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Who bears the risk? Incentives for renewable electricity under strategic interaction between regulator and investors

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ABSTRACT

Energy policies for promoting investment in renewable energy sources have become crucial for deploying green energy technologies worldwide. Conventional incentive systems assign risk to either policymakers or investors. In this paper, we combine option theory and game theory to obtain optimal parameters for incentive schemes with different degrees of risk-sharing. We present an empirical application to the Spanish electricity market for 2013, when the Feed-in Tariff scheme was still in force, and for 2019, when Feed-in Tariffs had been completely phased out but before the demand shock caused by COVID-19, the restructuring of market price limits, and the recent energy price crisis in Europe. Our results indicate that there are more flexible systems based on Fixed Tariffs and Premiums that can outperform conventional designs, since they may enable the same investment level to be reached at a lower regulatory cost. In addition, these hybrid schemes permit risk-sharing between both parties. Our results may also be useful for designing incentives awarded through competitive auctions.

1. Introduction

One of the biggest concerns at present is how to achieve a sustainable, clean energy system. To a greater or lesser extent, many countries worldwide have set the goal of fighting global pollution and have stopped relying on fossil fuel reserves, which are not only increasingly limited but also responsible for emitting polluting gases into the atmosphere. Although significant advances have been made in this regard, there is still a long way to go before a fully green, sustainable energy scenario is reached. The deployment of some Renewable Energy Sources (RES) is still more costly than that of other conventional sources, so a public subsidy is often required to create a feasible, attractive investment environment. Indeed, support policies and continual cost reductions are expected to be the main drivers of RES deployment in 2020–2025, particularly in the case of wind power (IEA, 2020).

There are numerous support schemes to promote green energy penetration worldwide. Renewable Portfolio Standards set an obligation on electricity suppliers to produce a specified fraction of their electricity from RES and may be supplemented by Tradable Green Certificates. These tradable assets are issued to RES producers, who obtain revenue by selling them to conventional energy suppliers so they can meet the quota set in the Renewable Portfolio Standard. Other support schemes include partial, or even full, exemptions from some taxes and levies for green energy producers.

Feed-in Tariff (FiT) schemes have become the preferred renewable energy support mechanism in many markets, as they provide greater certainty of remuneration for investors, which is particularly useful at the early stages of RES promotion (Hitaj and Löschel, 2019). FiT subsidies are usually based on a fixed tariff or premium. A fixed FiT scheme is a mechanism that allows RES producers

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to sell electricity at a fixed price for a given period. In a Feed-in Premium (FiP) scheme, however, the payment to RES suppliers is based on a constant premium above the system marginal price. Over the last 20 years, FiT policies have been a crucial driver for renewable power deployment in several countries. Cases in point of the positive effect of these incentive mechanisms on renewable capacity are Germany, China, Denmark, and Spain. FiT/FiP subsidies have been key for renewable energy penetration and may still play a role as long as they are carefully designed. Indeed, according to REN21 (2021), by the end of 2020 many countries worldwide had FiT/FiP in place as a support policy for RES.[1]

By contrast, there are also cases where FIT schemes have failed, possibly because of improper design (Japan, Argentina, and Indonesia, see Maekawa et al., 2022 and Guild, 2019). The main downside of such policies is that they often involve very high regulatory costs. For instance, in 2015 alone, the total expenditure for renewable energy support in the European Union and Norway was more than $65 billion, of which 37% came from FiT support and 32% from FiP policies (IRENA, 2018). Another implication of FiT/FiP type incentives is that they can alter the behavior of RES plants in the daily wholesale market, affecting the bids made and, for example, inducing the formation of negative prices (Pahle et al., 2016).

In some countries where there is already significant penetration of these RES technologies, investment costs have been gradually decreasing (Neuhoff et al., 2022). Several of those countries have thus been progressively transitioning from a system based on FiT/FiP schemes to others based on competitive auctions for new capacity. This is the case for Spain in 2013 (Ciarreta et al., 2014b). By 2020, auction-based support schemes had been introduced by several European countries to incentivize renewable energy production. However, the design and features of these auctions differ from country to country and over time, as most countries are still experimenting and adjusting their auction setup to enhance effectiveness and efficiency (Szabó et al., 2021). Although several of these auctions have been significantly successful in different markets recently, there is still a lack of evidence that they should be the main instrument of support at global level (Winkler et al., 2018). According to IEA, 40% of new wind capacity worldwide for 2020–25 is expected to be supported by government-set tariffs and 35% by auction schemes (IEA, 2020).

