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King Abdullah Petroleum Studies and Research Center

Policy Instruments and Market Uncertainty: Exploring the Impact on Renewables Adoption

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Key Points

Policymakers have a variety of financial tools to foster the deployment of renewables. Our study explores how these policy instruments impact a private investor's behavior, and the resulting differences in the adoption of renewable technology as well as costs to taxpayers and ratepayers.

Success of a renewable support scheme is typically measured by the cost involved, amount of chosen technology deployed, and speed of adoption.

All policy instruments (including feed-in tariffs, feed-in premiums and investment credits) can be designed to achieve the same amount of total renewable technology deployment. But each is likely to have a distinct societal cost, which is allocated differently between taxpayers and ratepayers.

Investment credit is the cheapest policy option for taxpayers because renewable technologies are capital intensive. However, if the objective is to expedite the maximum deployment of renewables in a short period of time, without regard to costs, then a contract-for-difference feed-in tariff is the preferred instrument.

We found that cheap loans increase the expected profits for private investors and also lead to slower adoption because it gives investors an incentive to wait. Finally, there are doubts over the common perception that investors prefer feed-in tariffs over investment credits and feed-in premiums due to the lower risks inherent in the former.

Summary for Policymakers

Renewable projects typically require government action to get started. However, it is often a struggle for governments to produce a renewable policy that achieves all its objectives because they usually compete against each other. The success of any renewable policy as such can be measured through three parameters:

- Total cost per megawatt (MW).
- Amount of renewable technology deployed over the lifetime of the policy.
- Speed at which the renewables are adopted.

Governments have a range of policies and instruments to promote the deployment of renewable energy, but we focus on the three most popular policy tools:

- Feed-in tariff.
- Feed-in premium.
- Investment credits.

The benefits and weakness of each tool are examined in this paper. The choice of which instrument to use depends on the government's priorities and targets. Furthermore, the government's choice is in part affected by how much private sector involvement it wants in the projects. Private investment in renewable energy will normally occur if there is an attractive balance between yield and risk. This study allows us to explore how policy instruments perform under different market conditions taking into account the impact of price volatility and uncertainty of those investments.

We developed a "renewable projects generator," using real Spanish onshore wind data, capable of identifying 1,000 feasible projects. Then, we defined the economic environment for those projects, using a stochastic future evolution of electricity prices. Finally, we calculated for each project, under each of the five policy instruments, what is its net present value and the best time to commission.

In reality, there is no ''best policy instrument,'' since there are trade-offs among the different policy instruments. The best policy, in other words, depends on the government's priority between the total deployment of renewables, speed of adoption and cost of policies.

Our findings show that a feed-in tariff, in particular the contract-for-difference feed-in tariff, is the policy that yields the fastest adoption of renewables, but it is also the most expensive. Investment credit is the cheapest, while at the same time it is very successful in the total deployment of renewable technology during the lifetime of the policy. The floor feed-in tariff (that sets a minimum price of electricity for renewable producers) achieves the largest success in terms of total deployment, with 98 percent of the 1,000 projects commissioned. Results from the other two instruments, the floor and cap feed-in tariff (that sets a minimum and a maximum price of electricity for renewable producers) and the feed-in premium rank them between investment credit and floor feed-in tariff.

According to our analysis, investment credit is the most attractive policy instrument for policymakers, since it is the cheapest of the five under realistic market conditions. This is due to the capital intensive nature of renewable technologies. The main setback of this policy instrument is that it requires a large upfront payment, rather than a flow of relatively smaller sums over a long period of time. If the objective of the policymaker is to expedite the maximum deployment of renewables in a short period of time, with no regard to costs, then a contract-for-differences feed-in tariff is the preferred option. We illustrate these trade-offs and their success rates in Figure 1 (over).

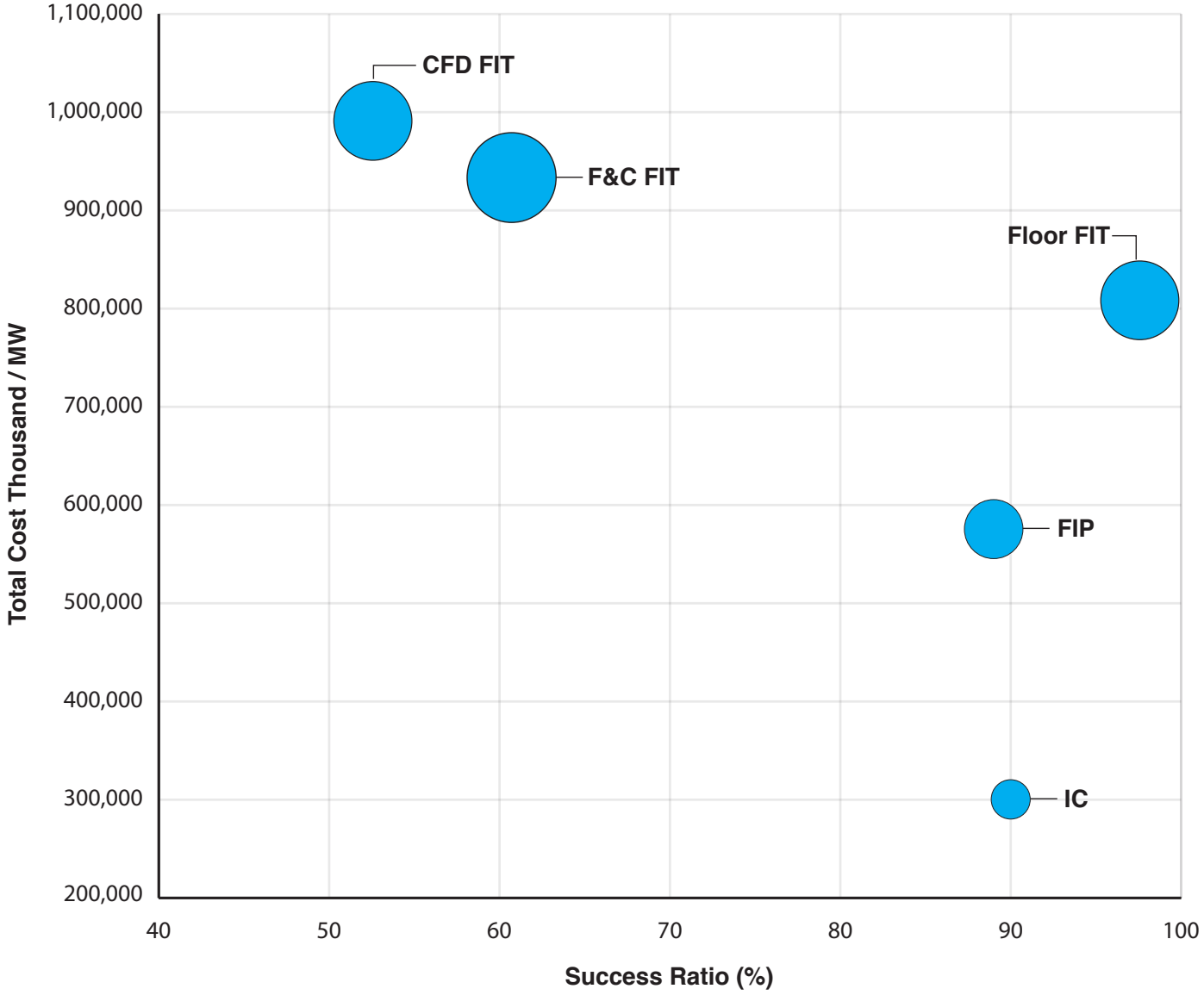

Figure 1. Policy instrument trade-offs.

Source: KAPSARC analysis.

Introduction

Governments and policymakers seek to promote renewable technologies through policies that simultaneously achieve a large amount of renewable projects commissioned, expedite the adoption of these technologies, and minimize the cost for taxpayers or electricity consumers. As a result, there are three variables that define the success of a policy. First, the cost of the policy; second, amount of renewables deployed over the timeframe of the policy; and third, speed of adoption of renewable energy. Renewable policies cannot achieve all three objectives at the same time. There are trade-offs between cost of a policy, speed of adoption and total deployment. In this study, we explore these trade-offs using models that we have developed to show the results of using five of the most popular policy choices.

In this context, our study seeks to understand how different policy instruments affect renewables adoption amid market uncertainty. Using real Spanish onshore wind data, a stochastic model is developed to understand how investors behave in real market situations. The key finding of this study is that some policy tools favor the deployment of renewable technology while others favor a higher speed of adoption, but there is a trade-off between these two objectives.

