fit, logarithm of GDP *per capita*, year indicators and country fixed effects	Increase Feed-in tariffs by 1 US dollar per KhW increases the percentage of change in renewable share by 0,11 points, meaning that FiT represents an effective way to increase Renewable Electricity generation

Table 3.1 (cont.): **Summary of Empirical Findings**

Authors	Periods	Samples	Empirical approach	Dependent variables	Independent variables	Main Results
Marques and Fuinhas (2012)	1990-2007	23 EU countries	Panel data model with fixed effects and random effects estimators	Contribution of RE to total energy supply	Energy *per capita*, C02 emissions *per capita*, Import dependency of energy, importance of coal to electricity generation, importance of oil to electricity generation, importance of gas to electricity generation	Until 2012 quotas obligations, tradable certificates, among others, had not yet produced the expected effect. On the contrary, evidence points to Feed-in Tariffs as an effective incentive to the deployment of RE.
Nicolini and Tavoni (2017)	2000-2010	France, Germany, Italy, UK, Spain	Pooled Ordinary Least Squares (OLS), fixed effects and random effects models	Incentivized production, total production and installed capacity	Amount of incentives, tariff, GDP *per capita*, C02 emissions *per capita*, share of electricity production from fossil sources, net electricity exports, electricity prices, cabinet composition, TGC	Positive correlation between subsidies and the production of incentivized energy as well as installed capacity, showing that FiT has been effective in promoting RE.
Kilinc-Ata (2016)	1990-2008	27 EU countries and 50 US states	Method not referred	Percentage of electricity capacity from Renewable sources	Fossil Fuels capacity, nuclear capacity, GDP growth rate *per capita*, coal price, gas price, electricity consumption *per capita*, Energy security, C02 emissions *per capita*	RE policy instruments play an important role in supporting RE sources, but their effectiveness differs from policy to policy. Fit, tenders and tax incentives are effective when compared to quotas.

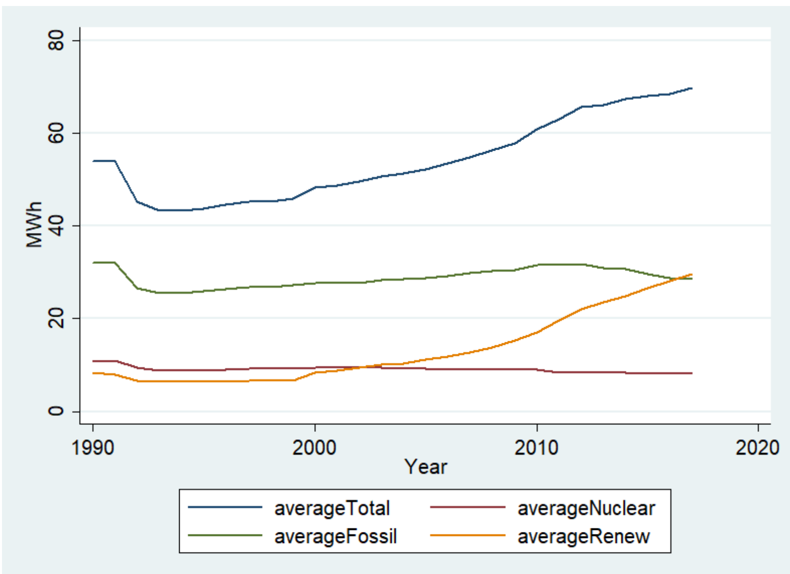
4 Data and methodology

In this chapter we present our dataset and the econometric approach used. We collected annual data ranging for the period 1990-2017 regarding 28 EU countries [1]. The choice of this sample is related with the several policies and measures implemented by the EU concerning renewable energies. From the single energy market to the support provided to the deployment of low-carbon technologies, EU presents a commitment to meet its energy-efficiency targets and move to a low-carbon society. One example for this is the Treaty on the Functioning of the European Union (TFEU) on which there is a designated section entirely focused on the environment, pointing to climate change as an explicit objective of EU environmental policy. From this Treaty, projects like the Energy Union, in 2015, appeared. Its main goal is to ensure and provide affordable, safe and sustainable energy for Europe and its citizens, by promoting energy security, an integrated internal energy market, energy efficiency, decarbonization of the economy and research and innovation.

4.1 The Evidence

We introduce this chapter by presenting the behaviour of renewable electricity capacity in the EU countries considering the period 1990-2017. We plot the yearly average renewable electricity capacity along with the yearly average total electricity capacity. The yearly averages for nuclear and fossil fuel electricity capacities were also included in the graph due to their substitute nature. For all the variables, the yearly average is computed across countries. Figure 1 shows a positive correlation (0.9674) between the electricity capacity generated by a renewable source and the total electricity capacity. This can be justified by the role of RE in meeting the increasing demand for energy when the two other sources are not able to cover it. This behaviour is highly evident from 2000 on-wards, where it is possible to observe a sharp increase in the renewable electricity capacity, overtaking both fossil fuel and nuclear electricity capacities. It is also clear the negative relationship between the traditional sources electricity capacity and the renewable electricity capacity.

Figure 1: **Yearly Averages for Renewable Electricity Capacity Shares and Total Electricity Capacity**



[1] Data was obtained from sources as the EIA, the OECD, the Eurostat and the IEA.

In the next sub-chapter we provide a detailed description of the dependent and independent variables as well as their possible relationships. The acronyms used in our database are defined between brackets. Table 4.1 and Table 8.1 (in the Appendix) present a summary of the variables (as well as their descriptive statistics) and a correlation matrix for those variables, respectively.

4.1.1 Dependent Variable (Renew)

We aim to explain the importance of non-hydro renewables to total electricity capacity (Renew). The dependent variable corresponds to the ratio between the electricity capacity generated from non-hydro RE sources and the total electricity capacity, both measured in MW. For this measurements, hydropower was excluded from the analysis since usually this technology is not eligible for subsidies under the policy scheme on which we will focus our attention, i.e. the FiT (Kilinc-Ata, 2016, and Arkasur and Gümüşoğlu, 2019). Regarding all the other renewable technologies, they are combined into this single measure. The choice of this variable is grounded on previous literature which considered it as a reflection of a country's renewable energies deployment. The data for both measures of capacity is obtained from the US Energy Information Administration (EIA)[2].