From the investor's perspective, the main drawbacks to the development of RES are their high capital costs (although they are decreasing over time), high investment risks, and uncertain returns. A major source of uncertainty in RES investment is reflected in volatility in both market prices and RES production levels, given that output is random due to the intermittent nature of some RES (e.g. solar and wind power). This in turn affects the volatility of electricity prices. Other sources of uncertainty are linked to the penetration of new electricity generation technologies and regulatory changes. The regulator must assess the costs and benefits of different incentive schemes taking into account decisions by investors under uncertainty.

In this context, option pricing techniques appear to be an appropriate tool for assisting in decision-making processes in RES investment; unlike traditional pricing methods such as discounted cash flow approaches, they enable investment opportunities to be valued according to their volatility (Lee and Shih, 2010). Several authors have applied option theory to the study of electricity markets and incentive schemes: Keppo and Räsänen (1999) use option pricing for retail electricity tariffs when consumption and wholesale prices are uncertain; Lyle and Elliott (2009) develop a model for pricing electricity derivatives; Haar and Haar (2017) employ option theory to quantify the costs of hedging and pricing the exposure faced by purchasers of renewable electricity; other authors use real-option theory to analyze different FiT schemes (e.g. Boomsma et al. 2012, Ritzenhofen and Spinler 2016, Lin and Wesseh 2013).

The optimal reaction of investors to policies has to be taken into consideration for FiT-based policies to be effective. Indeed, the strategic interaction between the regulator and investors may be an important element of the problem and some authors have used tools from game theory to characterize the outcome. Kim and Lee (2012) simulate the performance of a FiT program explicitly considering investors' payoff structure and the parameters relevant to the optimal response to regulation. Chang et al. (2013) use the Stackelberg sequential game framework to analyze the FiT scheme in which a conventional power plant purchases power from a small green power plant. Barbosa et al. (2018) analyze a FiT contract with a minimum price guarantee as a sequential game between policy-makers and investors. Papers on other support schemes include Zhu et al. (2021), who model renewable auctions for investors using both real-option theory and game theory.

Farrell et al. (2017) combine these two important elements of the problem-option theory and game theory-to model the optimal policy design problem as a strategic leader-follower game in which the policymaker optimally sets the parameters of the different incentives. In this paper, we follow that approach to analyze whether newly designed incentive systems could improve upon the usual FiT/FiP schemes. Moreover, these more flexible tariffs share market price exposure between regulators and investors. To that end, we extend the original model in different directions. First, in our model volatility depends on the penetration of renewables, so volatility is endogenous to the investor's optimization problem. Second, we take into account how penetration affects the likelihood of prices reaching a particular level. Finally, we allow for non-zero initial capacity. In our paper, we show that the incorporation of these new parameters into the model has a qualitative and quantitative impact on the expected value of the costs and benefits of the different incentive systems.

We also provide an analytical solution for the strategic interaction between the regulator and investors in the extended model. Along with the three policies discussed by Farrell et al. (2017) (i.e. Constant Premium, Shared Upside, and Cap & Floor), we also consider a Fixed Tariff which can be considered as a particular case of the Shared Upside and Cap & Floor and the benchmark case of No Subsidy. Finally, we apply our model to the Spanish electricity market in two years with different regulatory environments: 2013, when the FiT/FiP scheme was still in force; and 2019, after it had been abolished but before the demand shock caused by COVID-19, the recent energy price crisis in Europe, and the restructuring of market price limits (see BOE, 2021). In 2019, companies invested

[1] See Table 6 in REN21 (2021) for the list of countries.

in wind energy without public subsidies as market incentives were sufficient. In energy auctions held at that time participants were willing to invest in wind energy at market prices. Lower installation costs, higher electricity prices, and decreasing WACC were the main reasons for this. We focus on wind technology for several reasons. Firstly, it is by far the biggest renewable technology in Spain and will continue to be so. Secondly, incentives for technologies such as solar were so high in Spain that the probability of the average annual electricity price approaching those levels was practically zero. Finally, in Spain, wind energy had a financing mix of approximately 70% FiP and 30% FiT, while almost 100% of solar energy was under FiT. Overall, renewable resources that have a stronger correlation between their output and market prices have a higher likelihood of being embraced under a FiP rather than a FiT.