Investments will normally be made if there is an attractive combination of yield and risk. However, policies set by governments usually do not take into consideration investors' behavior when there are uncertainties. Governments implement policies on the assumption that they will be attractive for investors, regardless of future market conditions. In other words, policies designed for a specific market condition can be unsuccessful if market conditions do not hold, as Bauner and Crago (2013) highlight for solar PV technology.

Five policy instruments are considered including contract-for-difference feed-in tariffs (constant price tariff), floor feed-in tariffs (price floor tariff), floor and cap feed-in tariff (price cap and floor tariff), feed-in premium, and investment credits. We define policies that achieve the same economic profit for investors in a deterministic setting. This methodology, which ignores uncertainty, is a standard approach used to determine the level of financial support for renewable technologies. Once this set of policies is defined, we explore how investors react to each of these policies in a realistic stochastic environment. We then look at the final level of deployment of the technology, speed of adoption and total cost.

The policy with the highest speed of adoption is the contract-for-difference, since this instruments removes all volatility for investors. At the same time, the contract-for-difference is the most expensive in terms of MW of installed capacity. Investment credit is the cheapest policy and it achieves a high success ratio in terms of total deployment of renewables. The rest of the policy instruments show results that fall somewhere between these two tools in terms of cost, total deployment or speed of adoption.

In most cases, policies are designed with the objective of achieving a certain amount of total deployment within a set duration and, at the same time, minimize the cost for taxpayers or final consumers. In our opinion, compared to total deployment, the speed of adoption plays a secondary role for policymakers. Hence our view that investment credits is the most appropriate policy instrument to promote renewable energy under present market conditions. However, as it is pointed out by Bean et al. (2015), investment credits require a large upfront payment by the government, making this policy more difficult to implement politically.

Description of Data, Policies and Model

Overview

A short summary of our analytical framework:

In the description of projects, we built a 'project generator' based on the characteristics of the Spanish onshore wind projects committed between 2006 and 2013, generating a stochastic sample of 1,000 'realistic' projects.

Under the wholesale electricity prices section, we define an electricity price generating process that reproduces the characteristics of the main European markets.

In the policy levels and description section, we define five policy instruments that, in a deterministic setting, provide the same economic profit for the representative project, i.e., the average Spanish onshore wind project.

For each of the 1,000 projects and each policy instrument we calculate the expected net present value during the timeframe of the policy, which is 10 years. Using this information, we find the best moment to commission each project.

Finally, the study is set up by comparing the results of the five policy instruments in terms of total deployment of renewables technology or success ratio (1), the speed of adoption of these technologies defined by laggards (2), and early adopter (3), and the total cost of the policies in billion Euros (Eur/MW deployed).

(1) $$\left(\frac{Renewables\ Installed}{Total\ Potential\ Projects}\right)$$

(2) $$\left(\frac{Projects\ commissioned\ in\ the\ last\ month\ of\ the\ policy\ timeframe}{Total\ Policy\ timeframe}\right)$$

(3) $$\left(\frac{Projects\ commissioned\ in\ first\ year}{Total\ Policy\ Timeframe}\right)$$

Description of Projects

This analysis uses real Spanish onshore wind data collected from Bloomberg New Energy Finance (BNEF). The dataset includes financial and operational information on 318 onshore wind projects implemented in Spain between 2006 and 2013. Projects selected for the dataset are limited to those with a minimum installed capacity of 15 megawatts (MW) or more. The projects represent 10,732 MW of installed capacity, or about 83 percent of the 12,885 MW installed in 2006–2013 in Spain, according to the BP Statistical Review of World Energy 2014.

For each project we compute the levelized cost of electricity (LCOE), using the weighted average cost of capital (WACC) as the discount rate. The initial results of our analysis indicates that the LCOE of the projects have considerable variation from 36 €/MWh to 193 €/MWh. To avoid excessive dispersion in LCOE, this study uses the interquartile LCOEs, which means that the upper and lower cost limits in the spectrum are not considered. Based on the data, the projects in the analysis are normally distributed with an average LCOE of 72 €/MWh and a standard deviation of 8.6 €/MWh. Additionally, the WACC of the projects is normally distributed with an average of 7.2 percent and a standard deviation of 0.4 percent. The average installed capacity of each project is 33.7 MW and the average capacity factor is 25 percent. The maturity of the projects is 20 years.

Given these parameters, a population of 1,000 projects that are equal in capacity is randomly generated. As indicated by Manentau et al. (2003), this approach attempts to tackle the problem of lack of granularity in costs that some research

on renewable technology faces. In addition, a decline in the cost of technology occurs given a progress ratio of 0.97 as shown below. The LCOE of a particular project in time t is equal to:

$$LCOE_t = LCOE_{t=0} * time^{\ln(progress\ ratio)/\ln(2)}.$$

This progress ratio is calculated to fit the evolution of the LCOE of onshore wind technologies between 2009 and 2014, using data from the BNEF report titled H2 2014 Global Levelized Cost of Electricity Update. Obviously, the future cost of renewable technology is quite difficult to forecast, but simple approaches have been outlined by Neij (1997) and Witajewski-Baltvilks et al (2015).TK (Figure 2)

In our analysis the projects are developed when it makes sense to do so and, once a project is commissioned, the LCOE cost is locked in for the lifetime of the project. Therefore, once projects are developed they do not benefit from further cost reduction in the technology.

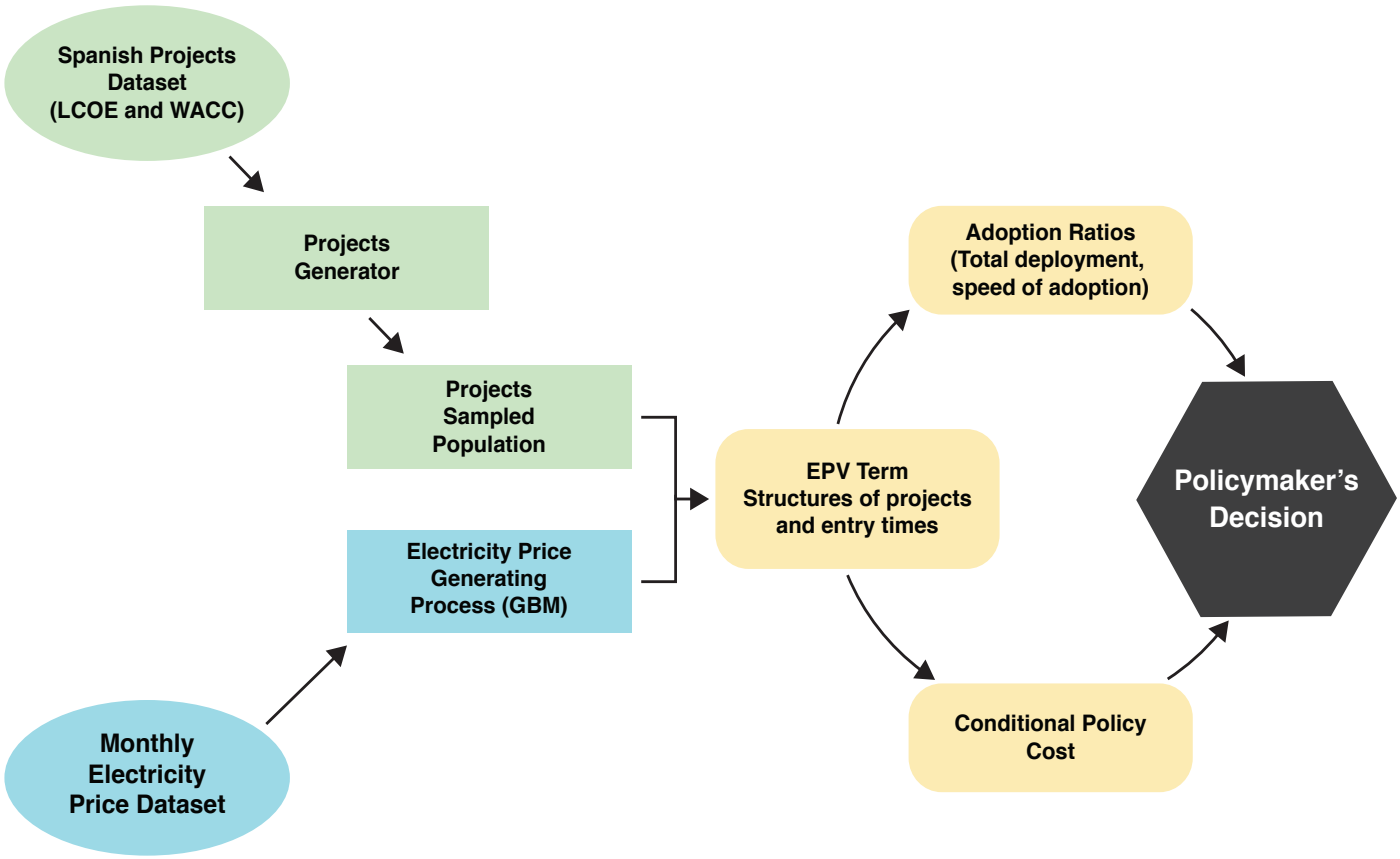

Figure 2. Developing the model — step-by-step process.