4.1.2 Independent Variables

Our explanatory variables are divided in five different sub-groups: the first regards policy variables and the other four correspond to control variables, namely the substitute energy variables, the economic variables, the security variables and the environmental variables. These last four subgroups are commonly used in the energy literature, by authors such as Marques *et al.* (2010), Jenner *et al.* (2013), Killin-Ata (2016), Nicolini and Tavoni (2017), among others.

4.1.2.1 Policy variables (feed-in tariffs)

As previously mentioned, from the different policy variables applicable to RE (FiT, tender, quotas, taxes, etc.), FiT appear to be the most significant when contributing to RE deployment – therefore, instead of analysing the contribution of the different policy instruments in fostering RE deployment (Killin-Ata, 2016), we decided to focus only on FiT. We chose to analyse the role of FiT differentiating by type of RE technologies, rather than considering only its use with no regard to the type of technology for which they were applicable. This method overcomes the problem of policy type heterogeneous: the policy instruments may influence the different renewable energy technologies in distinct dimensions and this effect is unaccounted in the previous approaches.

The policy variables represent FiT values comparable across countries, years and RE technologies, namely wind, solar PV, geothermal, marine, biomass and waste-to energy and they are the main explanatory variables in the analysis[3]. Dummy variables were used to perform the analysis since our goal was to evaluate whether the countries have implemented this policy and for which RE technology. They take the value of 1 if the country in question has adopted the FiT for a specific technology, and 0 otherwise. It is possible that more than one variable take value 1 simultaneously, since the application of the tariff to one technology does not imply the non-application

[2] `https://www.eia.gov/international/data/world`

[3] Please note that for each technology we do not use acronyms in our analysis, except for solar photovoltaic (SolarPV).

on the others. There are several cases where there are multiple tariffs being applied at the same time. This course of action follows the approach used by previous research as Johnstone *et al.* (2010), Carley (2009) and Killin-Ata (2016). Information for these variables was collected from the OECD database[4]. Based on the nature of the policy and grounded on the theoretical empirical evidence presented on the literature review chapter, it is expected that implementation of FiT in the different technologies will have a positive effect on fostering the deployment of renewable energies.

4.1.2.2 Substitute energy variables

Substitute energy variables are crucial for the analysis because RE sources act as a more friendly environmental substitute for the fossil fuel and nuclear sources. According to the literature, authors such as Marques and Fuinhas (2012), Jenner *et al.* (2013), and Nicolini and Tavoni (2017) believed that the political and economic strength of the traditional energy sources represent a potential barrier to the deployment of RE. Due to this substitute nature, it is expected that the lower the contribution of fossil fuel and nuclear sources to the total electricity capacity, the higher will be deployment of RE. The variables used to construct these measures are expressed in MW and they are taken from the EIA[2].

- **Importance of nuclear to electricity capacity generation (NuclearShare)**

It represents the share of electricity capacity that is generated from nuclear sources and it is the result of the ratio between the electricity capacity generated from a nuclear source and the total electricity capacity generated.

- **Importance of fossil fuel to electricity capacity generation (FossilShare)**

It represents the share of electricity capacity that is generated from fossil fuel sources and it is the result of the ratio between the electricity capacity generated from a fossil fuel source and the total electricity capacity generated.

4.1.2.3 Economic variables

- **Prices of traditional energy sources (CPI)**

The prices of traditional energy sources are often lower than prices of energy generated by a RE source. However, these prices do not reflect the environmental costs of its production. Therefore, it can be considered that the prices of traditional energy sources are ineffective in reflecting the real costs of their use when compared to the ones of RE. This strengthens the reasoning that prices of clean energy are not competitive enough in the short-term (REN21, 2020). It is expected that higher prices of coal, natural gas and oil promote the swapping from traditional sources to renewable ones, i.e., the price of energy produced from a traditional source can be significant in explaining the deployment of RE due to its substitute nature, as argued by Carley (2009) and Nicolini and Tavoni (2017). Besides, on one hand, Marques *et al.* (2010) found that, while prices of natural gas and oil were significant in explaining the importance of non-hydro renewable energy to total electricity capacity, coal seemed to have no effect on the proposed model. On the other hand, Killinc-Ata (2016) reached the conclusion that natural

[4]https://data.oecd.org/

gas prices were statistically non significant, in contrast with the statistically significance of coal prices in the effect on RE deployment. In either of the cases, the relationship verified was positive.

We were not able to collect the prices differentiated between the different fossil fuel sources due to its lack of availability, not being possible to take any conclusions on the prices separately. To overcome this problem, we adopted the consumer price index (CPI) as a proxy for traditional energy prices as a whole, based on Chang *et al.* (2009), Arkasur and Gümüşoğlu (2019) and Anton and Nucu (2020). The consumer price index reflects changes in the cost for the average consumer of acquiring a basket of goods and services (that may be fixed or variable at specific intervals, such as yearly). If, as above mentioned, individual prices had a positive relationship with RE deployment, we expect that the proxy used by us will also have a positive effect on the dependent variable. Data regarding the CPI, with 2010 as the base year, was collected from the World Bank Database[5].

- **Gross Domestic Product *per capita* (GDPpc)**

Jenner *et al.* (2013), Aguirre and Ibikunle (2014) and Nicolini and Tavoni (2017), among other authors, present Gross Domestic Product as one explanatory measure for the deployment of RE. Countries with higher income will be expected to sustain better the larger costs of generating energy from a renewable source. They may also encourage its production through economic incentives and by promoting sustainable environmental activities. Accordingly, we expect that income level would be positively correlated with greater RE use. We work in *per capita* terms for countries to be comparable. Data regarding the Gross Domestic Product was constructed at constant 2010 U.S. dollars and was taken from the OECD[4].

- **Electricity consumption *per capita* (Electpc)**

The electricity consumption represents the total consumption of electricity generated in all types of power plants (e.g., in nuclear, thermal, hydro, wind, photovoltaic or other plants) to be distributed to consumers through the grid or consumed locally. It is measured in tons of oil equivalence (TOE[6]). We use this variable in *per capita* terms by dividing the electrical energy consumption *per* year by the average resident population. Usually, electricity consumption represents the electricity needs of a country (Smith and Urpelainen, 2014; Killinc-Ata, 2016; Liu *et al.* 2019). Therefore, as the consumption of electricity increases, RE may help to meet this increasing demand. RE might represent a cleanest solution if the country do not pretend to increase pollution to face the new demand. Thereby, we expect to have a positive relationship between this variable and the deployment of RE. Data was collected from the Eurostat[7] and the IEA[8].