Irrespective of whether incentives are established by governments or auctions, they can be classified based on the payment mechanisms utilized. Indeed, most auctions involve a fixed price per MWh or a premium over the market price, except that in this case, contrary to conventional FiT and FiP schemes, these amounts are not predetermined by the regulator but are established in the auction itself (Szabó et al., 2021). Moreover, some renewable energy auctions are held with a secret price cap which is set by the auction organizer. This reserve price is the maximum price that a bidder can bid to qualify for project selection. Failing to correctly set this maximum price may jeopardize the auction results. The recently published results of the 2022 Spanish onshore wind auction revealed a disappointing outcome, with only 46 MW of new wind energy capacity awarded out of a total of 3.3 GW up for tender. The auction was conducted with a price cap. When designing the auction, the regulator failed to consider the increased costs of new wind energy projects due to current inflation, supply chain bottlenecks, and high raw material and shipping costs (WindEurope, 2022). This combination of factors resulted in a flawed auction outcome.

In our model, we assume away the problem of asymmetric information between investors and the regulator when calculating the optimal incentive level. In this context, if the regulator were to hold an auction, it would just set the reserve price at that optimal level and the outcome would be equivalent to a fixed incentive regime. Thus, under the assumptions of the model, our optimal parameters would also solve the problem of the optimal reserve price in an auction. The reason why the regulator may want to use an auction instead has to do with asymmetric information and the fact that an optimally designed auction may be a cost-revealing (truth-telling) mechanism and therefore more efficient in an asymmetric information context. The case of asymmetric information is outside the scope of this paper and would require a thorough analysis to determine the optimal value of the reserve price. However, if the regulator has good information about the cost but there is a small probability that the cost may be lower, it would make sense to set the reserve price of the auction at the optimal incentive level from our model and give the chance to investors to bid lower in the event that costs are lower than estimated by the regulator.

The results of our empirical application indicate that there are hybrid incentive schemes based on FiT/FiP that can outperform current FiT/FiP designs, since they may enable the same investment level to be reached at a lower regulatory cost. Our methodological approach could be implemented in any country facing similar challenges regarding RES regulation. Furthermore, our results have interesting policy implications for future renewable energy support, since the implementation of more flexible incentive systems opens up a range of possibilities, such as possible efficiency improvements or the possibility of risk-sharing, that should be taken into account in the design and/or updating of the next generation of incentive schemes.

The paper is organized as follows. Section 2 reviews different designs for FiT/FiP schemes and how risk is distributed between the regulator and investors under each one. Section 3 describes our methodology and the mathematical model. Section 4 calibrates the model with data from the Spanish electricity market and Section 5 presents the results of the numerical application. Section 6 discusses the main results and their policy implications. Section 7 concludes.

2. Risk distribution according to the incentive scheme design

When dealing with FiT/FiP policies, risk can be assigned to regulators or investors differently according to the scheme structure. Under a Fixed Tariff (FiT) scheme, it is the policymaker who is exposed to the risk associated with market price fluctuations, while investors' profits per MWh are fixed. By contrast, under a Constant Premium regime (FiP) scheme the policymaker's costs per energy unit are fixed while RES investors' profits per unit are fully exposed to market price fluctuations.

Between these two extremes, various intermediate policies can be designed which are a function of the stochastic market price and which permit risk-sharing (Couture et al., 2010), e.g. a Shared Upside scheme and a Cap & Floor scheme. From the investor's perspective, both provide minimum payments with certainty and some room for receiving additional profits from high market prices. From the policymaker's perspective, these tariffs imply commitment to a minimum subsidy payment but in the case of high market prices the cost of the subsidy would be reduced.

Fig. 1 shows how these four schemes work. We represent the evolution of the market price of electricity and the revenue per MWh that a renewable energy investor receives under each policy. Thus, the area denoted as **I** represents the total cost of the subsidy for the policymaker and the total area (**I**+**II**), corresponds to the total revenue that the investors will receive.

As shown in Fig. 1(a), a Fixed Tariff scheme prevents investor exposure to low market prices, leaving the policymaker as the one who bears the risk of market price variability. By contrast, Constant Premium policies remove the policymaker's risk. As shown in Fig. 1(b), under a FiP scheme, area **I** is independent of the market price. Since the premium (denoted as Δ in the figure) is independent of stochastic market prices, the policymaker has certainty about the cost per MWh that the public subsidy will entail when designing the policy. However, under a FiP scheme, investors are exposed to the full impact of market price fluctuations. The effectiveness of FiTs has been attributed to the reduced risk that they entail for investors (OECD, 2008), so transferring all the risk to them might be counterproductive. The conclusion is that adequate management of these risks is of capital importance when designing public subsidy policies to promote RES penetration.

