Achieving neutrality: An ABM approach to RES support in the Spanish electricity market

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1 Introduction

The effect of anthropogenic emissions on the Earth's environment has severe consequences not only for its ecosystems through climate change but also hinders efforts to attain Sustainable Development goals, causes water scarcity, food production, transmission of diseases, mass displacement in affected areas, and other damages sustained through Extreme Weather Events (EWE) by cities, settlements, and infrastructure (IPCC, 2022). The severity of these effects has prompted the international community and the national governments to launch several policy measures to meet the net emissions goals. In the European Union (EU), this goal is set to reduce net greenhouse emissions to 55 percent by 2030 and achieve climate neutrality by 2050 defined by the European Climate Law, binding for all EU member states (Parliament and of the European Union, 2021). For these goals to be met, reducing emissions from the energy sector should be a priority, since electricity and heat generation combined account for more than 21% of all CO_2 emissions in the EU (Agency, 2023). The International Energy Agency (IEA) has identified in its 2022 World Energy Outlook that phasing out fossil fuel generation in favor of clean energy technologies, mainly Renewable Energy Sources (RES) by boosting investment is a key step to reducing emissions, and thus achieve the carbon neutrality targets (IEA, 2022).

Over the decades, most European countries have adopted some form of RES support policy to boost investment in renewables and meet renewable-generation targets. In Europe, the most popular policies are Feed-In-Tariffs or other kinds of premium payments, with Spain as one of the few countries without a sizable market-based RES policy in place, just allowing net metering instead (REN21, 2023), which is a support policy that allows small RE producers (such as a regular household) to get billed only by their net electricity consumption. The implementation of one of these policies could help to achieve the national emission reduction goals, but a careful study of each available policy, considering the interactions and inter-dependencies between economic agents should be conducted beforehand to ensure the correct measure is chosen by policymakers. Thus, our objective for this study is to perform an analysis of the effect of these support policies at the macro-level (e.g.; Prices at the energy exchange) and look at the incentives generated on the micro-level (the differential revenue between baseline model without RES and several counterfactuals with different support policies). In the end, we aim to issue a policy recommendation based on our results and a strong theoretical background on renewable energy support policies and finally answer the question: What policy can we implement in electric markets to help us achieve our emission reduction targets?

To build the baseline and counterfactual models, we'll make use of AMIRIS (Center, n.d.). It stands for Agent-Based Market Model for the Investigation of Renewable and Integrated Energy Systems, which is a popular model for electricity market simulation with several publications behind its back, such as Nitsch et al., 2021 and Deissenroth et al., 2017. The rationale for using an Agent-Based

Model (ABM) to study energy markets is well established in the abundant literature that covers this topic. Three main approaches to model energy markets can be identified: optimization, equilibrium, and simulation models, with the ABM approach belonging to the latter. While equilibrium models are often used to study macroeconomic developments from a top-down perspective, they lack the level of detail necessary to discern the complex web of interactions and incentives typical of the sector due to the high level of aggregation required in Computable General Equilibrium models (CGE). An example of this approach can be seen in Akkemik and Oğuz, 2011 which makes use of a CGE to examine the benefits of full liberalization of the Turkish electricity market. At the same time, O'Ryan et al., 2020 develops a Dynamic General Equilibrium model to establish baseline CO_2 emission levels for the Chilean economy. Optimization models, otherwise, are well suited for public utilities expansion guidance given the high amount of detail they're able to integrate, but they lack the information on incentives relayed by interactions vital for the study of policy and are susceptible to deviation from the assumed behavior of the players. An example of this model is Leuthold et al., 2010 with a large-scale spatial model of the whole European Electricity Market, which he uses to analyze an array of policy, design and management questions with a bottom-up approach to maximize welfare subject to technical limitations. Simulation methodology, and in particular ABM has been growing in popularity in the field of Energy Market Research due to the additional opportunities presented by this approach, mainly the ability to make more granular and realistic models (Sensfuß et al., 2007). Thus, ABM has been implemented in a wide range of geographical locations and applications, from market power to investment decisions, and from the Texan energy Grid to our market, the "Mercado Ibérico de Electricidad" or MIBEL (Deissenroth et al., 2017)

The remaining of this thesis will proceed as follows. First, we will establish a brief theoretical background on the operation of an electricity market, and MIBEL, followed by a description of the four RES policies available to test with AMIRIS. After this, we will formally introduce AMIRIS, and describe the base scenario, which will be a simulation of the MIBEL market calibrated with empirical data from a given year, and we will perform an external validation of the base model by comparing it to the actual data for that year. Then, we will simulate and compare the counterfactuals with the base model and extract relevant policy conclusions from it. Finally, we will close the thesis with a brief discussion of the results and the conclusion.

2 Theoretical Background on Electricity Markets and MIBEL. RES policies.

2.1 Origins and inner working of MIBEL

The origins of our current electricity model lie in the liberalization period following 1996's First Energy Package, a piece of European legislation aimed at breaking the standing national electricity monopolies, to generate national markets which could then be unified into a single European Internal Energy MarketWeigt, 2009.
Spain incorporated the new European directives by passing the Spanish Electricity Power Act in 1997 (Weigt, 2009) which organized the wholesale market into a handful of sequential markets depending on the amount of time left till the energy has to be delivered to the system or pool. These are the day-ahead, with delivery time frames up to the next 24 hours, intraday auction market, and intraday continuous market, which operate within the day to make small adjustments to the day-ahead schedule. In 2001, the Portuguese and Spanish governments agreed to integrate their national energy markets into a unified Iberian market, thus giving birth to MIBEL, which was formally started in 2007, with the two separate market operators merging into OMIE (*Operador del Mercado Ibérico de Energía*)
Since then, the biggest change has been the coupling of the day-ahead market with the North-Western Region in 2014 (2014), Which incorporated MIBEL to the growing Internal Energy Market, allowing energy producers to submit energy bids from anywhere across all the coupled regions, as long as transmission capacity holds.

The day-ahead market, which is formally known as SDAC (Single Day-Ahead Coupling) since 2014, is the main instrument for setting up electricity prices on the wholesale market. Its description and operation are regulated by law on the approved new rules for the electric market since 2018 (Ministerio de Energía, 2018). Its main purpose is to organize and determine the price and quantity of electricity produced for the next day, in an hourly fashion. Thus, the market is structured on 24 different sessions, one for each hour of the day, in which producers and consumers make bidding offers, with a quantity and price. Especially for producers, the bidding can include several different conditions, in what is known as a complex bid. These conditions range from indivisibility (sell all or nothing) to guaranteed minimum earnings and have to be taken into account in the pairing process. Once the deadline for bidding submissions closes, the market operator runs all bids through an algorithm called Euphemia, which is set up to maximize economic welfare, or the sum of the producer's and consumer's surplus. Furthermore, Euphemia also takes into account international energy transfers. If electric transmission capacity between two bidding areas is not capped out, then the price for both areas will be the lowest one of both (COMMITTEE, 2020). From this process a price and quantity are determined for each hour of the day, reflected on the daily schedule published by OMIE, telling producers how much they must produce. This schedule is sent to the network operator REE (Red Eléctrica Española) to ensure the feasibility of market results given the network constraints.

The final price will correspond with that of the last paired production bid, and all sellers will receive that price. Thus, if a seller puts a lower price in its bid than the one finally determined by the market, it will have extraordinary profits. Given that the market is set up in hourly sessions, price variation happens between hours, to take into account the fact that electricity cannot be reliably stored, and thus must be produced in a just-in-time manner to ensure maximum efficiency.

Once the daily schedule is set up, deviations from it are allowed through interactions in the different intraday markets, with an auction market divided into six different bidding sessions a day to ensure supply nationally, and a continuous market for the EU intraday coupling.

2.2 Renewable Energy Support Policies

RES Policies, initially, can be described as any measure put in place by the governing body of a state to increase, promote, and support renewable energy generation, to the detriment of other non-renewable sources. Given that the electricity generation sector of each country varies wildly, from liberalized market-based systems such as the one described above to national monopolies, RES policies vary wildly between countries.