- **Foreign Direct Investment (FDI)**

Technology progress has proven to be a key factor in the RE deployment process and a consequence in the process of moving to a low-carbon economy. However, most of the countries do not have economic conditions to self-sustain the costs of a RE project. This is where the foreign direct investment (FDI) appears as a solution to

[5] `https://data.worldbank.org/`

[6] A TOE equals the amount of energy released by burning one tonne (1000 kilograms) of crude oil. This unit of measurement is usually used to compare energy produced from different sources

[7] `https://ec.europa.eu/eurostat/data/database`

[8] `https://iea.org/data-and-statistics`

the very expensive initial costs of its implementation. They represent an important driver of modern technology, and they have been growing in this particular sector (Hanni *et al.* 2011). This variable was used by authors as Hanni *et al.* (2011), Pfeiffer and Mulder (2013), Arkasur and Gümüşoğlu (2019) and Anton and Nucu (2020) as an explanatory variable to the deployment of RE. The FDI variable is calculated as its net inflows as a share of GDP, i.e., new investment inflows less disinvestment, from foreign investors, divided by the Gross Domestic Product. FDI is expected to promote the deployment of RE since it will act as an investment incentive. The data for this variable was taken from the World Bank Database[5].

4.1.2.4 Security variables

- **Energy imports dependency rate (ImpDep)**

Energy imports dependency rate represents the total share of energy a country needs to import to meet its total demand. It is calculated by dividing the net energy imports by the gross available energy and it is used as a proxy for energy security. According to Marques and Fuinhas (2012), Jenner *et al.* (2013), Aguirre and Ibikunle (2014) and Nicolini and Tavoni (2017), we expect that as energy imports dependency increases the incentive for a country to invest in its own renewable sources would increase as well. Energy security will then act as a promoter of RE deployment by substituting energy imported for energy produced locally and, therefore, reducing the energy dependency towards other countries (Arkasur and Gümüşoğlu, 2019). This variable was provided from the Eurostat[7].

4.1.2.5 Environmental variables

- **Carbon dioxide emissions *per capita* (CO_2pc)**

Carbon dioxide emissions are mainly represented by the emissions generated by stemming from the burning of fossil fuels. These emissions are the principal responsible for global warming and for creating pressure on the environment. Marques *et al.* (2010), Kilinc-Ata (2016) and Liu *et al.* (2019) suggest that higher emissions of CO_2 lead to higher incentives to widespread the use of RE and increase its deployment, so we expect a positive sign for CO_2 estimator. The CO_2 emissions is measured in metric tons *per capita*, and the data was collected from OECD databases[4].

4.2 Summary of Descriptive Statistics

Table 4.1 presents a summary of the descriptive statistics regarding all the variables described in this chapter.

Table 4.1: **Summary Statistics**

Variables	Number of Obs.	Mean	Std. Dev.	Min	Max
Renew	796	0.1389	0.1643	0.0000	0.7314
SolarPV (dummy)	504	0.468254	0.4994869	0.0000	1.0000
Wind (dummy)	504	0.5039683	0.500481	0.0000	1.0000
Biomass (dummy)	504	0.444444	0.4973977	0.0000	1.0000
Waste (dummy)	504	0.4543651	0.4984078	0.0000	1.0000
Geothermal (dummy)	504	0.3829365	0.486586	0.0000	1.0000

Table 4.1. (cont.): **Summary Statistics**

Variables	Number of Obs.	Mean	Std. Dev.	Min	Max
Marine (dummy)	504	0.265873	0.4422359	0.0000	1.0000
NuclearShare	796	0.1159009	0.14410519	0.0000	0.5541542
FossilShare	796	0.5875509	0.2450483	0.0420521	1.0000
CPI	806	81.70213	25.16606	0.0233889	115.4553
gGDPpc	812	0.0274854	0.0351063	-0.1481416	0.2516253
Electpc	812	0.4699138	0.2660296	0.130000	1.400000
FDI	733	9.435436	32.54451	-58.32288	451.6393
ImpDep	812	0.5514577	0.2764915	-0.50602	1.10631
CO_2**pc**	711	8.122645	3.624125	2.682623	27.43143

The main conclusion that can be taken by analysing the previous table is that, on average, FiT were applied more often to Wind and to SolarPV when compared to Geothermal and Marine. It is also possible to notice that the average value of Renew is higher than the average value presented by the variable NuclearShare. However, fossil fuels are still the most used source (on average), presenting a much higher average value than Renew.

4.3 Econometric Methodology

4.3.1 Stationarity

Once defined the variables, we conduct unit root tests to check whether time-dependent variables are stationary or not. To perform this analysis, we chose to use the Im-Pesaran-Sin (2003) test due to the characteristics of our panel data set: few cross-section units covered for a small period of time for most of the variables. Since the number of observations is not the same for all the individuals i, we are in the presence of an unbalanced panel. If we find evidence of non-stationary, linear transformations will be applied to the respective variable.

The Im-Pesaran-Sin (IPS) test defines as null hypothesis that all panels present unit roots, synonym for non-stationarity, while in the alternative hypothesis it assumes stationarity exists in at least one panel. We perform the IPS test by choosing a maximum of four lags, removing the auto-regressive components of high order. The test is conducted by subtracting the cross-sectional averages, with the goal of reducing the impact of cross-sectional dependence, as proposed by Levin, Lin, and Chu (2002).

According to the IPS test, almost all the variables are stationary, with the exception of four: the dependent variable Renew, the substitute energy variables NuclearShare and FossilShare, and the economic variable GDPpc. After applying the first differences to the first three they become stationary, being the acronyms used in our dataset now defined as, respectively, dRenew, dNuclearShare and dFossilShare. For the last one, the approach was to use its growth rate instead of applying it in levels or just computing the first differences, for which the variable was non-stationary: data was available for this transformation, i.e., the yearly average GDP *per capita* growth rate (defined as gGDPpc), in the same source as for the original one.