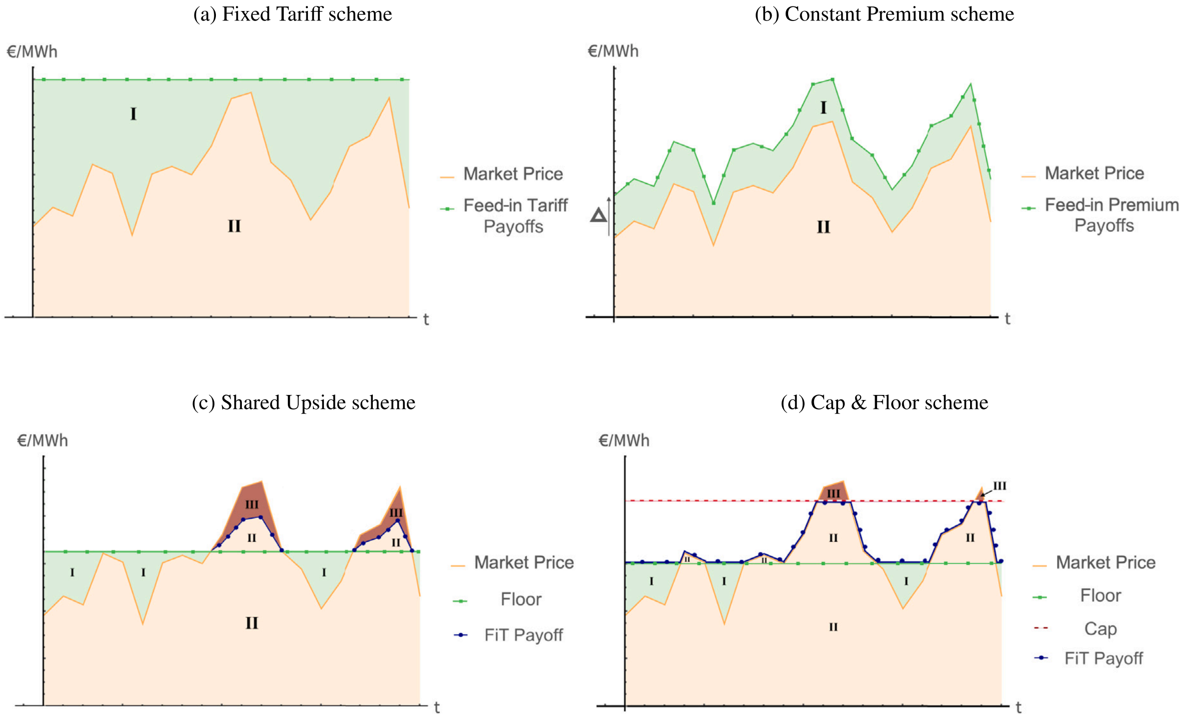

Fig. 1. Feed-in Tariff performance according to design.
Source: Own work.

Fig. 1(c) represents the Shared Upside subsidy, consisting of a guaranteed minimum price that investors receive if the market price falls below a given floor. If, by contrast, the market price exceeds that floor, the investor and the policymaker share the excess remuneration according to a predefined rule, which may range from 0% to 100%. For example, in the case depicted in Fig. 1(c), the shares are 50% each. The shaded area **III** represents the proportion of the market excess revenue recovered by the regulator.

Finally, Fig. 1(d) illustrates how the Cap & Floor scheme works. Under this scheme the investor receives a guaranteed minimum price as long as the market price is lower than the floor, and a maximum price if the market price exceeds the cap. When the market price is higher than the floor but lower than the cap, the investor receives the full market price.

3. The model

In this section we characterize the optimal policy design using the tools of game theory and stochastic financial calculus. First (Section 3.1), we model electricity prices considering that both the drift and volatility of annual wind electricity prices depend on the penetration of wind power. Second (Section 3.2), following Farrell et al. (2017), we model the policy design problem as a strategic leader-follower game where the policymaker (leader) takes into account the strategic response of the investors (followers) for each tariff design under consideration. Third (Section 3.3), we solve the stochastic model to find analytical solutions for the evolution of expected profits and policy costs under different schemes: (1) No Subsidy (benchmark); (2) Fixed Tariff; (3) Constant Premium; (4) Shared Upside; and (5) Cap & Floor. Considering the expected evolution of profits and policy costs, the regulator chooses the optimal tariff parameters that promote the desired quantity of RES deployment at the lowest possible regulatory cost.