Source: KAPSARC analysis.

Wholesale Electricity Prices

A representative wholesale electricity price for Europe is created using the average of monthly data from Germany, France, Italy, Spain and Nordpool market for January 2006 to March 2015. The wholesale traded electricity prices evolve as a geometric Brownian motion with a volatility of 39 percent. The Brownian process has a drift, which is set at 1.5 percent annually, and represents an expected evolution of inflation in Europe over the period of analysis, given the mandate of the European Central Bank. The initial wholesale representative price for our analysis is 49 €/MWh. We model electricity prices as a Brownian process, given that we focus on investment decisions over a long period of time: 30 years. Modelling electricity prices as a Brownian process has been attempted by some researchers such as Biondi and Moretto (2015), Lucia and Schwartz (2002) and Fleten et al (2007).

As a simplifying assumption, we did not model the potential effect of the deployment of renewable technology on electricity markets. However, as Sensfuss et al (2008) point out for Germany, the adoption of renewables has an impact on electricity prices. Instead, we assume some market intervention to predict the profitability of incumbent generators, as is now being considered through capacity payments.

Policy Levels and Description

The duration of the policy is 10 years, to allow the achievement of long-term objectives in terms of deployment of renewables. However, each project under the policy receives financial support for 20 years from the date of entry. After 10 years the renewable policy ends and renewable projects compete with other technologies under market conditions. Five policy instruments are considered for analysis, including contract-for-difference (CFD) feed-in tariff (FIT), floor FIT (without a price cap), floor and cap (F&C) FIT (with a price cap), feed-in premium (FIP) and investment credit (IC).

Under a CFD FIT scheme, the government sets a constant FIT level for each megawatt hour (MWh) produced. This eliminates price uncertainty from revenues for investors. On the other hand, under a floor FIT the government sets a price floor for the FIT. When traded prices are above the floor FIT level the investors receive the market price. In terms of the F&C FIT, the government sets two fixed FIT levels with one acting as a price floor and the other acting as a ceiling. According to Bürer and Wüstenhagen (2009), FITs are the favorite policy instrument from the point of view of investors.

The FIP is defined as a fixed amount, on top of the electricity market price, for each MWh generated. This amount moves in parallel with the electricity prices. As for the IC, it is an upfront subsidy on the initial investment given by the government in order to reduce the initial cost of the technology. Unlike FITs and FIPs, IC reduces a project's LCOE without interfering with electricity prices and the revenues for the project. We must highlight that these two policy instruments do not protect investors from uncertainty and volatility of electricity prices, as Couture and Gagnon (2010) point out.

As a starting point, a representative project is designed under deterministic settings with an LCOE of 72 €/MWh, a WACC of 7.2 percent and an installed capacity of 33.7 MW. The characteristics of the project are set to yield equal levels of net present value (NPV) for the floor FIT, FIP and IC under deterministic conditions. Setting the floor

FIT at 79 €/MWh, the FIP at 23.9 €/MWh and the IC at 40 percent resulted in a 10 percent yield on initial investment or capital employed. The cost per project is 23.1 million euros for the FIT, 24 million euros for the FIP, and 16.6 million euros for IC. These policy instruments are equally attractive for investors regardless of the uncertainty associated with price market fluctuations. The aforementioned levels are used as a basis for the study, however the representative project is replaced with a population of 1,000 projects with random traded electricity prices. This makes future guaranteed prices unknown for the investors.

Under a stochastic environment, the initial policy support for CFD FIT is 79 €/MWh for projects entering in time zero. The CFD FIT, as well as the other FIT support schemes, moves in parallel with the LCOE. This means that each policy declines similar to the LCOE over time. For example, at month zero the initial level of a CFD FIT is 79 €/MW and at month 120 this level falls to 64 €/MWh. The floor FIT uses the same primary conditions as the CFD FIT, however these conditions are considered a price floor. Meaning that if the market price exceeds the floor FIT level, the projects receive the market price. The F&C FIT uses the same primary conditions as the CFD FIT and the floor FIT, however it has a price ceiling. For our analysis the price ceiling is 30 percent above the price floor, defined as {1.3 **CFD FIT Level*}. For example, at time zero the price floor will be 79 €/MW and the price ceiling will be 103 €/MW. The F&C FIT case is an intermediate case between the floor and the CFD cases.

Setting Up the Analysis

The study consists of 1,000 projects, equal in capacity and in capacity factor. Each project is defined by two parameters: the initial LCOE and the WACC. These parameters are generated using the normal distributions defined in Section 2.1: Description of Projects. As previously mentioned, a decline in the cost of the technology occurs given a progress ratio of 0.97. For each project the expected net present value (EPV) is calculated, on a monthly basis, by using the expected price or guaranteed subsidy. The EPV is calculated for 120 months, given the policy timeframe. The entry month for each project is defined by the month at which the EPV is at its maximum. If the EPV is negative during the policy timeframe, the projectis not commissioned. Once the project is commissioned, the LCOE and the policy support, regardless of the policy, are fixed for the duration of the project; see Figure 3: Study Framework.

Based on the study by Kim and Lee (2012), we assume that investors are risk neutral. This is a simplification of reality because in our model two projects that have the same NPV are equally attractive for an investor regardless of the risk of investment. Some policies are less risky for investors than others, and the study does not take that into account. In any case, there was not enough data to accurately define a valid relationship between risk of a project and the required return on investment, constraining us to assume risk neutrality.

In our analysis, a minimum of 10 percent yield on total investment is required in order to commission a project. We assume cost on equity is 10 percent given the structure of the WACC, which consists of cost on equity and cost on bank loan. A description of the methodology used to solve the problem can be found in Appendix I.

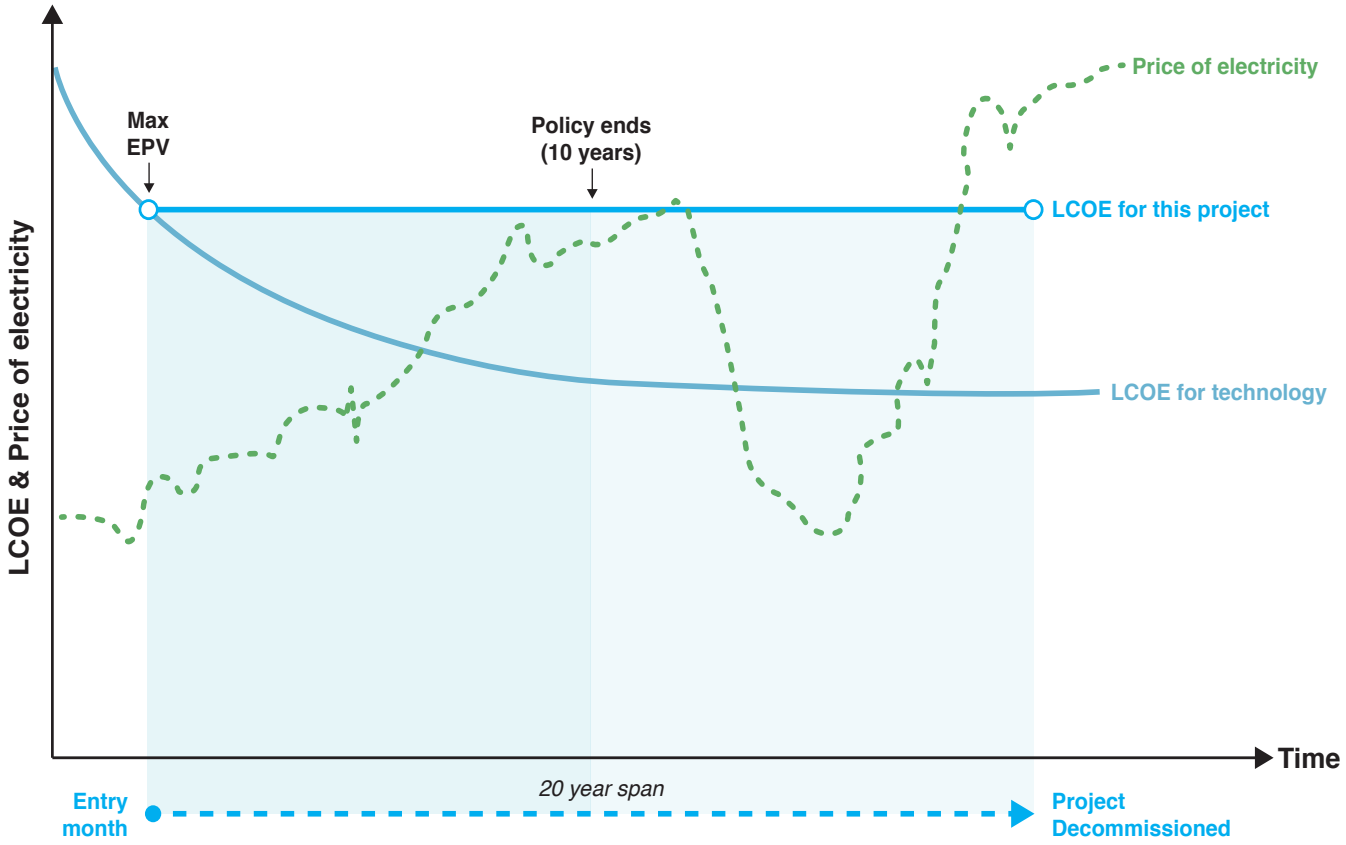

Figure 3. Study framework.