4.3.2 Econometric Method

One of the advantages of using data converted in a panel format is the possibility to account for the different characteristics among the different individuals (in our case, the countries), also known as individual effects. To analyze these unobserved effects, we can adopt two different approaches: on one hand, we can suppose the unobserved country specific effects are fixed, meaning they are assumed to be correlated with the explanatory variable; on the other hand, these effects can be evaluated as random, being therefore uncorrelated with the explanatory variables. If the unobserved country heterogeneity is treated as fixed, we will be only able to estimate the coefficient of the time-variant explanatory variables, while with the random effects model, both time-variant and time-invariant variables' coefficient can be estimated. To conclude which model should be used in this analysis, the Hausman Taylor test will be performed. This test is a standardized comparison of fixed and random-effects' model coefficients. Its null hypothesis assumes the unobserved individual effects are not correlated with the regressors so that both random and fixed-effects mode are consistent and efficient: since the random effects model will produce smaller standard errors, the choice would be to employ a random effects model. In the alternative hypothesis, the unobserved individual effects are not correlated with the regressors so that only fixed-effects model is considered consistent and efficient. We used the Stata software.

The result of the Hausman test suggests the application of the random effects model, allowing for covariance between the unobserved individual effects and the explanatory variables.

Our model has the following general form:

$$dRenew_{i,t} = \beta_0 + \sum_{j=1}^{J} \beta_j FiT_{j,i,t} + \sum_{k=1}^{K} \delta_k X_{k,i,t} + v_i \tag{1}$$

where $dRenew_{i,t}$ is the dependent variable. The β's are the coefficients related to the vector of feed-in tariffs related variables in country i at year t, $FiT_{j,i,t}$. The δ's are the model coefficients associated to the vector of the remaining control variables, namely the substitute variables, economic variables, security variables and environmental variables, $X_{k,i,t}$. $v_{i,t} = \alpha_i + u_{i,t}$, where α_i represents the unobserved individual effects and $u_{i,t}$ represents the idiosyncratic error term. For the entities, i corresponds to $i = 1, ..., N$; for time, t satisfies the condition $t = 1, ..., T$; for the main independent variables $FiT_{j,i,t}$, $j = 1, ..., J$ and for the remaining explanatory variables $X_{k,i,t}$, $k = 1, ..., K$.

After the estimation of the random-effects model, we performed three post-estimation tests to check if there is evidence of cross-sectional dependence, serial-correlation and heteroskedasticity. The first test, *xtcsd* command in Stata, tests if there is evidence of cross-sectional dependence (i.e., if the residuals are correlated across entities). The null hypothesis is that residuals are not correlated and, being rejected, the estimator will be considered inconsistent. The second test, *xtreghet* tests the presence of heteroskedasticity in the random-effects model, having as null hypothesis homoskedasticity. In the case of a rejection of the null, the estimator in the model is consider inconsistent. The third and last test, *xtserial* in Stata, tests if there is evidence of serial correlation in the standard errors, assuming a null hypothesis of no serial correlation. As before, if the null is rejected, the estimator will be consider inconsistent. If the tests present evidence of inconsistent estimators, it is necessary to account and correct these factors. A solution could be the re-estimation on the random-effects model considering the feasible generalized least squares model (FGLS). With this modification, it is possible to control for cross-sectional dependence, heteroskedasticity and serial correlation, generating robust standard errors.

5 Empirical Findings

The results obtained by the estimation of the random-effects model are presented in Table 5.1. The results already account for the correction applied by the FGLS model in order to obtain the robust version of the standard errors.

Table 5.1: **Results for the Entire Sample**

Variables	Coefficient	Robust standard errors
SolarPV	.0012008	.0023228
Wind	.0137897***	.0034998
Biomass	-.0054001	.0028762
Waste	-.0080913**	.0029441
Geothermal	-0,0018913	0021029
Marine	.0027286	.0017489
dNuclearShare	-0.4503756***	.0396666
dFossilShare	-0.6046695***	.0265728
CPI	.0001480**	.0000566
gGDPpc	-.0152489	.0183300
Electpc	-.0013913	.0027037
FDI	-.0000159	.0000149
ImpDep	.0009689	.0022145
CO_2**pc**	.0003368	.0002107
Intercept	-.0109182	.0053887

Note: ** and *** reflect statistical significance at 5% and 1% levels, respectively.

In the next sub-chapters, we analyse the main findings for each variable by presenting their reasoning, always following a *ceteris paribus* approach. It is important to recall that first differences were applied to the original dependent variable. Therefore, any conclusion will concern the variation of the share of electricity capacity generated by a non-hydro renewable source and not the share itself.

5.1 Feed-in tariffs

When analysing the FiT variables it is relevant to remind the fact that we are dealing with dummy variables, so the interpretation of the coefficient when it assumes a value of 1 in the year the tariff is applied will be always compared with the case where it takes a value of 0 in that same year. In other words, the coefficients of the dummy variables measure the average difference between the application of the tariff and the possibility where the tariff is not applied.

5.1.1 Wind

Regarding the variable Wind, it presents a positive coefficient as expected: when this tariff is applied it promotes dRenew by 0.0137897, when compared with the case where no tariff was being applied to this technology. It is possible to conclude that the implementation of the tariff is contributing to the deployment of renewable energies.

According to the World Energy Outlook (2019) by IEA, wind power is planned to become the leading source of electricity in Europe, until 2050, overtaking both nuclear and natural gas, supporting our result.

5.1.2 Waste

In the case of the variable Waste, we got a negative coefficient on the regression estimation. As mentioned before, this is not the expected result. The application of the tariff to Waste punishes the differenced share of electricity capacity generated by a non-hydro renewable source by 0.0080913 in the year it is applied, when compared to the opposite scenario. Although at first sight this might appear odd, the explanation could lie on the fact that our dependent variable is measuring the capacity regarding the entire group of renewable technologies, and not each of them individually. According to each country's specific characteristics, some technologies can be perceived as more efficient that others (e.g., technologies for which the natural resources are more available, or the distribution channels are more efficient, etc.). Assuming the case where there is an yearly fixed budget regarding FiT, the application of a tariff on a more efficient technology can produce more beneficial outputs when compared to its application to technologies in early developments. In other words, the tariff application to Waste can be seen as an opportunity cost: if the tariff is being applied to a least efficient technology there is a certain amount of money (from that fixed budget) not being applied to a technology that indeed would provide a positive return on the capacity generated and which is more efficient. This does not imply that FiT regarding the most efficient technologies are not being applied when the Waste tariff exist: it just means that if a higher monetary amount, which is deterred by a subsidy application on Waste, had been allocated on them they would most likely produce higher increases or lower decreases in the share of RE capacity. Although we formulate this hypothesis, we would need further research to test it since we did not had the needed data at the time this work was developed.