3.1. A stochastic model for electricity prices and output

The evolution of market prices of electricity is uncertain. We model that uncertainty through a stochastic process. Renewable energy investment is a long-term decision, so long-run price trends are particularly relevant, even when analyzing markets where electricity prices have hourly, daily, or monthly fluctuations. Similarly, policymakers do not base their decisions on daily electricity price fluctuations but rather focus on longer periods such as annual periods. Moreover, considering annual time-steps avoids undesired intra-annual seasonal effects (which are highly noticeable in electricity markets). These are some of the reasons why the approach of assuming that long-term electricity prices follow a Geometric Brownian Motion (GBM) process has been widely used in the literature (see for example Blazquez et al., 2018b, Farrell et al., 2017, Zhu, 2012, Haar and Haar, 2017, Tolis and Rentizelas, 2011, and Hou et al., 2017).

For generation sources such as wind, the amount of electricity generated varies greatly depending on the time of day: for example, wind can blow very differently at night from during daylight hours. On the other hand, electricity demand is lower at night, so the market price is usually lower. Thus, a more representative measure of the prices received by a wind-power supplier is the Volume-Weighted Average Price (VWAP), where each hour's price is weighted according to the amount of electricity generated by that technology at that hour.

Denote the VWAP at time t by S_t.[2] After a time interval dt, the price will change by an amount dS_t. Assuming a GBM process, the corresponding change in the price breaks down into two contributions: On the one hand there is a deterministic contribution given by a function μS_t, where μ is the drift of the process (i.e. the average trend of growth). On the other hand there is a random contribution to price change in response to unexpected external effects, given by the product of the deterministic function σS_t, where σ is the volatility of the process, and the differential dW_t containing the randomness, which is modeled as a Wiener process (see Franke et al., 2004):

$$dS_t = \mu(Q)S_t dt + \sigma(Q)S_t dW_t \tag{1}$$

As shown in Eq. (1), these coefficients are allowed to depend on the total amount of wind capacity installed (Q). The electricity market price tends to decrease with the penetration of RES such as wind or solar, given that they bid at low prices (De Miera et al., 2008). Moreover, with increasing renewable penetration more volatility is to be expected due to their intermittent nature (see for example Dong et al., 2019 or Ballester and Furió, 2015). Hence, the annual percentage drift μ and volatility σ, will eventually depend on the installed capacity Q. That means that these two parameters will be endogenous to the investor's optimization problem. This is the main difference between the approach in Farrell et al., 2017, where the latter parameter is assumed to be fixed, and our model (see Appendix B for a comparison between the two).

Wind generation is random, and therefore so is the amount of wind electricity generated by suppliers, but we approximate the aggregate expected annual wind generation $g(Q)$ for each period as a deterministic concave function of the capacity Q. The unitless parameter γ captures the decrease in generation per unit installed as capacity increases, due to limited site and resource availability: $g(Q) = Q_{max}\kappa(1 - e^{-\gamma Q})$, where Q_{max} is the wind deployment potential (i.e. the maximum wind capacity that it is technically feasible to deploy), κ is the amount of equivalent operating hours.[3] For the sake of simplicity, we assume that these parameters are constant over time. As a consequence, the electricity expected to be generated will also be identical in all periods. At the time the investment is made there are already Q_0 units installed, so during each period of operation the additional electricity generated by the deployment of the new extra capacity (Q) can be expressed as:

$$G(Q) = g(Q_0 + Q) - g(Q_0) = Q_{max}\kappa(e^{-\gamma Q_0} - e^{-\gamma(Q_0+Q)}) \tag{2}$$

The consideration of a preinstalled wind capacity Q_0 is also an extension of the model in Farrell et al. (2017).

3.2. A game theoretic approach to wind energy investment

Following the approach proposed by Chang et al. (2013), Farrell et al. (2017) characterize the optimal FiT mechanism by modeling the process as a Stackelberg sequential strategic game, in which the policymaker (leader) moves first, choosing the FiT, and then the investors (followers) implement their strategy (investment level) after observing the FiT selected by the leader.