Nonetheless, in market-based electricity systems, certain types of RES policies tend to emerge. They can be, generally, divided into two distinct groups, Quota or amount systems and Price systems (Gipe, 2006) . The first group of policies tends to set a renewable generation target, which has to be met with support from the policymaker in the form of subsidies (such as Green Certifications) or setting up buddings for the construction and operation of renewable power plants. The second group, on the other hand, tends to set the price politically, and the amount of renewable energy generated is determined by the market.
Our interest lies mainly with the second group of RES policies, given that AMIRIS models different price-based support schemes. These are Feed-In-Tariffs (FIT), Feed-In-Premiums (Both variable and Fixed)(FIP), Contracts for Differences (CD) and Capacity Premium(CP).

Of these four, the most common to implement are Feed-In-Tariffs, followed by both variants of Feed-In-Premiums (REN21, 2023). A FIT consists of a long-term purchase agreement of the generated electricity, while also guaranteeing access to the electricity grid. Typically, these contracts last for 15-20 years, and the payment levels are set based on the cost of generation and some extra profit. The most simple FIT consists, thus, of a fixed revenue offered over a long period, usually based on a price incentive. The energy producer tends to have privileged dispatch over nonrenewable sources, and this method is usually coupled with some other fiscal and administrative benefits. An important point to notice about this policy is that the market price of electricity is no longer relevant for the RE producer, given that the agreement will stipulate a fixed amount per kWh produced. It has been argued in the literature (Couture et al., 2010) that the steady stream of revenue expected from the agreement lowers financing costs, given the relatively low risk. These policies were first put to use in Germany, during the 1990s, and have been gradually replaced by the more advanced Feed-In-Premiums

FIP policies represent an evolution over the previous tariffs. One of the main issues of FIT policies is that they heavily distort market price, with its effects growing as RE sources become more prevalent in the energy grid, and thus increasing the inefficiency derived from the price distortion. Thus, new policies were designed to try to recover some of those lost market incentives. In a Feed-In-Premium scheme, the energy producer receives a premium over the market price. This premium works as a Pigouvian subsidy, normally fixed to internalize the positive externalities of RE generation. Thus the producer gets paid the wholesale market price, plus a percentage of that as the "premium". The way of determining this percentage is extremely important, given the nature of the wholesale electricity market where prices can vary wildly depending on the mix of technologies being used. The easiest way is to determine a fixed percentage, which as stated before can cover externalities, some extra profit for incentives, or both. Another method is to implement a sliding or variable premium, dependent on the market conditions, to ensure that the premium grows when prices are low, to ensure covering the cost of generation, and decreases when prices are high, to avoid an excess of extra profits (Couture et al., 2010). In AMIRIS, the cost of generation is called the Levelized Cost of Electricity (LCOE) and is specific to each technology.

AMIRIS also covers two other lesser-known RES policies, which have not seen so much actual implementation. Contract for Differences is a variant of the sliding Feed-In-Premium scheme, where under a certain threshold (mainly when the price of electricity is over the LCOE and thus regular market conditions offer extraordinary benefits) the energy producers stop receiving support, and instead start paying a tax to correct for this extra benefit. Finally, the last RE support scheme offered is a Capacity Premium. One of the main criticisms of FIT and FIP policies is that they do not tackle the main issue when trying to incentive renewable energy generations, which is the extremely high upfront cost (Couture et al., 2010). The capacity premium can be set up by itself or has a complementary subsidy, in which the rewarded value is not the amount of energy produced, but the installed capacity of the electricity plant. Thus, the bigger the project, the higher the expected revenue.

An important aspect to notice about RES support, especially with FIT and FIP schemes, is that they are flexible enough to offer multiple payment differentiation opportunities. Project size, technology type, resource quality, or even location can be taken into account when designing these policies to promote diversification and high-quality projects. AMIRIS allows us to set up different schemes depending on the technology being used, or even separate similar technologies in different clusters.

3 Agent-based modeling for Energy Markets, AMIRIS, and our baseline model

3.1 Electricity Market Modeling and ABM

Since the liberalization process started in the 90s, the energy sector has been undergoing profound structural changes. The climate emergency has propped up the incorporation of more renewable energies (RE) each year, while a series of outages in Canada and the USA have put into question the security of supply under a market system (Senfuss et al., 2007). Especially important is the matter related to RE sources, due to the high volatility of production associated with this kind of technology, which severely affects the reliability of traditional optimization models to elaborate predictions of demand, supply, and prices.

This has motivated the development of new approaches to electricity market research, to incorporate certain features that are each day more and more common in the actual markets, such as asymmetric information, producer and consumer heterogeneity, seasonal loads in the system, etc..... with simulation approach growing in popularity over the years, being the Agent-Based Modeling (ABM) approach one of them.

ABM is an approach that consists of a series of computational simulations where normally heterogeneous entities, which represent the economic agents of a system, interact with each other in a predefined environment and under a set of rules defined by the researcher based on the theoretical and/or empirical findings. The modeling of such a system is usually heavily based on a strong theoretical substrate. This allows not only for the study of the aggregates but also the emerging properties of the system and the interaction of the agents, information that otherwise is lost in other approaches such as optimization or even game theory models. As such, ABM is uniquely suited for electric market simulation, given its ability to model a dynamic and stochastic environment with to which our agents can react. Researchers have been aware of these advantages for years now, leading to a rich literature covering the topic. Multiple literature reviews and State-of-the-art discussions have been published, with the latest corresponding to Priyanka Shinde and Mikael Amelin, from the KTH Royal Institute of Technology in Stockholm, Sweden (Shinde and Amelin, 2019).

As of 2019, ABM has been applied to a multitude of electric markets, with different applications such as market power research and strategic agent behavior.Tellidou and Bakirtzis, 2007 ,develops a model to study withholding and collusion instances under high concentrations and competitive environments, respectively. Shafie-khah et al., 2016 studies the market power of wind producers, and Sousa and Saraiva, 2017 elaborates a model to analyze the learning capabilities of agents on MIBEL. Another important application would be electricity market design, with early experiments on this matter going as far back as 2001 (Atkins et al., 2004) where a joint electricity market ABM and an urban population simulation feed into each other results to create an accurate model of an electric market for a small town, to research three different electricity pooling mechanisms. Lately, ABM approaches have been also utilized to research the implementation of Smart Grid Systems or to study energy storage. Some interesting findings made through this approach in other studies include that shifts to hourly bidding leads to increased prices due to the inelastic nature of the market in peak hours (Bower and Bunn, 2000) and that congestion of the system produced by grid constrains makes prices surge on the regions affected by it (Ernst et al., 2004). Our particular interest lies in the use of these tools to research policy effects on an already liberalized market, and this is where AMIRIS, and its framework, FAME, come in.

3.2 AMIRIS, an ABM for RES research

3.2.1 FAME

AMIRIS is built on top of FAME, which stands for open Framework for distributed Agent-based Models of Energy systems. It was developed by researchers at the German DLR (Deutsches Zentrum für Luft-und Raumfahrt or German Aerospace Center) with the intention of providing the growing electric market modeling community with a common tool to build their models.

At its core, FAME it's just an easy framework to build specialized agent-based simulation models, thus enabling researchers with a rudimentary understanding of computer science to create their models. Furthermore, FAME is especially well suited for scientific research, due to a series of features such as ease of reproducibility by allowing identical results under the same parameterization, high maintainability of already created ABMs, highly available resources and documentation, its ability to work without problem in many computer setups and most important of all, it's nature as open source software, which allows not only free access to the framework for all researchers but also guarantees that all developments based on FAME will also be open to the general public.

FAME works, in a rudimentary way, by providing the scaffolding necessary for our models to work.

In Figure 1 we can see a quick visual aid of how the different components of FAME work. In short, FAME reads an input from a certain configuration file and a database, injects it into the Core, which stands for the model created by the researcher, and then generates a predefined output in the form of a .CSV file. During the simulation process, FAME also can implement parallelization (Shown in the graphic as FAME-Mpi) which allows the framework to process different strings of data at the same time, an advantageous feature to allows less powerful computers to run the models efficiently.