To complement the previous argumentation, according to the report Renewables 2020 Global Status Report (REN21), wind power was the only technology for which investment has continuously increased in the last years. On the other side however, the majority of RE technologies struggled to attract investment, in its various forms. The most dramatic one was the investment on waste-to-energy, which decreased almost 50%.

5.1.3 Solar PV, Biomass, Geothermal and Marine

Regarding the remaining technologies, they present non significant coefficients for our sample. There are several possible explanations, from where we can highlight the fact that, possibly, some of the technologies are already in a stage of deployment and development where there is no longer the need to attract investment, and it is possible for the technology to finance itself. Other explanation could be related with the application of the wrong mechanism to the technologies. According to the characteristics of the resource, auctions or TGC could provide a more suited approach.

5.2 Substitute energy variables

Regarding the substitute energy variables, dNuclearShare and dFossilShare, they seem to have statistically significance in influencing the deployment of RE. Their negative coefficient suggests that the greater the use of fossil fuels, like coal, natural gas and oil, and nuclear energy, the lower will be the quota available for the renewables in the energy market. More precisely, a 1 p.p. increase in dNuclearShare leads the variation of the electricity capacity generated by a non-hydro renewable source to decrease about 0.4503756 p.p., while a 1 p.p. increase in dFossilShare will lead to a decrease of the variation of the dependent variable by of 0.6046695 p.p. As it can be seen, the impact is higher for a fossil fuel source. These findings may be explained by the fact that, as population and energy consumption increases, countries tend to adopt more easily a traditional energy source, most of the times by economic reasons, such as its lower price. These factors are often related to the existence of lobbying industrial activities that difficult and restrain the deployment of RE: the stronger the lobby effect, the lower the likelihood of switching from traditional to renewable sources. The result is shared among several authors such as Marques *et al.* (2010), Marques and Fuinhas (2012), Aguirre and Ibikunle (2014) and Nicolini and Tavoni (2017).

5.3 Economic variables

In what concerns the economic variables, the only one that shows itself statistically significant in our model is CPI. The positive coefficient is expected and goes along with the findings of Chang *et al.* (2009), Arkasur and Gümüşoğlu (2019) and Anton and Nucu (2020). In this case, an increase of 1 p.p. of the prices of traditional energy sources will lead to an increase of 0.000148 p.p. of variation of the quota available for the renewables in the energy market. This supports the belief that the different energy sources are substitute and that higher prices of fossil fuel sources will imply a greater incentive to the deployment of RE.

Regarding the remaining three economic variables, our results are in accordance with previous literature empirical findings pointing in different or unexpected directions. In our model, gGDPpc seems to not affect RE installed capacity, considering the years and countries chosen. Jenner *et al.* (2013), Aguirre and Ibikunle (2014), Killinc-Ata (2016) and Nicolini and Tavoni (2017) also present a non significant coefficients for this variable. Among these authors, a current explanation lies on the fact that, as income increases, economic growth could induce more demand. This demand however is often matched by an increase in consumption of fossil fuels rather than renewable energy. The same happens for the non significant coefficient of electricity consumption *per capita*, i.e., more demand for energy is not necessarily translated in an increase of the share of electricity produced from a renewable source. In fact, for Electpc, different authors present different empirical evidence, while Killinc-Ata (2016) analysis shows a negative empirical relationship between electricity consumption and RE deployment, Marques *et al.* (2010) and Liu *et al.* (2019) found a positive relationship as expected by the theory. Both findings, for gGDPpc and Electpc, are a reflection of countries adopting the cheapest option when faced with the increasing demand. The results concerning FDI suggests that foreign direct investment is not a main driver in explaining the deployment of RE. For our time spam and countries chosen, the variable is not significant, not following the work of Pfeiffer and Mulder (2013), Arkasur and Gümüşoğlu (2019) and Anton and Nucu (2020). The reason for this to occur is the fact that, at the same time, we have foreign direct investment improving RE associated technology but also improving corporate investment behaviour and the consequent reduction of energy use: the two effects work in opposite directions and may cancel each other out, leading to the non significance of this variable.

5.4 Security variable

When analysing the security variable, we found that the dependency of energy imports, ImpDep, shows itself not statistically significant when accounting for the deployment of renewable energies. This result is in line with the work of Jenner *et al.* (2013), Aguirre and Ibikunle (2014), Killinc-Ata (2016) and Nicolini and Tavoni (2017). One of the factors that could influence this behaviour is the openness and competitiveness of EU energy markets that allied to the technological development has enabled access to deposits of fossil fuels that were not previously accessible, turning energy security less concerning in this subject (Aguirre and Ibikunle, 2014).

5.5 Environmental variable

In what concerns the environmental variable, it seems that carbon dioxide emissions, CO_2, have no effect in the share of electricity capacity generated by a renewable source. Although the theory predicts a positive and statistically significant effect for this variable, most of the authors in the energy literature reached the same conclusion: a negative and not significant coefficient means that emission levels do not encourage the promotion of renewables and the switching from fossil fuels to clean energy (Marques *et al.*, 2010; Marques and Fuinhas, 2012; Killinc-Ata, 2016; Nicolini and Tavoni, 2017 and Arkasur and Gümüşoğlu, 2019).

6 Robustness

To evaluate our results' validity, we performed several robustness exercises: we divided the entire sample according to the different European sub-regions, we analysed the existence of outliers in the attribution of FiT and we tested if the OECD membership influences the deployment of renewable energies. In the three cases previously mentioned, we estimate new regressions and afterwards the results are compared with the original estimation.