Source: KAPSARC analysis.

Historical Case versus Benchmark Model

In this section we test the benchmark against historical data. Taking historic Spanish wind capacity, from the BP Statistical Review of the World Energy 2014 and Espejo-Marin (2004), we observe that the installed capacity follows an S-curve. Spain began its first policy to support wind energy in the early 1990s and virtually finished in 2013, as explained in Bean et al. (2015). Unlike the commonly held practice of assuming an S-shaped adoption curve, this study produces S-shaped adoption curves as a result rather than as an input. This temporal pattern for the diffusion of new products and technologies was developed in 1969, as Bass 2004 points out.

Since 1990, support for renewable energy has been subject to a number of different policy instruments. Therefore, we conducted an analysis to replicate the evolution of the installed wind capacity, using a single and constant policy instrument, Floor FIT, as the representative benchmark.

As illustrated in Figure 4; Historical Spanish Wind Adoption Curve, the theoretical model used to demonstrate adoption of renewable technology is a useful instrument to understand how renewables are deployed under real life scenarios. In reality, a model with a single policy cannot replicate the real world; nevertheless, it can provide useful guidance for policymakers to understand the effects of different policies.

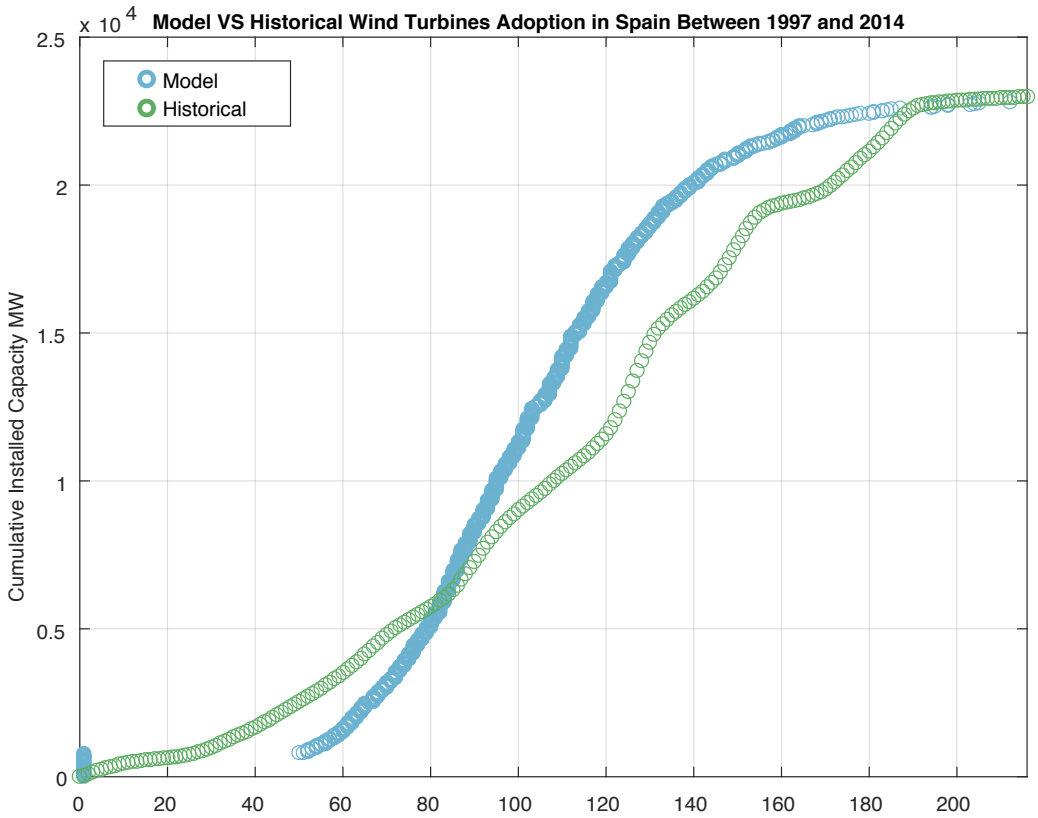

Figure 4. Historical Spanish wind adoption curve.

Source: BP statistical review of the world energy 2014, Espejo-Marin (2004) and KAPSARC analysis.

Results

Policy Comparisons

Each of the five policy instruments are evaluated under the same parameters, comparing the amount of early adopters (projects commissioned in the first 12 months), the success ratio (number of commissioned projects over total number of potential projects), number of laggards (projects commissioned in the 120 month of the study) and total cost of the policy.

TK Table 1 illustrates the results for the adoption under each of the five policies (see Appendix II for a description of the EPV term structure of early adopters, laggards and typical projects). Under a CFD FIT the number of early adopters are around 52 percent, which also represents the success ratio. Under this policy there is no uncertainty in income or cost, which implies that at time zero it is known if the project is going to be economical. This explains why all the projects are commissioned at the beginning of the life of the policy because there is no reason to wait.

Unlike the CFD FIT, the Floor FIT early adopter's ratio is very low at 3.4 percent. This is due to the structure of the Floor FIT policy, where there is an incentive to wait to profit from the drift and volatility in electricity prices. An estimated 26 percent of the projects are laggards, however 98 percent of the projects are commissioned before the end of the policy timeframe.

Table 1. Summary of adoption under five policies.

Policy	Early Adopters (%)	Laggards (month 120) (%)	Success Ratio (%)	Total Cost (€ Billion)	MWs Deployed	Total Cost / MW
CFD FIT	52.1	0.0	52.1	17.4	17,556	991,131
Floor FIT	3.4	26.0	98.0	26.7	33,026	808,454
F&C FIT	34.8	0.0	60.4	19.0	20,355	933,441
FIP	0.0	5.6	89.2	17.3	30,060	575,508
IC	0.0	26.2	90.9	9.2	30,633	300,327

Source: KAPSARC analysis.

The high percentage of laggards indicates that there is a strong incentive for project developers to wait. This is why the policy generates a gradual adoption of renewables or an S-shaped adoption curve.

The F&C FIT has an estimated 35 percent early adopters with a success ratio of 60 percent. The F&C FIT lies between the CFD FIT and the Floor FIT. There are no laggards under this policy. This is because the structure of the FIT, with its price floor and price ceiling, generates an incentive for project developers to wait on commissioning instead of becoming early adopters. However, the incentive is not strong enough and so it discourages laggards. Under a F&C FIT, if the price ceiling is increased the policy begins to converge with the Floor FIT.

As for the FIP and IC, neither policy encourages early adoption. They generate a clear incentive to wait since the project developer can profit from the drift in prices and from the decline in the cost of the technology. This explains why there are no early adopters and the number of laggards are significant for both policies with FIP at 6 percent and IC at 26 percent. Both policies achieve a success ratio of around 90 percent. Under a FIP and IC, price volatility does not affect the EPV term structure of the projects. These policy tools do not protect investors from price volatility and conversely neither could they profit from taking advantage of the volatility.

Observing the trade-off between speed of adoption and deployment of the technology or success ratio suggests that a CFD FIT and a F&C FIT are policy instruments that can be used to speed the process of adoption, but at the cost of a lower success ratio.

IC is the cheapest policy option with 9.2 billion euros in total costs (300,327 EUR/MW). Two key factors contribute to this result. Firstly, the tendency of developers to wait until the end of the policy in order to take advantage of the decrease in the cost of the technology, hence the high level of laggards; and secondly, since renewable technologies are capital intensive, the most cost-effective policy option to promote a single project is through an initial reduction of capital costs rather than an incremental subsidy in revenues over a long period of time. The FIP is the second most attractive policy option given its relatively cheaper cost, 17.4 billion euros, and high success ratio. Although the Floor FIT has the highest success ratio, it is three times more expensive than the IC, which also achieves a high success ratio.