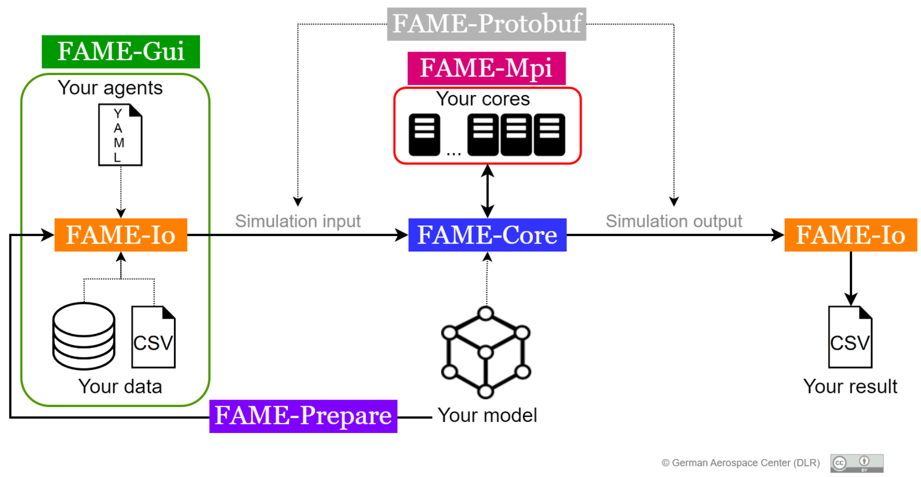

Figure 1: FAME workflow (source: FAME GitLab Wiki)

3.2.2 AMIRIS

AMIRIS is one of the models developed under the FAME framework. Also developed by the DLR, its name stands for Agent-Based Market Model for the Investigation of Renewable and Integrated Energy Systems (Center, n.d.). Designed specifically to address the difficult task of researching the effects of public policy in energy markets, it computes a simulation of a given country (or area) electricity market, with prices being determined endogenously based on the strategic bidding behavior of a series of prototyped market actors, such as market operators, forecasters, energy producers, etc... AMIRIS does not only take in to account marginal costs to determine prices but also can introduce other factors such as the effect of a diverse array of RES policies (Mentioned in the previous section), market power, limited information, and uncertainty.

AMIRIS has been used in several scientific publications with a diverse array of topics, such as Nitsch et al., 2021, which researched the possible revenue for battery storage facilities operators in a context of high shares of renewable energies and the presence of automatic frequency restoration markets. They found that there will be a shift in the composition of revenue in favor of the Day-ahead market (in contrast with our current situation where the intraday markets represent the main source of revenue for battery storage operators) due to increased instability in prices as the share of renewables grows. Furthermore, the technical specification of the battery storage system will be crucial to determine the amount of revenue these operators may perceive, with the ability to provide power quickly leading to higher revenues. Another article that made use of AMIRIS is Deissenroth et al., 2017 where the authors research the effects of switching from a FIT tariff to a FIP system, using the baseline scenario of Germany in 2019, with the results showing that careful planing of this minor changes in policy are necessary to ensure the survival of vulnerable elements of the economic system such as startups, and how intermediate agents have to be considered when planing this policies given the possibility of new interactions and inter-dependencies arising form the policy change.

Another advantage of AMIRIS over other competing models is the accessibility, which is related to the way the simulation works. Given that AMIRIS makes use of the FAME framework, Its structure is similar to the one presented for FAME, with a core where all the interactions are defined, and a series of supporting files to calibrate and set up the scenarios. The setup, calibration, and simulation can be done through AMIRIS-py, which allows the researcher to easily interact with AMIRIS through Python scripts, much more accessible than the native Java language in which FAME, and thus AMIRIS, is written. To this we add it's excellent documentation, support provided by its creators, and a vibrant community of researchers built around it, making it one of the most accessible research tools for energy markets.

The interactions between agents can be summed up in Figure 2, along with the different types of agent present, color coded.

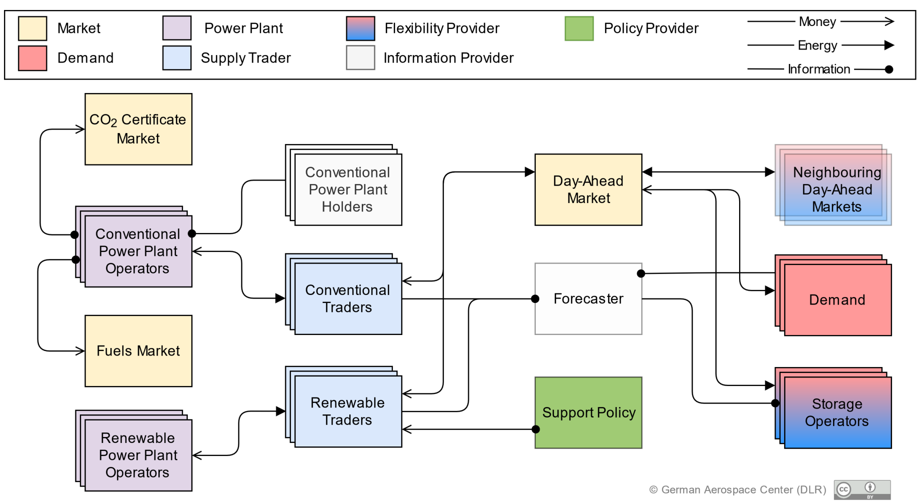

Figure 2: AMIRIS Interaction scheme. Source: AMIRIS Wiki

Each one of the agents generates a series of products that are sent to another agent, which in turn uses it to generate its value. The most important agent of this simulation is the day ahead market, where the energy generated by both plant operators is sent and coupled with demand to generate a price. The agent follows the same rationale for price coupling as most real-life market operators, which is the maximization of the general utility (i.e. the revenue for producers and excess utility for consumers).
Furthermore, AMIRIS is also capable of modeling complex areas of an electricity

market, such as a diversified support policy dependent on the area or technology, different sets of conventional and renewable technologies working at the same time on the grid, the existence of electricity storage facilities such as hydro pumping or chemical batteries and the effect of electricity imports-exports to neighboring markets. This array of features makes it especially useful for conducting research in European electricity markets, given the prevalence of such agents and features, and the huge relevance of energy market coupling across the EU due to the Internal Market.

The only real limitation of AMIRIS is the fact that RE sources are fixed through the duration of the simulation, given the fact that investment in renewables is currently not included in the simulation. Thus AMIRIS limits us to short-run experiments where we maintain a more or less fixed RE powerplant park. Nonetheless, AMIRIS outputs changes in revenue for RE producers, allowing us to study one of the main drivers of investment, the expected revenue.

AMIRIS agents can be subdivided into six different classes:

Power plant operators: Provide generation capacity to traders. They do not interact in the market, and can be further subdivided into RE operators, which make use of a series of renewable energy carriers such as wind-on-shore, wind-off-shore, Photovoltaic (PV) solar energy, hydro, hydro pumping, biomass, etc.... and conventional operators operating plants that use some kind of fuel, such as nuclear, oil, gas (both combined cycle and regular has turbine) coal, etc... They are represented in light purple in Fig. 2

Traders: They are in charge of bidding and operation decisions on the Day Ahead Market, operating under a series of profit maximization strategies. Each set of technologies can have its own trader, or different sets can be agglutinated into one single bidding agent. Represented in light blue.

Marketplaces: The trading platform of the model, organizes market clearing according to the utility maximization rule mentioned above. Shown in light yellow in the figure above.

Support Policies: Define the regulatory framework by which renewable energies are marketed. They influence the behavior of other actors by changing the expected profits for Renewable traders, thus changing the amount of RE produced and affecting the overall price in the wholesale market. Represented in green in Fig. 2

Demand and Flexibility Agents: They buy directly on the market. Flexibility Agents are also able to send information to the forecaster and sell energy on a marketplace. Coded in pure red for the demand and in a combination of blue and red for flexibility agents, of which we find two, the international markets agents and the energy storage agents.

Forecaster: It receives information from all major agents in the simulation to create a forecast, or schedule, of expected demand and expected supply. Along the conventional plant holders represents the information providers, coded in white.