6.1 European Sub-region Division

According to the United Nations' group of experts on geographical names, there was a need to subdivide Europe into smaller groups, due to the increasing heterogeneity between the different countries. This division is based on the geopolitical, economic, social, religious and cultural characteristics of each region, and four divisions were established. Considering our sample, we have the Northern Europe, including countries such as Denmark, Estonia, Finland, Ireland, Latvia, Lithuania, Sweden and the United Kingdom; Western Europe, formed by Austria, Belgium, France, Germany, Luxembourg and The Netherlands; Eastern Europe, covering Bulgaria, Cyprus, Czech Republic, Hungary, Poland, Romania and Slovakia; and finally, Southern Europe, including countries such as Croatia, Italy, Greece, Malta, Portugal, Slovenia and Spain.

This robustness exercise was chosen because we believe the heterogeneity existent between the different European countries might influence the deployment of RE. One simple example of this heterogeneity could be the availability of natural resources, which could play an important role in determining the share of electricity that is produced from a renewable source. Table 6.1 presents the results concerning this robustness test for the division in European sub-regions.

Table 6.1: **Results by European Sub-region Division**

Variables	Northern Europe	Western Europe	Eastern Europe	Southern Europe
SolarPV	.0123463*	-.0041085	.0009769	.0085223**
	(.0072026)	(.0108167)	(.004944)	(.0040433)
Wind	.0095963	.0111921	-.0001554	-.0053246
	(.0083557)	(.00739)	(.0097917)	(.0061292)
Biomass	-.0150913**	-.0109616	-.0047875	.0091729
	(.0063472)	(.0106972)	(.0081421)	(.0073365)
Waste	-.0068866	.0056146	0	-.0035245
	(.0064787)	(.0174852)	(omitted)	(.0049139)
Geothermal	.0049673	-.0016121	.0059623	-.0081651
	(.0061051)	(.0044507)	(.0040111)	(.006682)
Marine	-.0042087	.0008201	.0028147	.0006195
	(.0061847)	(.0032447)	(.0039294)	(.0044123)
dNuclearShare	-.4657305***	-.9358642***	-.5626926***	-.3350904
	(.0491255)	(.1648581)	(.0788789)	(.2584456)
dFossilShare	-.7041654***	-.2567399***	-.7329625	-.7160727***
	(.0423701)	(.0439591)	(.0589103)	(.073515)

Note: regressors' coefficients are presented and standard errors appear between brackets; ** and *** reflect statistical significance at 5% and 1% levels, respectively.

Table 6.1. (cont.): **Results by European Sub-region Division**

Variables	Northern Europe	Western Europe	Eastern Europe	Southern Europe
CPI	.0001018 (.0001279)	-.0000245 (.000178)	.0001434** (.000069)	.0001725 (.000141)
gGDPpc	-.0706498** (.0295306)	-.0021894 (.0560841)	-.0243408 (.0307987)	.0256026 (.0361292)
Electpc	-.0023054 (.003344)	-.0627825** (.0281191)	.0117949 (.0304656)	-.0446464* (.0260064)
FDI	.0005832** (.0002306)	-.000044 (.0000685)	-.0000175 (.0000323)	-.0000115 (.000016)
ImpDep	.0028888 (.0044578)	.0299587** (.013963)	-.006698 (.0088369)	-.0055613 (.0068009)
CO_2**pc**	-.0000924 (.0004287)	.0014116* (.0008275)	-.0002273 (.0010923)	.0013758 (.0016764)
Intercept	-.0052632 (.0115013)	.0185053 (.0160255)	-.0095573 (.0076268)	.0012531 (.0152012)

Note: regressors' coefficients are presented and standard errors appear between brackets; ** and *** reflect statistical significance at 5% and 1% levels, respectively.

The output obtained by running the four different regressions proves the results are not entirely robust, since the experiment caused changes in the variables' significance. When comparing it with the results obtained before, none of the variables that affected dRenew shows itself significant in the four regions at the same time. dNuclaerShare and dFossilShare stand out, being significant in three out of the four regressions. Regarding its impact on the dependent variable, a 1 p.p. increase in each of the shares leads to a decrease of the variation of the share of electricity capacity generated by non-hydro renewables by 0.4657305 p.p. and 0.7041654 p.p. in Northern Europe and by 0.9358642 p.p. and 0.2567399 p.p. in Western Europe, respectively. In Eastern Europe, an increase of 1 p.p. in dNuclearShare leads the dependent variable to decrease around 0.5626926 p.p., while in Southern Europe, an increase of 1 p.p. in dFossilShare leads the to a decrease of approximately 0.7160727 p.p.

CPI proved to be significant in Eastern Europe, with a smaller impact of 0.0001434 p.p.; Biomass gains significance, and a 1 p.p. increase in this variable leads the dependent variable to decrease by 0.0150913 p.p. when analysing the Northern Europe case. The variables Wind and Waste lose their significance in this experiment.

Regarding the explanatory variables that before did not influence the variation of the share of electricity capacity generated by non-hydro renewables, they now demonstrate some significance, spread across the four regions. In Northern Europe, gGDPpc and FDI appear as significant where an increase of 1 p.p. will impact the variation of dRenew by -0.0706498 p.p. and 0.0005832 p.p. respectively. In Western Europe, an increase of 1 p.p. in ImpDep, CO_2pc and Electpc leads the dependent variable to increase around 0.0299587 p.p. and 0.0014166 p.p. and to decrease approximately by 0.0627825 p.p., respectively. Lastly, in Southern Europe, the only explanatory variable that stands out as significant is the Electpc: a 1 p.p. increase in this variable leads to an impact of -0.0446464 in dRenew.

We can therefore conclude that the results from the main regression are not robust when compared with the estimation of the European sub-division sub-samples. The main conclusion produced by this test relies on the idea that the different European region where the countries are inserted very heterogeneous in terms of individual characteristics (e.g., the weather conditions). Since we grouped the countries in smaller groups, for the same time period the number of cross sections is much lower than before. Therefore, sample differences should be a possible reason for why results are not robust.

6.2 Feed-in Tariffs Outliers

When dealing with the application of FiT on the different countries, we found that four of the countries, in our time span, never applied them at any of the several technologies under study. The motivation behind this could differ from country to country. In fact, in Belgium, the array of incentives given to RE is very complex and complicated, and it its mostly represented by green certificates. (IRENA, 2019). Romania, on the same line of thought, also has as predominant incentive scheme the green certificates, mostly dominated by solar and hydropower (technology excluded from our analysis) (IRENA, 2019). According to the annual report produced by Malta Resources Authority, this country already adopted the FiT mechanism. However, the tariffs are almost only eligible for hydropower plants, and therefore, not covered by our study. In what concerns Poland, data shows that almost 90% of the electricity produced is still generated from coal, due to the country's huge reserve of this source. As so, the incentives for the deployment of RE are still very small and weak, mostly dominated by green certificates as well. According to IRENA (2019), there has been pressure by the EU in order to reform Poland's legislation in what concerns renewable energies, with the goal of implementing FiT as main investment incentive.