To sum up, if the objective of policymakers is to achieve a quick deployment of renewable energy they should opt for a CFD FIT, understanding the high costs associated with the policy option. Alternatively, if policymakers wish to achieve a designated country objective for renewables at a low cost to society, the IC will be the policy option to implement.

Figures 5 illustrates the evolution of the adoption of the projects commissioned over time. Excluding the CFD FIT and, to a lesser extent, the F&C FIT, the policies implemented result in an ‘S’ shaped adoption curve. Figure 5 also shows that the Floor FIT and the IC generate a clear incentive for project developers to wait.

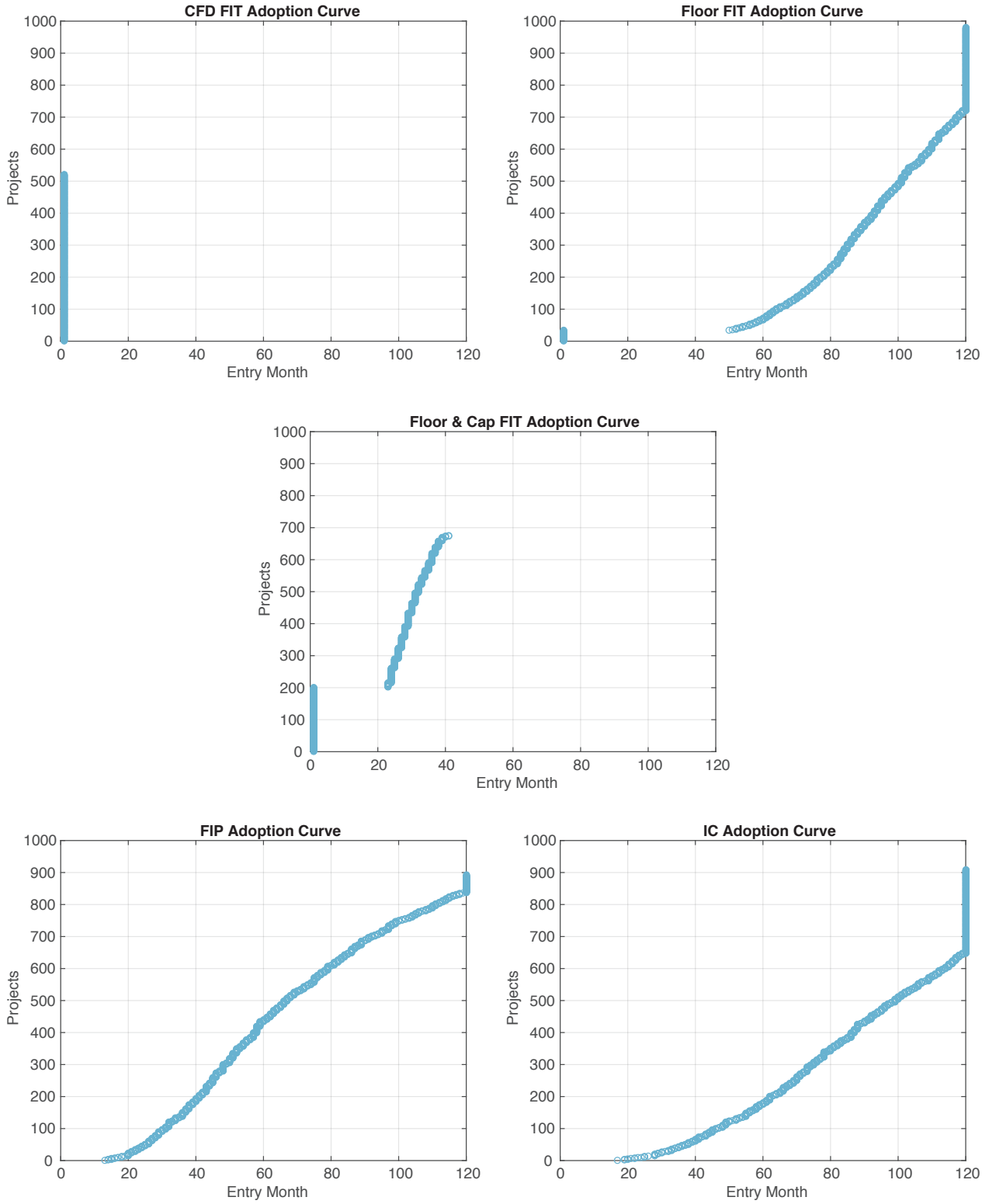

Figure 5. Adoption of project and entry month.

Source: KAPSARC analysis.

Sensitivity Analysis

A sensitivity analysis helps to understand the relationship between the lifetime of the policy, the electricity price drift, the WACC, and the adoption success ratio under the five policy options.

In Figure 6 we show that the success ratio for the given policies range from 52 percent to 98 percent, with policies becoming more successful as time is expanded in all the cases, excluding the CFD FIT. In the case of the F&C FIT after a three-year policy the success ratio stabilizes at 60.4 percent. Under a one-year policy span, the IC is the least successful with 52 percent. However, a Floor FIT is the most successful under these circumstances with a 58.7 percent success ratio.

The key element to ensure the success of the policy is to make transparent the overall length of the policy, since there is an incentive for investors to wait in four of the five instruments. In general terms, as you expand the length of the policy the success ratio increases and the laggards decrease. This result may not hold if investors know that the policy support will expand over time. A relevant insight from Figure 6 is that the success ratio improves substantially when the policy timeframe is between

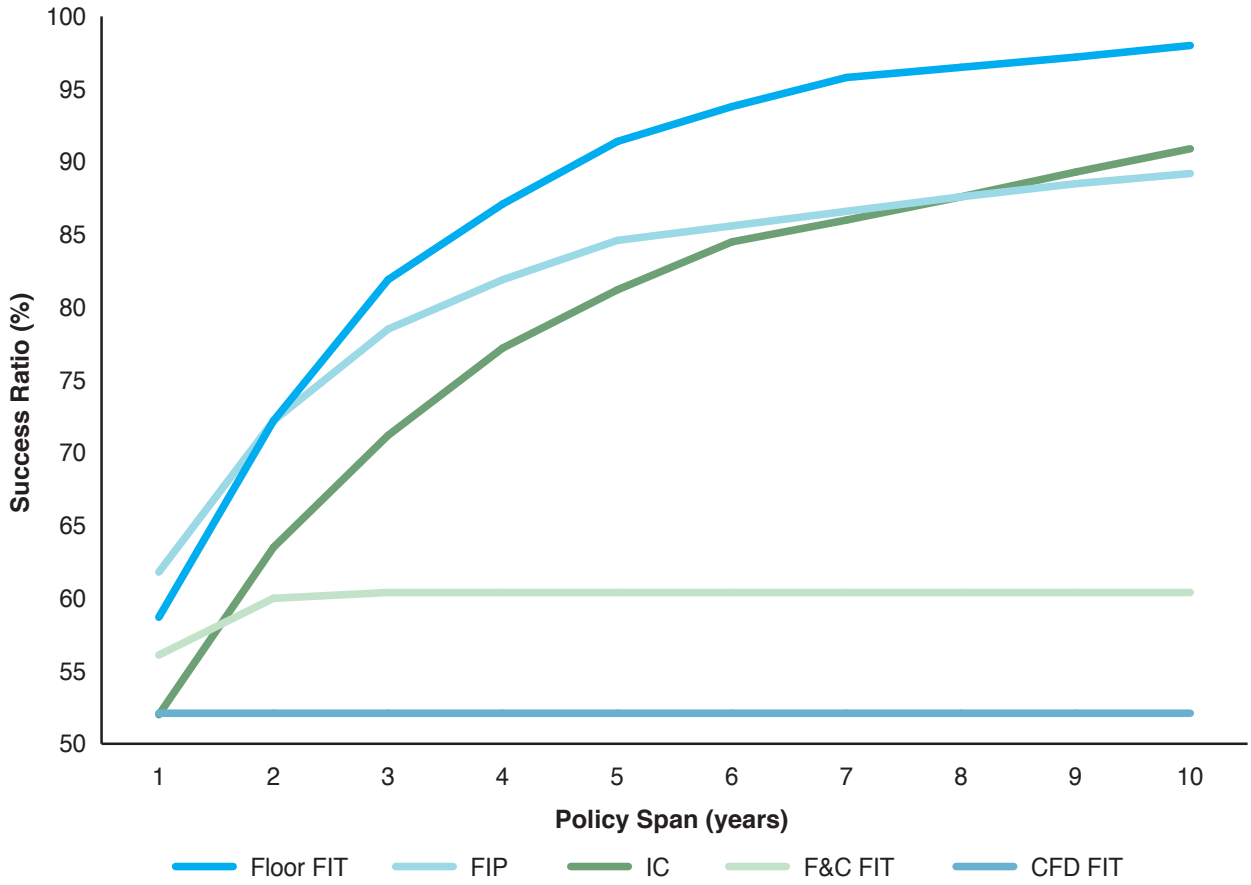

Figure 6. Success ratio under different policy spans.