The objectives of the regulator and the investors. We assume that there are currently Q_0 operating units of wind energy (measured in MW) and that the policymaker wishes to incentivize investment for the deployment of at least Q_I additional units. The regulator's objective is to implement Q_I at the lowest regulatory cost possible. On the other hand, we model the investors' decision problem as the optimization of expected returns. Under this assumption, their objective is to maximize at time $t = 0$ the total discounted profits of the potential investment. We model the total investor's costs as the sum of the capital costs (A) incurred in period $t = 0$, plus the discounted maintenance and operation costs (O), which are incurred during the operative lifetime of the wind turbines installed (T_F). We assume that the maintenance and operation costs are constant and identical, reflecting the current state of technology at the time of installation. Thus, the total production costs per MW (C) are calculated as: $C = A + \sum_{t=1}^{T_F} e^{-rt}O$, where r is the fixed interest rate (discount rate).

We assume that investors are homogeneous and competitive, so we have aggregated their decision problem. In this model there is no strategic interaction between investors.

The timing of the game. In this sequential game the first mover is the policy maker, who chooses the policy instrument in period 0. The regulator takes into account what the optimal response of the investors will be, and chooses the FiT parameters that will implement the desired level of renewable capacity. Once the policy instrument is fixed and made public the investors decide on the level of new renewable capacity to maximize investment returns. Period 1 is the first production period and it begins once the capacity has been built.

Solving the game. We solve the sequential game by backward induction. The optimal response function of investors is first calculated and then incorporated into the policymaker's decision function. This procedure ensures that the policy instrument of the regulator implements the desired level of investment.

[2] In practice the intervals handled when using a stochastic model are discrete, but the continuous formulation is usually used for analytical convenience.

[3] The product of the number of operating hours per year and the actual energy output divided by the maximum possible energy output over that period.

Under a given regulation, the payoffs that an investor perceives per MWh supplied at each t are denoted by P_t. In general, the expected remuneration per MWh ($E[P_t]$) depends on the price (S_t), which in turn depends on the total installed capacity (Q). Therefore, investors will try to maximize expected total profits (Π) over T_F periods by deploying Q new units of wind capacity.[4]

$$\max_{Q} \left\{ \Pi = \sum_{t=1}^{T_F} (e^{-rt} E[P_t(Q)]G(Q)) - CQ \right\} \qquad s.t: \qquad Q \geq 0 \tag{3}$$

The First Order Condition (FOC) for this problem is given by:

$$\left.\frac{\partial \Pi}{\partial Q}\right|_{Q=Q_M} = \sum_{t=1}^{T_F} e^{-rt} \left(E[P_t(Q)] \frac{\partial G(Q)}{\partial Q} + \frac{\partial E[P_t(Q)]}{\partial Q} G(Q) \right) \bigg|_{Q=Q_M} - C = 0, \qquad Q_M \geq 0 \tag{4}$$

The investor decides to invest in an amount Q_M based on market conditions and the prior decision of the incentive level set by the policymaker.

The regulator knows that the level of actual investment will be characterized by (4) and therefore chooses the incentive level for that equation to hold at $Q_M = Q_I$. that equation For the two quantities to coincide ($Q_M = Q_I$), the regulator must take into account the optimization problem that the investor will face when setting the regulation. To deploy Q_I units, the policymaker sets an incentive level such that when investors solve problem (3) they find it optimal to invest in the installation of $Q_M = Q_I$ units. Denoting the cost of supporting the policy per supplied MWh at period t as F_t, the expected total discounted cost of the subsidy (Γ) over a duration of T_1 years, which need not coincide with the time for which the installed capacity is operative ($T_1 \leq T_F$), is given by

$$\Gamma = \sum_{t=1}^{T_1} e^{-rt} E[F_t] G \tag{5}$$

As $E[P_t(Q)]$ depends on μ and σ, which in turn depend on the installed capacity, the derivatives of these two parameters with respect to Q will play a role in the optimization problem (4). In the model in Farrell et al. (2017), μ and its derivative $\left(\frac{\partial \mu}{\partial Q}\right)$ are endogenous to the investor's optimization problem. Following their approach, we use the following functional form:

$$\mu(Q) = a + be^{-cQ} \tag{6}$$

The drift μ summarizes the many factors behind the long-run tendency of electricity prices (the evolution of energy input prices, environmental costs, gradual closure of coal-fired plants, etc.). This long-run tendency is modulated by the level of renewable investment Q. For example, a long-run upward tendency in environmental costs of some technologies would be reflected in a positive drift for the electricity prices, and the lower the renewable capacity Q the higher the exposure of electricity prices to the upward tendency of environmental costs. Assuming that b and c are positive, the drift is decreasing in Q.[5]

In addition, we also consider that renewable capacity modulates the volatility of electricity prices σ and its derivative $\left(\frac{\partial \sigma}{\partial Q}\right)$ are functions of the installed capacity and hence endogenous to the optimization problem. We use the following functional form:

$$\sigma(Q) = \alpha - \beta e^{-\delta Q} \tag{7}$$

As other authors have concluded, the volatility of electricity prices increases with the growing dependence on intermittent energy sources such as wind (Blazquez et al., 2018a). Therefore, assuming that β and δ are positive, the above functional form may be suitable for reflecting the effect of renewable energy on price volatility. Farrell et al. (2017) leave this parameter constant throughout their study, but our formulation with volatility increasing as wind capacity increases provides more flexibility.