Table 6.2 presents the outcome concerning this robustness test where the four countries previously mentioned were excluded.

Table 6.2: **Results Not Considering the Outliers**

Variables	Coefficient	Robust standard errors
SolarPV	.0015374	.0024921
Wind	.0138922***	.0037473
Biomass	-.0054993*	.0031711
Waste	-.0076784**	.003163
Geothermal	-.0020039	.002262
Marine	.0026034	.0018698
dNuclearShare	-.4255138***	.0429213
dFossilShare	-.5836897***	.0290117
CPI	.0001446**	.0000722
gGDPpc	-.0155161	.0207624
Electpc	-.0015888	.0030465
FDI	-.0000177	.000027
ImpDep	.0003881	.002611
CO_2**pc**	.0003276	.0002315
Intercept	-.0103157	.0068125

Note: ** and *** reflect statistical significance at 5% and 1% levels, respectively.

When analysing the results obtained, it is possible to conclude that they are in accordance with the original regression. All the variables that show signs of significance present the same sign as the one verified in the regression for the entire sample.

The effect of taking out the four countries is very tenuous. An increase of 1 p.p. in Wind leads the dependent variable to increase by 0.0138922 p.p., a slight higher effect than before. Biomass, now becomes statistically significant: a 1 p.p. increase in this variable leads the variation of dRenew to reduce by 0.0054993 p.p. For Waste, we now obtained a higher estimator but a lower effect: a 1 p.p. increase in this variable leads the dependent variable to reduce by 0.0076784 p.p.

Both dNuclearShare and dFossilShare present now smaller impacts than before: an increase of 1 p.p.. in each of the variables leads the variation of the share of electricity capacity generated by a non-hydro renewable source to decrease by 0.4255 p.p. and 0.5837 p.p. respectively. The impact of CPI in this robustness test is very approximated to the original one: an increase of 1 p.p. in CPI leads the variation of the dependent variable to increase by 0.0001446 p.p.

All the other explanatory variables remain not significant when accounting for the deployment of RE in our sub-sample.

It is then possible to conclude that this test produces robust estimators, since the existence of countries which do not apply feed-in tariffs to the technologies under study do not affect our original result.

6.3 OECD membership

OECD is an international organisation that aims for shaping policies that foster opportunity, equality and prosperity for everyone.

Considering our entire sample of European Union countries, five of them are not members of OECD: Bulgaria, Croatia, Cyprus, Malta and Romania. This could represent a step-back for renewable energy deployment, in several dimensions. In fact, it is not possible for a country to be part of IEA without being a member of OECD. IEA is one of the international organisations most committed to modelling a secure and sustainable energy future by providing data, policy recommendations, and realistic solutions to help countries dealing with energy efficiency, energy security and with the deployment of clean energy technologies. By not being a member country of OECD, they are being automatically excluded from the benefits IEA provides. Following this idea, there are countries that belong to the EU for which, for some variables, was not possible to find data, so we anticipate this as a problem for our analysis. Therefore, we ran the econometric regression in two phases: in the first we considered only countries that are members of OECD and in the second regression we ran the five non-OECD member countries alone. The results can be found on Table 6.3.

Table 6.3: **OECD Membership**

Variables	OECD Members	Non-OECD members
SolarPV	.0046225 (.0027398)	.0011652 (.0054551)
Wind	.0196693*** (.0040832)	.0193505** (.009308)
Biomass	-.0100108** (.0035969)	.0006147 (.0075073)
Waste	-.0122007*** (.0032154)	-.0161827** (.0075307)
Geothermal	-.0025071 (.0023483)	.0139038** (.0069395)
Marine	.0022294 (.0018812)	-.0135229 (.0084027)
dNuclearShare	-.4687001*** (.0421044)	-.336207 *** (.1233573)
dFossilShare	-.6188112*** (.0280744)	-.4323871*** (.079374)
CPI	.0001359** (.0000698)	.0001342 (.0001028)
gGDP*pc*	-.0154762 (.0203671)	.0005294 (.0376149)
Elect*pc*	-.0014299 (.0028292)	.0387258 (.0537149)
FDI	.0000474 (.0000629)	-.0000132 (.0000146)
ImpDep	.0022896 (.0024958)	-.0022729 (.013059)
CO_2***pc***	.0002049 (.0002339)	-.0052941 (.0027581)
Intercept	-.0099645 (.0067263)	.0117008 (.0134726)

Note: regressors' coefficients are presented and standard errors appear between brackets; ** and *** reflect statistical significance at 5% and 1% levels, respectively.

Considering the division mentioned before, Wind, Waste, dNuclearShare, dFossilShare and CPI still present statistically significant coefficients in what concerns the OECD country's members. On the second regression, the results in terms of significance are very similar, with the exception of CPI that presents a non significant behaviour.

In what concerns the FiT variables, both Wind and Waste exhibit the same signs as the ones found in the main regression. However, the variables in the first regression present higher coefficients than the ones in the second regression: on one hand, in the OECD membership regression, when the tariff is being applied on Wind and Waste, the first promotes dRenew by 0.0196693 and the second decreases the dependent variable by 0.012007, when compared to the case where no tariffs are being applied to these technologies, respectively; on the other hand, when Wind and Waste assume the value 1 for countries outside the OECD, the first contributes to increase dRenew by 0.0193505 while the second decreases dependent variable by 0.011827, when compared to the case where no tariffs are being applied to these technologies, respectively. In addition to these two variables, Biomass and Geothermal also present signs of a significant impact on the variation of the share of electricity capacity generated by a non-hydro renewable source. In the regression that estimates the OECD member countries, when Biomass assumes the value 1, dRenew decreases by 0.0100108, when compared to the case where no tariff is being applied to this technology. This effect is not the expected one, similarly to the Waste case, so that the same reasoning presented in the main results can be applied here. In what concerns the variable Geothermal, it shows signs of significance in influencing the dependent variable when analysing the countries that do not belong to OECD. The positive sign of the coefficient is the expected one, as in the case of Wind. In this situation, when the tariff on Geothermal is being used, when comparing to the case where no tariff is being applied to this technology, the variation of the share of electricity capacity generated by a non-hydro renewable source tends to increase by 0.0139038.