Besides these major subgroups, other agents are relevant to the outcome of the simulation. The CO_2 and fuels marketplaces establish the cost for conventional plant operators. Furthermore, the conventional electrical power-plant park can be modified through the construction of newer plants with better technology, set up by the researcher in the scenario.

Energy prices are determined by the Wholesale market in AMIRIS following the equation:

$$MCP_{XM}(t) = min(MC_{PPconv}| \sum_{i=1}^{n} q_1 \leq RL) \tag{1}$$

Where the price is set by the minimum marginal cost of a conventional plant once the sumatorium of all the electricity produced by conventional sources reaches the residual load, i.e the amount of demand not satisfied by renewable sources, which have priority. Thus prices are almost always set by conventional sources. Renewable sources affect the market price by increasing or reducing the residual load, which in turn changes the minimum marginal cost the satisfies the residual load restriction. The marginal cost is sent hourly by the marketeers to the market operator in the bidding process described in the previous section.

The marginal costs are set as a linear combination of fixed and variable cost of primary products, such as fuel, the C02 emission certificates cost, the generation efficiency (determined by the technology type and an empirically determined variation range) plus other variable cost such as estimation for insurance.

Direct Renewable Marketers organize their respective Power Plant Operators (PPO's) to maximize their profits by signaling how much energy to produce. It's profits are given by:

$$p(t) = i(t) - c(t) \tag{2}$$

The difference between revenues $i(t)$ and costs $c(t)$. For marketeers, these revenues are determined by the participation on the market. Cost are composed off fixed and variable costs, following equations 3 and 4:

$$c_{fix} = C_{IT} + c_{trade,fix} \tag{3}$$

Where C_{IT} represent cost in Information Technologies and $C_{trade,fix}$ represents fixed trade fees to enter the market. Variable cost are composed of:

$$c_{var}(t) = c_{XM,trading}(t) + c_{pers,var}(t) + c_{bal}(t) + c_{fcst}(t) + c_{bonus}(t) \tag{4}$$

or variable trading fees, personnel cost, balancing cost (which can be part of the revenue, explained further bellow), the cost of the forecast and the extra bonus paid to PPO's, respectively.

The full desegregation of revenues is:

$$i(t) = i_{XM}(t) + i_{CE}(t) + i_{bal}(t) \tag{5}$$

Where $i_{XM}(t)$ represents the day ahead market revenues, $i_{CE}(t)$ income from the control energy market (support payments) and $i_{bal}(t)$ (The counterpart of $c_{bal}(t)$ shows extra cost or revenues from energy market re-balancing operations, which is a system where imbalances in the scheduled set by the system operator can be penalized or rewarded, depending if those imbalances contribute to reduce or increase global imbalances in the region.

$$i_{XM}(t) = V_{XM}(t) * (\Pi_{XM}(t) + M(t)) \tag{6}$$

Further desegregation of $i_{XM}(t)$ shows that market revenues are given by the sold volume of energy multiplied by wholesale market price $\Pi_{XM}(t)$ and a marketer premium $M(t)$. Similarly, $i_{CE}(t)$ can be separated in:

$$i_{CE}(t) = V_{CE}(t) * (\Pi_{CE}(t)) \tag{7}$$

Where $\Pi_{CE}(t)$ is the support scheme payments. Under a FIT scheme, there are no revenues from the market, $i_{XM} = 0$. Meanwhile, under a FIP scheme, Π_{CE} is set to a fix or variable percentage of the market price Π_{XM}. Under no support scheme, $i_{CE} = 0$

After the marketeers revenues are calculated, they have the choice of increasing profits for themselves or increase the amount of revenue to the PPO's. This mechanism ensures that PPO's have incentives to change marketers, creating a realistic environment where marketeers have to compete for the PPO's exclusivity through a contract.

Thus, the effect of renewables in prices is felt through the amount they produce. The support schemes affect prices by changing the incentives of marketeers, artificially increasing the revenues from sold energy, thus motivating the marketeer to signal the PPO to produce more. This increase reduces the residual load, and in turn reduces the marginal cost the market operator chooses as the price. For further details, please check Deissenroth et al., 2017

3.3 Calibrating AMIRIS. Spain's 2019 scenario

AMIRIS calibration is performed by imputing data through a series of configuration files set up by AMIRIS-py. These files are:

Scenario: Sets up the actual scenario, configuring the agents. It's here where we input the electrical power-plant park of our country, with detailed information about installed capacity for each technology, average power block (plant size), trader markup, etc... All the other files support Scenario in one way or another.

Schema: Initialises the agents. In simple terms, is where we find a detailed description of all variables our agents are able to take, which will be later configured in the Scenario file.

Contracts: The Contracts section of the model contains a series of files that describe the products of each agent and the time it takes for them to be sent to the next agent. In other words, it broadly configures the interactions between agents and the time in which they're conducted.

Timeseries: In this section, we can find the myriad of time series, in .CSV format, necessary to support Scenario. Broadly speaking, it contains all the external input necessary for the agents to work. Of important mention are the different RE profiles, which relay how much of the installed capacity is being used at any point in time. This information is crucial, due to the fact that RE sources tend to vary over time due to weather conditions and other non-market related issues. Alongside RES profiles we can also find fuel prices and demands with imports-exports, which is also externally determined.

This calibration process is carried out by creating the necessary agents with the correct specifications to represent the region we are trying to simulate (Scenario file), then adding external data such as fuel prices or maximum variable RE capacity we have at a given point in time (Timeseries Files). Furthermore, adjustments have to be made to the interactions (Contract files) to path out the interdependencies of the simulation.

3.3.1 Origins and description of the data

To build an apt simulation of the Spanish energy market, we needed all the relevant data described above. We decided to depart from the included 2019 Germany's electric market example and calibrate the model for Spain to 2019. This gave me a few advantages, to note:

-Due to the EU internal market, fuel prices are broadly similar, especially for oil and coal. Data on fuel prices for the Spanish electricity sector is not readily available, except for gas (GLP and non-GLP) which is coincidentally the only fuel where the prices diverge. Thus, we were able to use the baseline German prices for nuclear, oil and coal fuels, and use our own data provided by the Comisión Nacional de Mercados Y Competencia (CNMC) for gas (both combined cycle and regular turbine). Prices given by the example correspond with the Brent oil barrel and the API2 Amsterdam coal prices indicator.

-The same can be said about CO_2 emissions permits, which are regulated at the EU level and are traded on the internal market. Thus permit prices are the same across the continent.

-Electricity production technologies, especially when talking about thermal plants, are broadly standard. Both Spain and Germany have similar technologies, which allowed me to skip most technical details about energy efficiency. Nonetheless, We still needed to configure the nuclear park. Luckily, Spain's nuclear plants all belong broadly to the same type, Light Water Reactor's (IEA, 2022), and we were able to obtain an energy efficiency estimate for this technology from the US Department of Energy ("Quadrennial Technology Review 2015", n.d.)

-Spain doesn't have, currently, any sizable RES support policy in place, so for this calibration exercise, we just needed to remove the Support Policy Agent from the German example.

The most challenging part of the process was obtaining the different RE profiles necessary to take into account climate and other external factors on the use of variable renewable sources. For this, we had at our hand ESIOS ("ESIOS database", n.d.), an open information portal operated by Red Electrica de España (REE) and its API. To build the profiles, we needed both the installed capacity and the actual RE production by technology, then calculate the percentage of the capacity used for any given hour during the year. All of this data was readily available through ESIOS and its API.

The last necessary data for the calibration process was the average markup applied by marketers over production costs. For this, we used a minimum value of 40 percent and an upper value of 60 percent, following the findings of a study realized by Ángel Estrada (Banco de España) (Estrada, 2009). The results of the calibration process and a quick description of the baseline scenario are presented in the following section.

3.3.2 Baseline Scenario Results

A description of the development of the market during 2019 can be obtained from The Spanish Electricity System Report, an annual publication by Red Electrica de España (REE) that summarises the most relevant data for the electricity sector. (REE, 2020).