Source: KAPSARC analysis.

1 to 5 years. Inversely, when the policy reaches the 7 to 10 year mark the success ratio only has incremental improvements.

Figure 7 illustrates the relationship between the success ratio and changes in the electricity price drift. There is a positive relationship between success ratio and electricity price. Higher prices in the future improve the profitability of current projects, resulting in a higher number of projects commissioned. In the case of the CFD FIT the success ratio is constantly at 52 percent, since investors cannot take advantage of higher prices.

The high success ratio of Floor FIT is due to the structure of the instrument, which creates asymmetric incentives regarding electricity volatility. Investors like this instrument because a minimum yield is guaranteed in addition to profits from uncertanty and volatility. A potential policy insight from this experiment is that policy support can be lower if investors expect higher electricity prices.

Policy length and price drift play an equally important role in expediting the success of adoption. Higher drift and a longer timeframe lead to a higher success ratio. The sensitivity analysis suggests

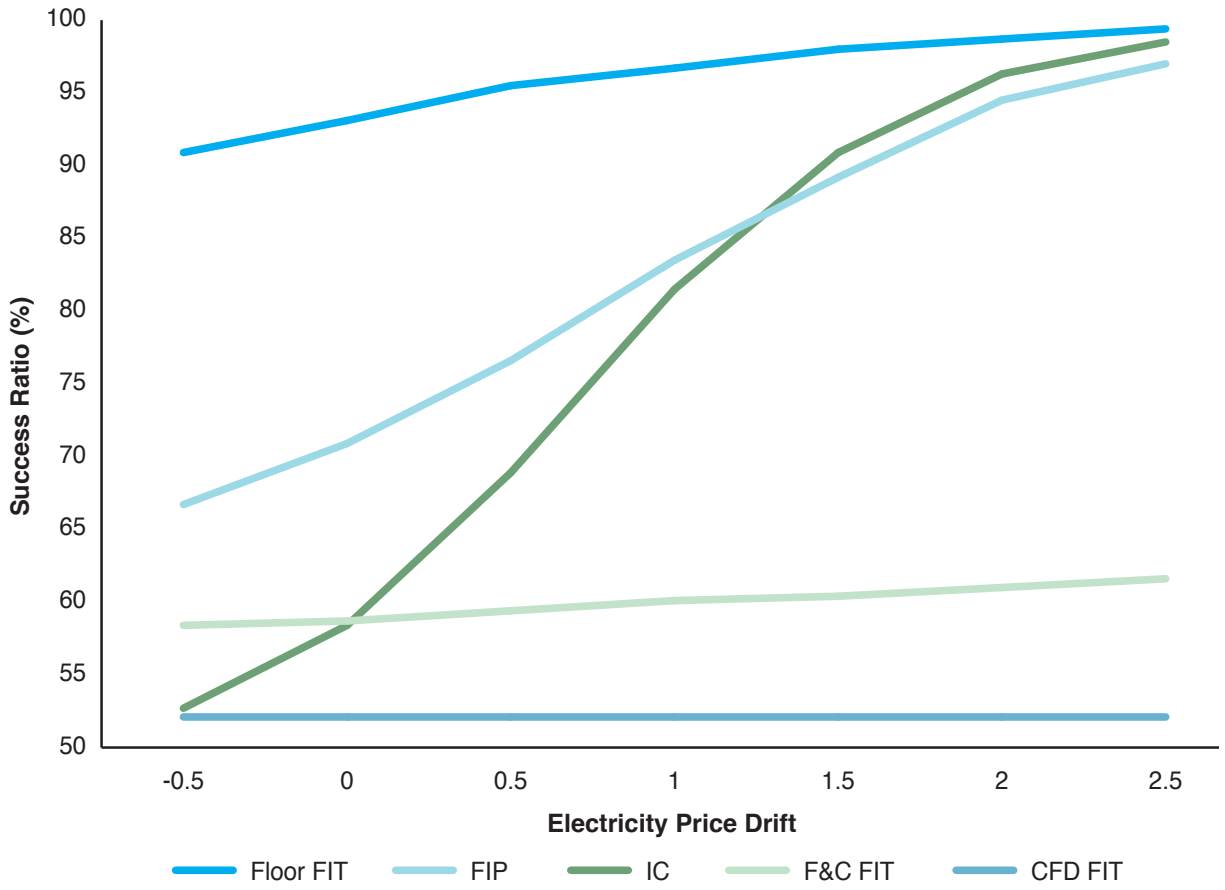

Figure 7. Success ratio under different electricity price drift.

Source: KAPSARC analysis.

that the impact on the success ratio differs for each policy. For the CFD FIT, the policy lifetime, and electricity price drift are irrelevant to the investor's decision to enter the market. However, for both the FIP and IC the policy lifetime and electricity price drift play a key role, where the more the drift and the longer the timeframe the higher the success ratio.

Table 2 illustrates the relationship between the average WACC of the distribution and the success of adoption. In this case we obtain a counterintuitive result: the higher the WACC the higher the speed of adoption, an insight represented in the table above. As the WACC increases the success ratio halfway through the timeframe (60 months), the policy decreases.A lower WACC increases the NPV of a project, but at the same time it generates an incentive to wait since investors value future revenues more.

A lesson from this experiment is that policies that reduce the WACC, like subsidized loans, benefit investors since they increase thenet present value of the projects, but delay the commission of the projects.

Figure 8 shows the cost of the policy per megawatt (MW) deployed under different price drifts. The success of the policy depends on price drift. As previously mentioned, low drift leads to a lower adoption of the technology, which in turn leads to lower total cost of policies. For this reason Table 2 focuses on the cost per MW deployed. It illustrates that the higher the drift the lower the cost per MW deployed. The reason for this is that as price of electricity increases, the need for financial support decreases, which results in a lower burden on ratepayers.

Table 2. Success ratio under different electricity price drift.

Ratio of adopters halfway through the policy (60 months) [total policy span 10 years]

WACC (%)	*6*	*6.5*	*7*	*7.5*	*8*	*8.5*	*9*	*9.5*	*10*
CFD FIT	52.1	52.1	52.1	52.1	52.1	52.1	52.1	52.1	52.1
Floor FIT	99.9	99.7	99.6	99.3	99.3	98.8	98.5	98.1	97.7
F&C FIT	63.2	62.4	61.7	61.2	60.6	60.1	59.8	59	58.6
FIP	98.1	97.5	97.1	96.7	96.2	95.5	94.9	93.3	91.9
IC	99.3	99.3	98.7	98.5	98.1	97.9	97.1	96.8	96.3

Source: KAPSARC analysis.