We assume that investors have the right to decline participation in the RES promotion program as long as such a decision is made in advance. That is, once they are under the support scheme they are committed and cannot decide to charge the market price when it is higher than the regulated price.

3.3. Expected price under different FiTs

We now solve our model for the benchmark case (No Subsidy) and the four policies discussed in Section 2: (1) Fixed Tariff, (2) Constant Premium, (3) Shared Upside, and (4) Cap & Floor. To solve the investor's problem (4), we obtain analytical solutions for the expected payoffs of each policy in each period ($E[P_t]$).[6]

As per the definition of the GBM in Eq. (1), S_t is log-normally distributed; that is, $\log S_t$ is normally distributed with mean and variance given by: $\log S_0 + (\mu - \sigma^2/2)t$, and $\sigma^2 t$, respectively. An important feature of log-normally distributed variables is that they

[4] We are assuming that investors make the optimal decision on capacity in period 0 and therefore they would not need to change that decision from period 1 onward. In practice, we observe that producers sometimes gradually add new capacity, but that may be due to initial financial constraints or to new information, aspects that we are assuming away for simplicity.

[5] This is also consistent with the merit-order effect, where the increase in renewable generation shifts the supply curve to the right, reducing the wholesale price of electricity (Ciarreta et al., 2014a).

[6] Detailed mathematical procedure for each scheme is presented in Appendix A.

can take any value between zero and infinity, thus excluding negative prices. According to the Feynman–Kac theorem, for any asset following Eq. (1), given the initial value (S_0) at time $t = 0$, the expected value of a random variable function $h(S_{t'})$ at time $t' = t$ defined as $E[h(S_t)|S_0]$, has the following solution (see Shreve, 2004):

$$E[h(S_t)|S_0] = \frac{1}{\sigma\sqrt{2\pi t}} \int_0^\infty \frac{h(\xi)}{\xi} \exp\left(- \frac{\left(\log\left(\frac{\xi}{S_0}\right) - (\mu - \frac{\sigma^2}{2})t \right)^2}{2\sigma^2 t} \right) d\xi \tag{8}$$

This result enables the expected benefits and costs to be computed under different incentive schemes and for different times t. The solutions for each tariff, for the duration of the subsidy ($t \le T_1$), are shown below. For the rest of the periods ($T_1 < t \le T_F$), investors obtain the market price S_t under any scheme, and thus the policymaker bears no policy cost. The cost of supporting the FiT policy in each period is the difference between the price that the supplier receives and the market price at time t:

$$F_t = P_t - S_t \tag{9}$$

3.3.1. No subsidy (benchmark)

The desired expected values are obtained by substituting the function $P_t(S_t)$ of each subsidy in Eq. (8) for the generic function $h(S_t)$. For the benchmark case $P_t(S_t) = S_t$, which leads to:

$$E[S_t] = S_0 e^{\mu t} \tag{10}$$

3.3.2. Fixed tariff

A fixed tariff scheme offers a guaranteed payment (K_A), which is totally independent of the electricity market price. Under this scheme, the payoffs that an investor perceives in each period ($t \le T_1$) are: $P_{A,t} = K_A$. Therefore, the policymaker's costs at time t are: $F_{A,t} = K_A - S_t$. From Eq. (8) we obtain the expectations:

$$E[P_{A,t}] = K_A \tag{11}$$

$$E[F_{A,t}] = K_A - S_0 e^{\mu t} \tag{12}$$

The FOC for the investor's problem described in Eq. (4) leads to the following optimal solution for K_A:

$$K_A^* = \frac{C - \sum_{t=T_1+1}^{T_F} \left[S_0 e^{(\mu-r)t} \left(t\frac{\partial \mu}{\partial Q} G + \frac{\partial G}{\partial Q} \right) \right] \Big|_{Q=Q_I}}{\sum_{t=1}^{T_1} e^{-rt} \frac{\partial G}{\partial Q} \Big|_{Q=Q_I}} \tag{13}$$

where $\frac{\partial G}{\partial Q} = Q_{max}\kappa\ \gamma e^{-\gamma(Q_0+Q)}$, and $\frac{\partial \mu}{\partial Q} = -bce^{-cQ}$.