The Spanish electricity market of 2019 was marked by a milestone, with renewable energy sources surpassing non-renewables in installed capacity since historical records began. It was also characterized by decreasing demand, reversing the upward trend that started in 2014 with a 1.6 percent decrease in comparison with 2018. Hotter temperatures than average countered this phenomenon with a positive effect on demand during the summer season. Nonetheless, the annual maximums were below 2018, both in winter and summer. Concerning energy production, and despite the milestone previously mentioned, RES accounted for a smaller share of the Spanish energy pool concerning 2018, with 38.9 percent (a 2 percent points decrease) due to lower hydroelectric generation derived from lesser rainfall during the year. Coal-fired production decreased by 69.4 percent, while combined cycle (CC) generation increased by 93.7 percent. Wind power generation remained the main RE source, with a share of 55.2 percent concerning other sources.

Prices were, on average, 17 percent lower than in 2018, with an average of 53.4 euros per MWh, and 47.6 on the DA market. This drop was felt especially in the last 5 months of the year, with an average reduction of 33 percent with respect to 2018. The Day Ahead (DA) market accounted for 90.9 percent of this price. The amount of energy traded in the DA market fell by 1.6 percent points, in line with the overall demand fall. A general decrease in gas prices led to increased use of CC technologies, which ultimately was used to phase out coal-fired generation, but had little effect on final prices.

Our simulation makes an excellent work of replicating 2019 actual energy prices. Results can be viewed in the figure 3 and 4 below:

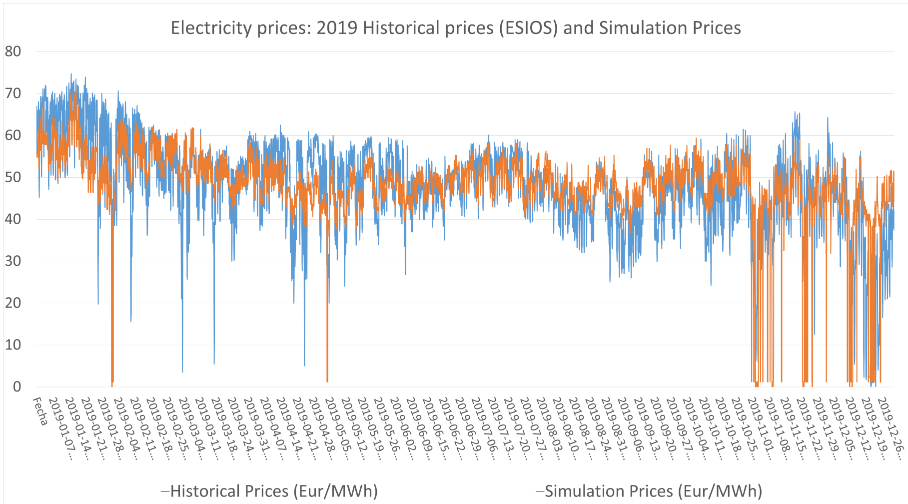

Figure 3: Comparison between historic and simulation prices

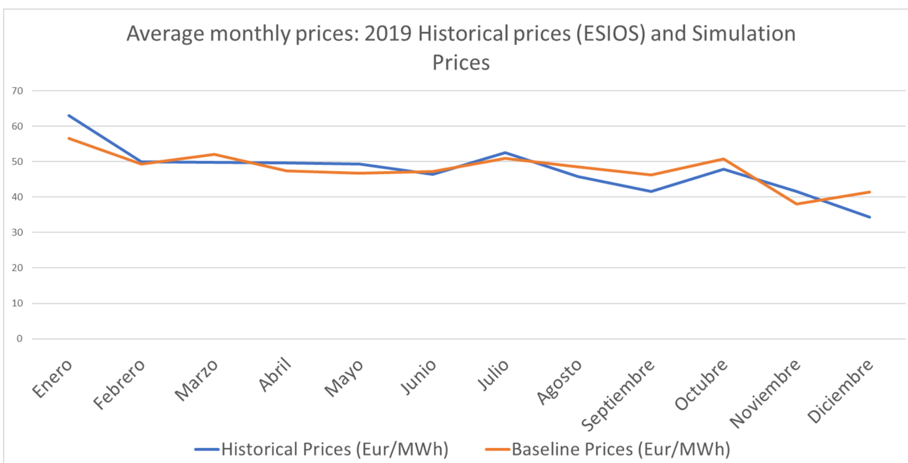

Figure 4: Comparison between average historic and simulation prices

The average price yielded by the simulation is 47.46 Eur/MWh, which represents a near-perfect match of the historic average price for the DA market. Furthermore, it can be seen on the graph how the simulated price correctly mimics the tendency and evolution of the actual prices across the year. We can identify a downward trend from January to June, with the rest of the year keeping several upward and downward cycles. By the end of the year, the replenishment of hydropower reservoirs and increased wind power production due to better atmospheric conditions allow prices to drop dramatically.

Nonetheless, we can find several discrepancies with the actual prices.

First, we have 0 or even negative price spikes across the year, especially at the end of the year. The origin lies with the energy storage producers such as hydro-pumping, discharging at certain hours making prices fall dramatically. The more abundant excess power is, the more they can charge, thus in seasons with a high abundance of rain the more spikes we can see. In reality, under these market conditions, the intraday continuous market takes the lead, and renewables increase their markup considerably for that given hour, stabilizing prices.

Further discrepancies in prices can be seen from August to October, where prices are consistently overestimated, with an average simulation price of 48.138, for an actual historical average for this period of 44.795. Something similar happens in January, with prices being on average 18 euros lower than what they should be. These discrepancies can be explained due to differences in the energy production mix derived from simplifications of the model, such as a slight overproduction of nuclear or a higher production of coal during January.

Lastly, AMIRIS prices tend to have less variance than actual historic prices. This may be because fuel prices are given on a monthly basis, thus ignoring all of the daily variations in prices. Furthermore, markup variables data may not be correctly estimated for all energy carriers due to the lack of available data, thus giving rise to these discrepancies.

Moving to an analysis of the energy mix, or how much and by whom is the energy being produced, we can see that AMIRIS also does an excellent work at replicating historical data:

As we can see in Fig.5, total production is close to actual production. The main reason for the slight difference is that we incorporated exports and imports, into the demand, thus at some point in the year when we are net importers our grid is going to produce less than what is being consumed. For that same reason, there are some points in the year in which production is slightly higher than on historic data. To add to this issue, a small amount of the installed capacity which could not be pointed to a particular technology accepted by the model has been modeled as an aggregation of different renewable sources, thus diminishing the accuracy of the configuration data due to aggregation. This difference is, nonetheless, small, with around a loss of 1GW and a gain of 0.2GW being the maximum lower and upper differences.

The share of different technologies on the simulation is fairly close to the historical data, with some of them displaying over-production and others under-production. Coal is under-represented in the mix at the beginning of the year, but by the end of it, it contributes only 0.45 percent less. Nuclear and solar are over-represented, with each of them producing 1.6 percent more than in real data. For nuclear this implies a 9 percent difference concerning real data, but for solar, it's a 44 percent increase, representing a big discrepancy. This may be caused again by small discrepancies between the real PV solar markup and the