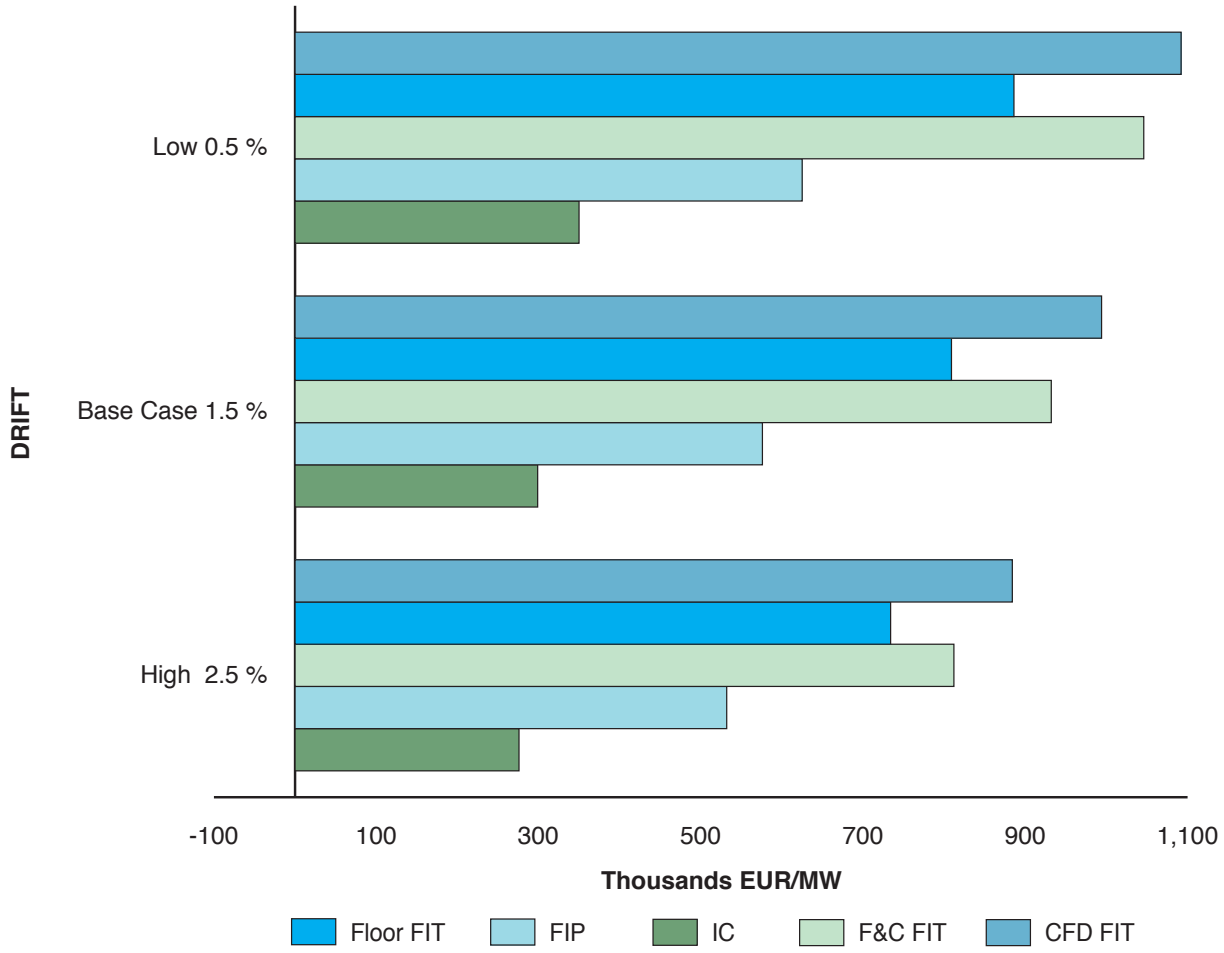

Figure 8. Total cost of policies (Thousand EUR / MW) given drift of electricity prices.

Source: KAPSARC analysis.

Conclusion

Understanding that these policy instruments cannot 'kill two birds with one stone', governments and policymakers must decide what they wish to achieve; large deployment of renewables, accelerated speed of adoption of renewables, or cheap cost of renewable policies. With this objective in mind, this study shows how different policy instruments affect these three parameters that define a policy.

According to our results, based on current market conditions in Europe, it is possible to design a feed-in premium, a feed-in tariff and an investment credit policy that achieve similar levels of total deployment of renewable technology. Under these conditions, policymakers can focus on the cheapest policy instrument, which is an investment credit. While investment credits are the most attractive policy instruments from a cost minimization point of view, a contract-for-differences feed-in tariff is the best policy instrument (even though it is the most expensive), if the objective is to accelerate the deployment of renewables.

Furthermore, as goverments extend the duration of a policy, the deployment of renewables increases. This result is driven by the reduction in the cost of the technology over time. Similarly, policy support can be reduced if investors expect an increase in electricity prices. Investors benefit from higher drift in prices and are more willing to invest given the same level of policy support.

Perhaps unexpectedly, the analysis suggests that cheap loans, which reduce a project's WACC, lead to a reduction in the speed of adoption. Subsidized loans can be attractive for investors since they increase the net present value of the projects while, at the same time, they generate an incentive to wait before entering the market.

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Appendix I

This study utilized a model that involves the following tools, geometric Brownian motions (GBM), partial differential equations (PDE) and expected present values (EPV). The GBM process was used to represent wholesale electricity prices, whereas the EPV term structures were constructed from the analytical solutions of certain PDEs. The link between the GBM process and the PDEs were established through the Feynman-Kac theorem. Using a closed-form solution in this analysis allows for the comparison of different policies in a speedy manner. Additionally, closed form solutions yield results free of Monte Carlo simulations convergence problems and extreme computational requirements.

The Brownian Electricity Market

We assume the wholesale electricity price to follow a geometric Brownian motion (GBM).

$$dS_t = \mu S_t dt + \sigma S_t dW_t$$

With drift μ and positive volatility σ, the GBM process admits a closed form solution.

$$S_t = S_0 exp\ (\mu t + \sigma W_t)$$

With W_t being a single-dimensional standard Brownian motion parametrized by time $t \geq 0$. We find supporting evidence in the literature (for example Pindyck 2001) that while short-term energy and commodity prices exhibit mean reversion, the long-term prices however exhibit a drift term, which nullifies the mean reversion, hence making the GBM appropriate for this modeling exercise. It is important to remember that policymakers in general do not base their policies on daily changes in prices, but on longer timespans such as monthly or annual variations. Additionally, the GBM process is tractable, and the functionality of the GBM process often admits a closed form solution.

From Expected Present Values to Adoption Curves

We assume that the policymaker sets a time-deterministic feed-in-tariff (FIT) policy with a floor $K_1\ (t)$ *and a cap* $K_2\ (t)$, *with* $K_2\ (t) \geq K_1\ (t)$, such that the government compensates investors for the difference between the floor and the traded price if the traded price is below the floor. The government allows investors to receive the traded prices when the traded price is between the floor and cap levels, and receives the difference between the traded price and the cap should the traded price exceed the cap. Under this general scenario, the guaranteed price an investor receives is

$$V_t = min\ (k_2(t), max\ (k_1\ (t), S_t))$$

It is crucial to find the expected guaranteed electricity price $\mathbb{E}[V_T|V_0]$ conditional on the known starting point V_0 as it forms a necessary component in building the term structure of expected present values which determine an investor entry point.

We can solve this conditional expectation by using the Feynman-Kac theorem, then one arrives at the following partial differential equation (PDE),

$$\partial_t V + rS\partial_S V + \frac{S^2\sigma^2}{2}\partial_S^2 V - rV = 0$$

With the terminal condition $V_T = min\ (k_2(T), max\ (K_1\ (T), S_T))$, and no other boundary conditions.

Black and Scholes (1973) proposes the same PDE, but with a different terminal condition to price European options. The PDE above admits the following closed form solution for any time t

$$V_t = Z_1(t,K_1(t)) + Z_2(t,K_1(t),K_2(t)) + Z_3(t,K_2(t))$$

With the functions { Z_1, Z_2, Z_3 } are given by

$$Z_1\ (t,K_1\ (t)) = e^{-rt}\ K_1\ (t) N(-d_2(K_1\ (t)))$$

$$Z_2\left(t, K_1(t), K_2(t)\right) = S_0 e^{(\mu - r)t}$$

$$\left[1 - N\left(-d_1\left(K_1(t)\right)\right) - N\left(d_1\left(K_2(t)\right)\right)\right]$$

$$Z_3\ (t,K_2\ (t)) = e^{(-rt)}\ K_2\ (t) N(d_2\ (K_2\ (t)))$$

With the functions $\{d_1\ (K), d_2(K)\}$ given by

$$d_1(K) = \frac{\ln\left(\frac{S_0}{K}\right) + \left(\mu + \frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}}; \quad d_2(K) = d_1(K) - \sigma\sqrt{t}$$

And the $N(x)$ being the standard Gaussian cumulative density function given by

$$N(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{\frac{-y^2}{2}} dy = \frac{1}{2}\left[1 + \mathrm{erf}\left(\frac{x}{\sqrt{2}}\right)\right]; \ \ \mathrm{erf}(x)$$

is the Gaussian error function.We need to emphasize that for each investor (i) we apply a different discount rate $r = r_i$.

In addition to the floor-cap FIT policy, the solution above also accommodates two other types of FIT policies: firstly the Floor FIT (policy with no cap), where the government does not claim back anything from investors no matter how high the traded price might become. In this case we set $K_2\ (t) = \infty$.

The other type is the contract-for-difference (CFD) where there is only one (floor) FIT level $K_1\ (t)$ such that the government compensates investors for when the traded prices are below the floor and reclaims all the differences for when the traded prices are above the floor level. In this case we set $K_2\ (t) = K_1\ (t)$. As such the CFD policy transfers all the market risk to the government, making the investors constant per MWh. Under a FIP scheme, $\mathbb{E}[V_t] = a + S_0 e^{\mu t}$, where a is the FIP level. Under an IC scheme, there is no guaranteed price V_t; the policy merely discounts the capital expenditure, hence reduces the LCOE, and as such the only expression we have is the $\mathbb{E}[S_t] = S_0 e^{\mu t}$. Finally, floor & cap (F&C) FIT policy with $K_2\ (t) \geq K_1\ (t)$.