Regarding the remaining statistically significant explanatory variables, both dNuclearShare and dFossilShare present higher impacts in the OECD members' regression and smaller effects for the non-OECD members: an increase of 1 p.p. in each of the variables leads the variation of the share of electricity capacity generated by a non-hydro renewable source to decrease by 0.4687001 p.p and 0.6188112 p.p., respectively, in the first regression; in the second one, a 1 p.p. increase in dNuclearShare and dFossilShare leads the dependent variable to decrease by 0.336207 p.p. and 0.4323871 p.p., respectively. For the OECD member countries, an increase of 1 p.p. in CPI leads dRenew to increase by 0.0001359 p.p.

Overall, it is possible to conclude that we are on the presence of robust estimators. Furthermore, the effects of the interest explanatory variables are higher in this exercise when compared with the results obtained in the main regression. In other words, being a member of OECD and UE simultaneously fosters the deployment of renewable energies in the respective countries.

7 Conclusion

Previous literature on the relationship between the deployment of renewable energies and respective government policies suffers from a major problem: this is related with the aggregation of the different renewable technologies into one single policy measure. In other words, most of the authors study the influence of the distinct renewable energy's policy instruments on renewables deployment but do not perform this analysis on a technology-specific level, neglecting the effect that different policy instruments could produce on different technologies. Since the majority of the studies point to FiT as the most efficient measure in influencing the deployment of RE, we decided to focus only on this policy instrument and to perform the analysis differentiating FiT by the several renewable technology types. The FiTs represent our variables of interest in explaining the share of electricity capacity generated from a non-hydro renewable source. Several sets of variables were also used as control variables to complement our analysis. With this goal, we perform a panel data analysis of 28 EU countries over an extended period of 28 years (1990-2017).

After performing a random effects model and correcting for all the possible estimation problems, our main results suggest that from the six FiT RE technologies under analysis only the ones applied to Wind and Waste influence the dependent variable, considering the entire sample. On one hand, Wind presents an expected coefficient meaning it is contributing positively for the deployment of RE. On the other hand, Waste appears to have an unexpected negative coefficient, for which we develop an hypothesis for further research to explore: applying a FiT to Waste might produce an opportunity cost since countries could be directing the spent money on this technology to more efficient ones which indeed promote the deployment of renewable energies. In what concerns the remainder technologies, they present non-significant coefficients which can be explained by their maturation or due to the implementation of the wrong policy mechanism, according to their individual characteristics. Regarding the remaining explanatory variables, the share of electricity produced from both nuclear and fossil fuel sources and the prices of traditional energy source present significant results with the expected sign.

To access the robustness of our results, we performed several exercises where we subdivide our sample in different groups according to different criteria. For the European sub-region division, we conclude that the different characteristics present in the several areas where the countries are inserted do not impact the renewable energy deployment. Concerning the countries where the FiT is applied to at least one of the technologies under study, we conclude the main regression is robust and the results for the entire sample are verified. At last, we found evidence that being a member of OCED influences the share of electricity capacity generated from a non-hydro renewable source since the results are entirely robust. In addition, and since the impacts of the variables are higher in this estimation than in the original one, it is also possible to conclude that being a member of OECD and EU simultaneously drives the deployment of renewable energies in the member countries.

Throughout our research, some limitations appeared and we had to overcome them. An example is the fact that in order to have available data for each country regarding the prices of traditional energy sources, this had to be proxied by the CPI. Furthermore, our approach of differentiating the FiT by technology types was innovative, at the cost of no possible confirmation with existing literature. With this in mind, we could not find any explanation for the negative sign of Waste in the authors we analyzed. We therefore present what we evaluate as a plausible hypothesis to explain it. Further research could then be conducted with the aim of verifying empirically the hypothesis used to explain the negative influence of Waste on the share of electricity capacity generated by a non-hydro renewable source.

8 Appendix

Table 8.1: **Variables' Correlations**

	Renew	**SolarPV**	**Wind**	**Biomass**	**Waste**	**Geothermal**	**Marine**	**NuclearShare**	**FossilShare**	**ImpDep**	**Elect*pc***	**gGDP*pc***	**CPI**	**FDI**	CO_2pc
Renew	1.0000														
SolarPV	0.1270	1.0000													
Wind	0.1414	0.8383	1.0000												
Biomass	0.2076	0.7970	0.8784	1.0000											
Waste	0.1954	0.7863	8956	0.8548	1.0000										
Geothermal	0.2017	0.7329	0.7720	0.7494	0.6931	1.0000									
Marine	0.1677	0.5562	0.5981	0.4209	0.4370	0.4209	1.0000								
NuclearShare	0.0483	-0.0952	-0.0827	-0.0252	-0.0335	-0.0787	0.1461	1.0000							
FossilShare	-0.4115	-0.1363	-0.2089	-0.2184	-0.1592	-0.1666	-0.1074	-0.4663	1.0000						
ImpDep	-0.1627	0.0545	0.0622	0.0528	0.0391	0.0025	-0.0388	-0.1029	-0.0375	1.0000					
Elect*pc*	0.2672	-0.0102	0.0955	0.0186	0.0945	-0.0091	0.0137	0.2000	-0.3797	0.0833	1.0000				
gGDP*pc*	-0.2111	-0.2057	-0.2197	-0.2062	-0.1656	-0.2377	-0.0625	0.0365	0.0990	0.0087	-0.1459	1.0000			
CPI	0.2896	0.2990	0.3353	0.3411	0.2847	0.3090	0.1198	-0.0884	-0.1165	0.0686	0.2279	-0.4211	1.0000		
FDI	-0.1612	-0.0659	-0.0617	-0.1261	-0.0394	-0.0136	-0.1162	-0.1363	0.2901	0.2729	-0.0128	-0.0523	0.0475	1.0000	
CO_2pc	-0.2028	0.0981	0.1986	0.1182	0.1800	0.0052	0.1103	-0.1537	0.1029	0.0559	0.5225	0.0298	0.0484	0.0251	1.0000

9 References

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