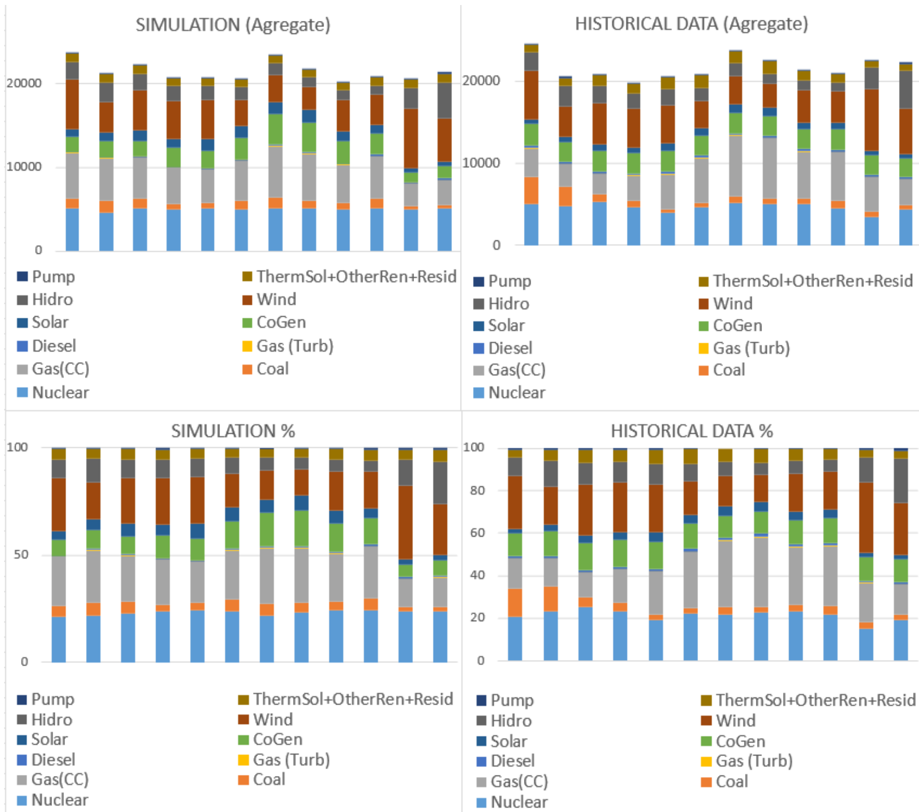

Figure 5: Electricity Mix (Simulation vs. Historical, Monthly.
(MW and Percent))

values imputed to the ABM. For the rest of the technologies, the differences with real data are small. There's a slight over-representation of conventional energy sources such as gas(CC) and also an under-representation of some renewables, such as hydro and wind.

All in all, this baseline scenario makes an accurate representation of the Spanish electricity market of 2019, upon which we can now start making modifications by introducing some of the mentioned RES policies.

4 Counterfactual Scenarios Analysis

4.1 Previous findings on the effect of RES policies in the short run

The effects of FIT and FIP support schemes on prices and quantity produced have been studied by several publications through the years. In Ballester and Furió, 2015 The authors performed extensive research on the effect of RES supply on electricity prices, and concluded that increased RES generation leads to temporarily lower prices and increased price volatility. Furthermore, Sensfuß et al., 2008 also reached similar conclusions after a detailed analysis of the German electricity market, specifically the effects of increased privileged RES generations on spot markets, with declining prices in the short run. The literature thus suggests that increased RES generation leads to decreasing prices.De Vos, 2015 suggests that the main driver of these lower prices is the market distortion created by the support policies, jointly with a lack of flexibility from markets to prevent electricity oversupply. These effects are increased as RES increases its share in the market. Finally, Paraschiv et al., 2014 indicate that the expansion of RES motivated by FIT schemes leads to the previous changes in prices.

Thus, from the literature, we can conclude that the main effect of FIT policies on wholesale markets is driven by increased production from RES given the distortion of incentives created by the schemes. Under a counterfactual scenario in which we don't allow investment to take place (Short Run Scenarios), the main difference with the baseline should be changes in profits for renewable operators, given that FIT policies tend to have priority dispatch clauses, we should also expect increased RES generation. Due to the nature of the Day-ahead market, peak prices should remain similar because these are usually determined by conventional sources, which tend to be more expensive than RES (except for nuclear). Price distortion concerning the baseline could be expected at low peak demand hours where RES tends to set prices.

4.2 The Scenarios

The paper has developed three different variations, departing from the baseline scenario described in the previous section. Each one of these scenarios is a simple policy experiment where we implement a different support scheme for all RES (photovoltaic solar, hydro, and wind) with the schemes being Feed-In-Tariff, Feed-In-Premium (Fixed), and Feed-In-Premium (Variable). As mentioned in the RES support schemes description section, AMIRIS supports two more variations, but I've chosen not to implement them given their relative obscurity in the real world and the fact that both of them are just variations of one of the three main support schemes. The scenarios are the following:

- **Scenario 1**: Feed-In-Tariff. The three different technologies receive different amounts of support, with the highest support to solar (375€/MWh) then hydro (110€/MWh) and finally wind (83€/Mwh). The values are taken from an average of received FIT payments in Spain before the dismantling of the previous policies, provided by a study from Costa-Campi and Trujillo-Baute, 2015

- **Scenario 2**: Fixed Feed-In-Premium. To calculate the fixed amount that producers would get on top of the market price, an arbitrary method is chosen to try to achieve similar levels of extraordinary benefits across the policies. The last scenario yields the average market price for each technology, averaging 47.8€/MWh for solar, 45.51€/MWh for wind and 47.4€/MWh for hydro, and by subtracting this amount from the previous Feed In Tariff we get out fixed premium rates: 327.2€/MWh, 37.5€/MWh and 62.6€/MWh, respectively.

- **Scenario 3**: Variable Feed in Premium. For this scenario, we needed to calibrate the Levelized Cost of Electricity (LCOE), which is a measurement of the estimated cost of production of electricity per MWh. The European Commission published a report elaborated by Trinomics in which estimates of the LCOE for each technology are already given (Baduard et al., 2020). For Wind-on-shore, at the year 2018 the LCOE for the EU27 was estimated between 41-89€/MWh, with 75 percent of results under 66€/MWh, PV LCOE ranges between 43-168€/MWh with the 75 percent mark at 112€/MWh, and hydro is estimated at around 44-140€/MWh, with 75 percent under 100€/MWh. The 75 percent values will be used for this experiment, given that low inflation during the time period makes it likely that real LCOE during 2019 will remain similar to the estimations for 2018.

An important point to notice about this scenario is that other than the implementation of the policy, all other factors remain equal. As mentioned before, available RES generation capacity is an exogenous variable determined at the base scenario, as the yield profiles are.

For Scenario 1 (FIT scheme), regular prices fixed by the market operator are replaced by the FIT tariff, which acts as the price at which supported energy is sold. Marketeers do not operate on the regular market anymore in favor of selling the energy directly to the government at the new favorable price. This increases the incentives for generation from PPO's, thus reducing the residual load and lowering market prices. Scenarios 2 and 3 follow a similar propagation mechanism, with the difference that marketeers operate in the regular market and then receive an amount of support depending on how much electricity have they sold, so their earning are the sum of the market price plus the premium. This premium is fixed in Scenario 2, and variable according to the LCOE in Scenario 3. Profits increase with respect to the baseline, thus stimulating RES production and lowering the residual load in the same manner as before.

4.3 Scenario Analysis

In the analysis will be studying price, production, and profit variations between the baseline and the different policy tests. For the first item on the list, a monthly average has been calculated, as well as a yearly average, given the difficulty of representing hourly data for a whole year. The data can be found in figures 6 and 7. Furthermore, you can find the actual tables in Appendix 1.

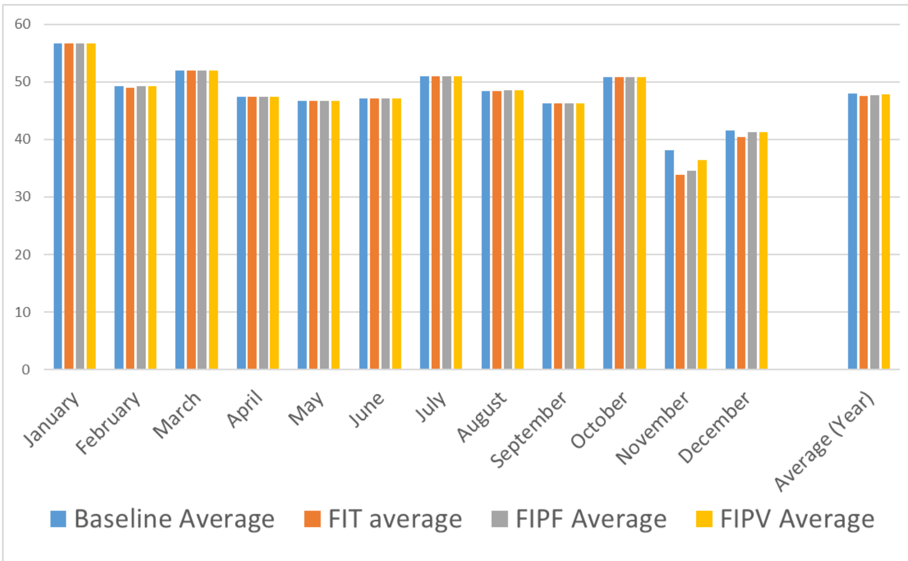

Figure 6: Average Price evolution under different support schemes (Eur/MWh)

The differences between the baseline and the different scenarios are small. In all of them, we can appreciate a small reduction in prices, in line with the findings of the previous literature stated before. The difference is greater for the FIT scenario, although this variation is heavily concentrated at the parts of the year with the heaviest use of renewables, especially wind. Both FIP implementations have comparatively less deviation from the baseline, also concentrated in months with a high share of renewables, with the Fixed implementation having almost double the distortion than the Variable Premium Scheme. This was expected, since a FIT tariff represents a more direct approach to RES support, bypassing the markets altogether, while the other two methods rely more on the market solution by making the amount companies receive change depending on prices.