We assume a risk-neutral, profit-maximizing population of investors. A typical experiment consists of 1,000 projects (or investors) with discount rates (WACC) and initial project LCOE sampled from 2 different normal distributions with means and standard deviations that are fitted from a recent database on wind turbine projects in Spain.

A typical investor will calculate the expected present value of her project at all admissible entry months (hence form the EPV term structure), then she decides to enter in the month at which the EPV is at its maximum. This procedure is repeated for all investors/projects in order to construct the adoption curve. The expected present value for each project is given by

$$H(t_1(i)) = \max_{t_1 \in [1, T_1]} \sum_{t=t_1}^{t_1+T_2} e^{-r_i t}\left(\mathbb{E}[V_t(i)|V_0] - L_{t_1(i)}\right)$$

Where $t_1\ (i)$ is the entry month of investor (i), T_1 is the policy span in months (assumed 120 months in most cases considered), T_2 is the project lifetime in months (typically 240 months), and $L_{t1(i)}$ is the

levelized cost of electricity (LCOE) at the entry month for that particular project. Upon entry at time $t1 \varepsilon [1,T_1]$, the investor gains a monthly stream of payoffs for each month in the lifetime of the project T_2 . The payoff for each month is random and is found using the solution of the PDE mentioned earlier.

We have to note that under the Floor FIT and F&C FIT policies guaranteed prices are affected by both the drift and volatility of prices, hence the EPV term structures and the expected entry times are also affected by both Brownian parameters. However, EPV term structures and expected entry times under the feed-in premium, defined as a constant premium added on top of the market price, and under the investment credit, defined as a discount on initial investment, are only affected by the drift parameter (as the volatility plays no role in the expected electricity prices). The most degenerate case when it comes to EPV term structures is the CFD FIT policy, as the expected electricity guaranteed prices under it are a constant number, hence making the adoption of technology under the CFD FIT policy independent of both parameters.

The Expected Policy Cost

The expected policy cost is calculated, conditional on adoption. This means, if no projects are constructed following the implementation of the policy, then the conditional expected cost of the policy on taxpayers is zero. To begin, we obtain the entry times and adoption curve as explained in the previous section. The expected cost formulas we present are scalable, and are presented by default per MWh.

The expected cost of the floor & cap type FIT policy is given by

$$C_t = \sum_{t=t_1(i)}^{t_1(i)+T_2} e^{-r_g t} \begin{pmatrix} \mathbb{E}\left[(K_1(t) - S_t)\mathbf{1}_{S_t<K_1(t)}\right] \\ -\mathbb{E}\left[(S_t - K_2(t))\mathbf{1}_{S_t>K_2(t)}\right] \end{pmatrix}$$

$$= \sum_{t=t_1(i)}^{t_1(i)+T_2} \mathbb{E}[G_t]$$

$\mathbb{E}[G_t]$ can be solved by using the same PDE mentioned earlier but with a different terminal condition, i.e.,

$$\partial_t G + rS\partial_S G + \frac{S^2\sigma^2}{2}\partial_S^2 G - rG = 0$$

With the terminal condition $G_T = max(0,K_1(T)-S_T)-max(0,S_T-K_2(T))$. Again, fortunately $\mathbb{E}[G_t]$ admits a closed-form solution, hence the expected policy cost formula per MWh becomes

$$C_t = \sum_{t=t_1(i)}^{t_1(i)+T_2} \mathbb{E}[G_t]$$

$$= \sum_{t=t_1(i)}^{t_1(i)+T_2} P_1(t,K_1(t)) - P_2(t,K_1(t)) - P_3(t,K_2(t)) + P_4(t,K_2(t))$$

With the functions $\{P_1,P_2,P_3,P_4\}$ are given by

- $P_1(t,K_1(t)) = K_1(t)e^{-r_g t}N(-d_1(K_1(t)) + \sigma\sqrt{t})$
- $P_2(t,K_1(t)) = S_0 e^{(\mu-r_g)t}N\left(-d_1(K_1(t))\right)$
- $P_3(t,K_2(t)) = S_0 e^{(\mu-r_g)t}N\left(d_2(K_2(t))\right)$
- $P_4(t,K_2(t)) = K_2(t)e^{-r_g t}N(d_2(K_2(t)) - \sigma\sqrt{t})$

With the same functions $\{d_1(K), d_2(K)\}$ given previously. Let r_g be the governmental discount rate (assumed 4 percent annually in our experiments).

The calculation of the feed-in premium policy cost is considerably easier. For a constant feed-in premium level (a), the policy cost is

$$C_t = \sum_{t=t_1(i)}^{t_1(i)+T_2} (ae^{-r_g t})$$

As for the investment credit policy cost, let the initial investment discount rate be (h), and the project capacity be (M), the initial investment of investor (i) at their investment time be $(B_i(t_1(i)))$ then the policy cost is given by

$$C_t = \sum_{t=t_1(i)}^{t_1(i)+T_2} e^{-r_g t} M(1-h)[B_i(t_1(i))]$$

It is important to note that the FIT policy cost is affected by both the drift and volatility of the electricity prices (even the CFD FIT). However the FIP and IC policies costs are functions of the drift parameter only (through the investor entry time $t_1(i)$, which is a function of the drift even though the policy cost formula does not show the drift term explicitly).

Appendix II

Figure 1 below illustrates the EPV term structure for three categories of projects: early adopters, typical projects and laggards. The first chart is a representation of two projects commissioned in the middle of the policy timeframe. The second represents the EPV structure for an early adopter. Finally, the third chart represents the EPV term structure for the laggards.

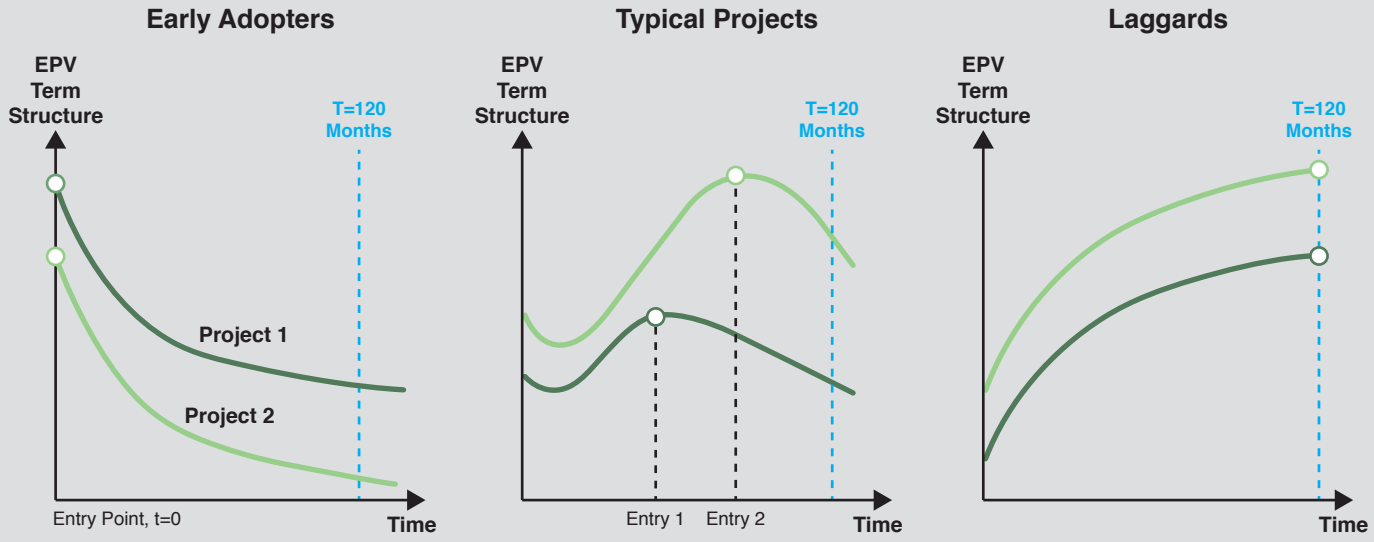

Figure 1. EPV term structures.

Source: KAPSARC analysis.

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About the Project

This project explores how different policy instruments perform under varying market conditions. We focus on most popular instruments such as feed-in tariffs, feed-in premiums and investment credits. These policy instruments have a different impact on private investor's behavior, resulting in different levels deployment of renewable technology, different speeds of adoption and different costs to taxpayers and ratepayers. The objective is to understand how private investors make decisions on renewable energy to help policymakers to choose the best policy to achieve their objectives.

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