The small amount of variation should not be any surprise, given the fact that renewables have an indirect effect on prices through the variation of the residual load. The main reason why RES do not have a direct effect is that, in the first place, RE Sources tend to have smaller generation costs than conventional electricity production, due to the lack of a need for fuel (other than nuclear), they are the first sold in case of a FIP support scheme or bi-pass the market

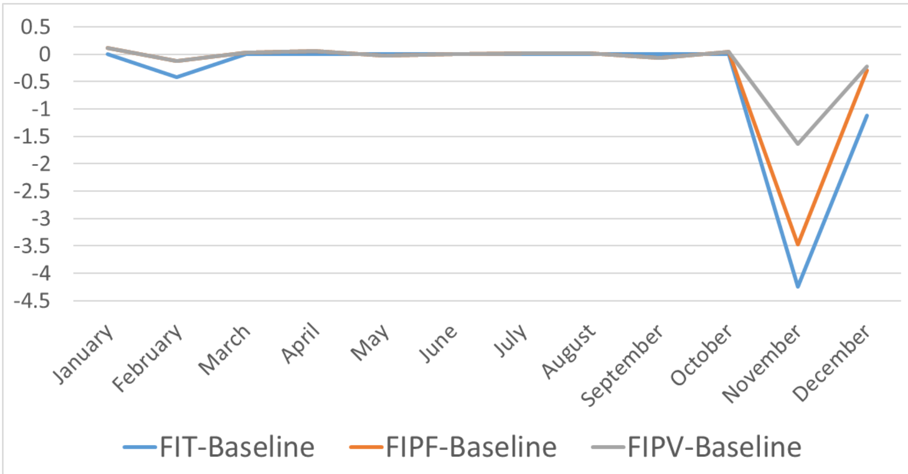

Figure 7: Price difference through the year between different scenarios (Eur/MWh)

altogether under a FIT scheme. In second place, the particular design of the support schemes heavily supports PV over Wind or Hydro. This technology has a comparatively low share of the energy mix and is most effective at peak noon hours, when electricity demand is high, thus minimizing its possible effect on prices by negating the increased production with an even greater increase in demand, nullifying any changes on the residual load.

Differences in the energy mix are also small in absolute values, as can be seen in figure 8. In general, FIT and FIPF schemes tend to increase energy production, while FIPV reduces it. The difference ranges from 104 GW to -14 GW across the year. In Figure 9 we can appreciate in all schemes conventional sources reduce their output, with a drop of almost 150GW in the FIP scenario and a barely noticeable -0.04 GW in the Premium scenarios. Renewable production soars under an FIP scheme, with an increase of 250GW, while FIPF displays a more moderate increase of 30GW and FIPV shows a reduction of 14GW. This anomalous behavior might be caused due to a bad estimation of the LCOE for wind generation, given that of all the three main RES, the wind is the only one that goes down.

These changes in production are, nonetheless, small. Overall, we can say that under a FIT scheme, renewables increase their share by 0.07 percent points against conventional sources when calculating the percentage difference between the baseline and the policy scenario, which can be seen at table 3 in the Appendix 1. For premium schemes, the difference is lower, 0.006 and 0.002 for fixed and variable schemes respectively. This difference is mainly fueled by an increased production of electricity, rather than a substitution of conventional sources with renewables.

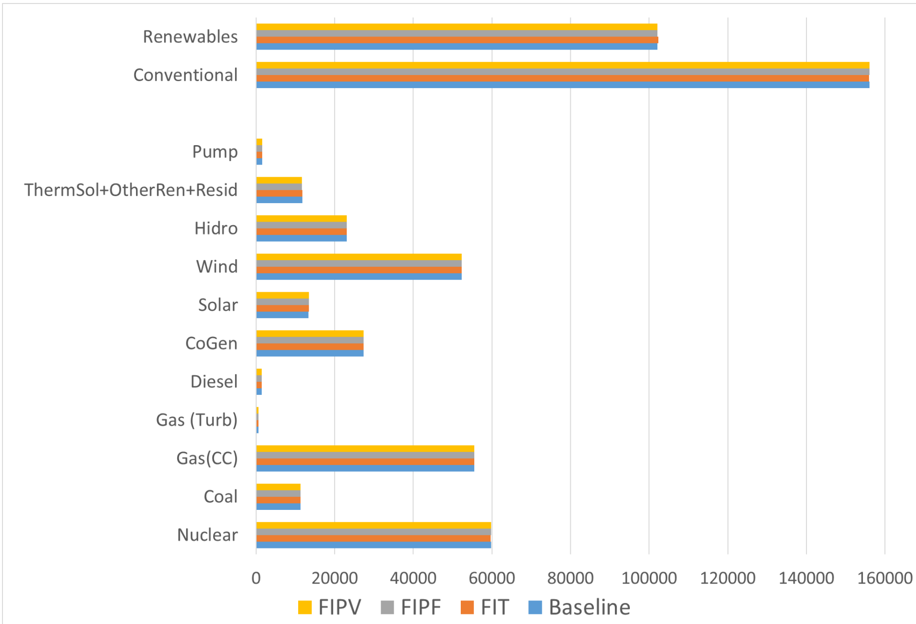

Figure 8: Electricity production by technology (GW per year)

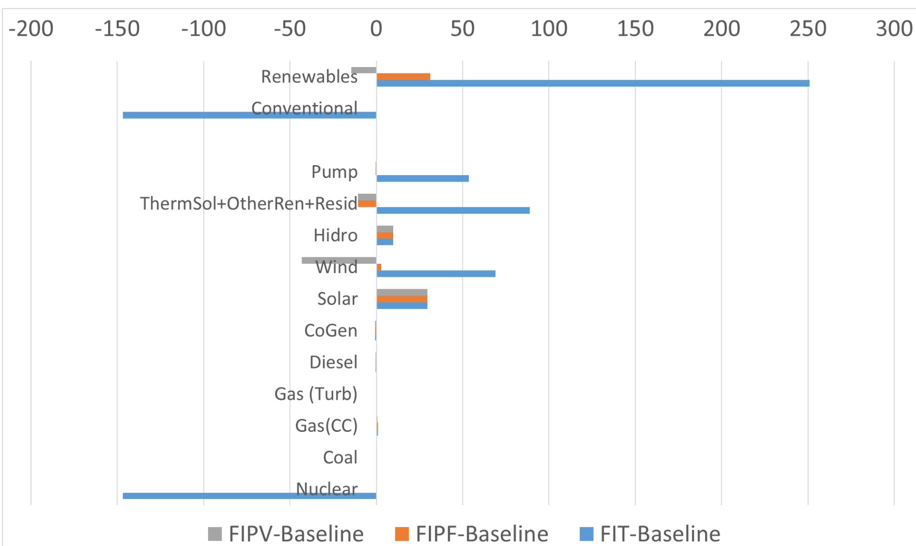

Figure 9: Production differentials by technology (GW per year

These results do not show any deviation from the literature review conclusions, which signaled that changes in production come as a result of the expansion of renewable installed capacity, not of increased production by already existing facilities which are already usually operating at maximum capacity.

Moving to the profit analysis, we can see big differences concerning the baseline scenario. These differences in profit are what the schemes are oriented to create, given that increased profits create bigger incentives to invest, thus expanding renewable capacity, its share in the energy mix, and its effect on prices. Thus we will analyze the difference in profit, and its composition between market revenue and received support. This analysis also includes the aggregation of other, non-

Technology	FIT	FIPF	FIPV
Solar	683.04621	682.35	133.87
Wind	81.825625	80.83	44.48
Hidro	8.1890119	9.3741	0.19688
ThermSol+OtherRen+Resid	0.028627	-0.012	-0.0125
Weighted Average	133.19779	132.86	40.3626

Table 1: Increases in Revenue (Percent Points)

supported renewable technologies such as Thermal Solar, with results summed up in Table 1. As expected, the difference in unsupported sectors is close to none. For supported renewables increases in profits are huge. Solar PV has the highest increase, with a difference of almost 700 percent concerning the baseline scenario profits for a FIT and FIPF schemes, and of 133 percent from baseline with a FIPV scheme. Hydro is the technology that benefits the less from these policies, due to the generally weak support given by design, favoring solar and wind instead. If we measure the overall increase in profit through all the renewable technologies, measured by calculating a weighted average based on the contribution of each technology to the energy mix, we can see how, overall, FIT and FIPF do a better job at generating incentives than FIPV.

Making a comparison in the composition of profit, we can see in Table 2. the desegregated components in percent and absolute values:

Scenario	Support (Ths of Mill)	Market Revenue (Ths of Mill)	Income (Ths of Mill)	Supp %	Market %
Baseline	0	4.744089169	4.744089169	0	100
FIT	11.9138971	4.113408569	16.02730567	74.335	25.665004
FIPF	7.793448315	4.132295677	11.92574399	65.3498	34.650213
FIPV	3.158802764	4.150761967	7.309564731	43.2146	56.785351

Table 2: Composition of profits based on Scenario (Thousands of millions)

For our FIT and FIPF scenarios, support transfers represent the majority of profits, with 74 and 65 percent, respectively, with only FIPV favoring market income. If we understand support transfers as a cost for the public sector, we can also make a small cost-benefit analysis. By calculating the ratio of a weighted percent increase in profits to spent thousands of millions in support, we get that for every thousand of millions in support, profits increase:

- 11.18 percent in a FIT scheme,
- 17.04 percent under a FIPF
- 12.77 percent for FIPV

Thus making the Feed In Fixed Premium as the most efficient support scheme to increase profits and thus generate investment incentives.

5 Policy Recommendations and Conclusion

Our different scenarios yield different results for the evaluation and effectiveness of the different policies. In terms of avoiding market distortion, a Feed in Variable Premium seems to be the most appropriate option, given its low impact on prices. An important thing to notice is that as the use of renewables increases, the effects on the prices of these support schemes are going to get higher. We can get a glimpse of the incremental effects on prices in November, in which renewables were the dominant source of electricity generation, and thus effects on prices spiked. Even in that case, the FIPV had a better result in terms of avoiding market distortion. Changes in prices have important effects on the energy mix, thus a small impact on prices tends to mean a small boost, or even none at all in renewables. In this case, FIP has the biggest effect, although a short-term change in production should not be the target of any policymaker looking to implement any RES Support Scheme. The most important metric to evaluate the effectiveness of this policies should be how much incentives it generates to boost investment and expand installed capacity. In this regard, the Feed in Premium with a fixed rate of subsidy seems to be the most efficient by generating similar levels of profit increase at a similar rate to a FIT scheme while having comparatively lesser costs for the public sector. Given its moderate success in the other measured areas, we conclude that a FIPF is the most appropriate RES support scheme for the stated objective of expanding RES installed capacity.

An important caveat to this recommendation is that the metrics used to determine which levels of support should be implemented are arbitrary, especially in the FIPF case. More concise research on the actual LCOE and the social benefits of RES support schemes in Spain should be conducted to fix an empirically based rate of support according to the positive externalities that investing in these technologies generates, which sadly was left out of the scope of this thesis.

To give some quick concluding remarks, I can state that we set out to answer the question:

What policy can we implement in electric markets to help us achieve our emission reduction targets?

To sump up, we confirmed what previous literature suggested: RES policies act mainly through stimulating investment, of which a Feed in Premium with a fixed rate seems to be the most effective scheme out of the three we researched.

Further lines of research should be centered on achieving a more accurate model of the Spanish economy, given its particularities that could not be appropriately imputed into the model, such as its huge share of Thermal solar energy, its lack of available data for the characteristics of the electricity plants and many other small adjustments that might hurt accuracy on the model currently developed. Furthermore, a better estimation of the Leveliced Cost of Electricity and estimations of the social welfare generated by the increased investment of renewables should be pursued, given its capital importance for researchers and policymakers alike. Current estimations are extremely dated for current-day research since most of them were done before 2020, with a different economic landscape.

6 Appendix

Month	Historic Average	Baseline Average	FIT average	FIPF Average	FIPV Average	FIT-Baselin	FIPF-Baselin	FIPV-Baselin
January	63.00347945	56.5985162	56.5998173	56.71619276	56.7148916	0.001301	0.1176766	0.1163754
February	49.88194521	49.30492167	48.885808	49.17959554	49.1795955	-0.419114	-0.1253261	-0.1253261
March	49.81141096	51.96727293	51.9672729	52.00378433	52.0037843	0	0.0365114	0.0365114
April	49.68876712	47.35719594	47.3571959	47.41954086	47.4195409	0	0.0623449	0.0623449
May	49.33727397	46.68613542	46.6861354	46.6533738	46.6533738	0	-0.0327616	-0.0327616
June	46.40720548	47.14244629	47.1424463	47.14166563	47.1416656	0	-0.0007807	-0.0007807
July	52.44439726	50.90434605	50.904346	50.92050951	50.9205095	0	0.0161635	0.0161635
August	45.77043836	48.44630575	48.4463057	48.46603233	48.4660323	0	0.0197266	0.0197266
September	41.63050685	46.24431191	46.2443119	46.18139988	46.1813999	0	-0.062912	-0.062912
October	47.86124658	50.77289123	50.7728912	50.82038151	50.8203815	0	0.0474903	0.0474903
November	41.64691781	38.08715091	33.8486418	34.61070711	36.4437971	-4.238509	-3.4764438	-1.6433538
December	34.36331447	41.48610761	40.3662374	41.1869279	41.2569243	-1.11987	-0.2991797	-0.2291833
Average (Ye	47.68573266	47.94293501	47.4616956	47.60286461	47.7613467	-0.481239	-0.3400704	-0.1815883

Table 3: Average Price evolution per month (EUR/MWh)

Technology	Baseline	FIT	FIPF	FIPV	FIT-Baseline	FIPF-Baseline	FIPV-Baseline
Nuclear	59851.1232	59704.44184	59851.12	59851.12	-146.6813625	0	0
Coal	11275.43786	11275.53753	11275.54	11275.59	0.099676259	0.099676259	0.153125662
Gas(CC)	55489.29753	55490.20414	55490.2	55489.99	0.906608038	0.901678485	0.690619921
Gas (Turb)	657.9123796	657.9123796	657.9124	657.9124	0	0	0
Diesel	1427.958334	1427.637395	1427.637	1427.637	-0.320938695	-0.320938695	-0.320938695
CoGen	27378.81285	27378.08407	27378.08	27378.24	-0.728780198	-0.728780198	-0.571171037
Solar	13377.50594	13407.17909	13407.18	13407.18	29.67314883	29.67314882	29.67314882
Wind	52299.0446	52367.97819	52301.88	52256.03	68.93359639	2.830895651	-43.01843117
Hidro	23078.15727	23087.84323	23087.84	23087.84	9.685968833	9.685968823	9.685968823
ThermSol+OtherRen+Re	11738.23656	11827.09806	11727.67	11727.67	88.8614959	-10.56275265	-10.56275265
Pump	1573.485788	1627.144867	1573.189	1573.189	53.659079	-0.296459	-0.296459
Conventional	156080.5422	155933.8174	156080.5	156080.5	-146.7247971	-0.048364149	-0.048364149
Renewables	102066.4302	102317.2434	102097.8	102051.9	250.813289	31.33080165	-14.51852517

Table 4: Analisis of the variation in production under RES schemes

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