3.3.3. Constant premium

For a constant premium tariff, the payment that investors receive is based on a constant premium (Δ) offered on top of the market price: $P_{B,t}(S_t) = \Delta + S_t$. Hence, the policymaker's costs in each period are deterministic: $F_{B,t}(S_t) = \Delta$. Thus, the expected profits and policy costs at time t are given by:

$$E[P_{B,t}] = \Delta + S_0 e^{\mu t} \tag{14}$$

$$E[F_{B,t}] = \Delta \tag{15}$$

Following the same procedure, we find the optimal solution for the constant premium Δ:

$$\Delta^* = \frac{C - \sum_{t=1}^{T_F} \left[S_0 e^{(\mu-r)t} \left(t\frac{\partial \mu}{\partial Q} G + \frac{\partial G}{\partial Q} \right) \right] \Big|_{Q=Q_I}}{\sum_{t=1}^{T_1} e^{-rt} \frac{\partial G}{\partial Q} \Big|_{Q=Q_I}} \tag{16}$$

3.3.4. Shared upside

The payoffs that an investor receives at ($t \le T_1$) are described by:

$$P_{C,t}(S_t) = \max\{K_C, \omega(S_t - K_C) + K_C\} = \begin{cases} K_C & S_t < K_C \\ \omega(S_t - K_C) + K_C & K_C \le S_t \end{cases} \tag{17}$$

where $\omega \in [0,1]$ represents the share of the market upside received by the investor, and K_C represents the price floor. Under this scheme, the policymaker's costs are

$$F_{C,t}(S_t) = \max\{K_C - S_t, 0\} + (\omega - 1)\max\{S_t - K_C, 0\} = \begin{cases} K_C - S_t & S_t < K_C \\ (\omega - 1)(S_t - K_C) & K_C \le S_t \end{cases} \tag{18}$$

If ω is one, then there is a FiT under which the investor charges the market price but has a guaranteed minimum price, in the case where the market price is lower than this floor. By contrast, if ω is zero there is a fixed FiT with a fixed price K_C. The expected profits and costs in each period are as follows:

$$E[P_{C,t}] = K_C(1 - \omega\Phi(d_2)) + \omega S_0 e^{\mu t}\Phi(d_1) \tag{19}$$

$$E[F_{C,t}] = K_C - S_0 e^{\mu t} + \omega(S_0 e^{\mu t}\Phi(d_1) - K_C\Phi(d_2)) \tag{20}$$

where Φ is the cumulative distribution function of the standard normal distribution, and d_1 and d_2 are defined as follows:

$$d_1(K,t) = \frac{\log\left(\frac{S_0}{K}\right) + \left(\mu + \frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}} \qquad d_2(K,t) = \frac{\log\left(\frac{S_0}{K}\right) + \left(\mu - \frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}} \tag{21}$$

Thus, the condition for a feasible optimal combination of K_C and ω is:

$$\begin{aligned} &\sum_{t=1}^{T_1} e^{-rt}\left\{\left[K_C^*\left(1 - \omega\Phi(d_2(K_C^*,t))\right) + \omega S_0 e^{\mu t}\Phi(d_1(K_C^*,t))\right]\frac{\partial G}{\partial Q} + \right. \\ &\left.\left[\omega S_0 e^{\mu t}\left(t\frac{\partial \mu}{\partial Q}\Phi(d_1(K_C^*,t)) + \phi(d_1(K_C^*,t))\frac{\partial d_1(K_C^*,t)}{\partial Q}\right) - K_C^*\omega\phi(d_2(K_C^*,t))\frac{\partial d_2(K_C^*,t)}{\partial Q}\right] G\right\}\Big|_{Q=Q_I} + \\ &\sum_{t=T_1+1}^{T_F} S_0 e^{(\mu-r)t}\left(t\frac{\partial \mu}{\partial Q}G + \frac{\partial G}{\partial Q}\right)\Big|_{Q=Q_I} - C = 0 \end{aligned} \tag{22}$$

where ϕ is the probability density function of the standard normal distribution and

$$\frac{\partial d_1}{\partial Q} = \frac{\sqrt{t}}{\sigma}\frac{\partial \mu}{\partial Q} - \left(\frac{d_1}{\sigma} - \sqrt{t}\right)\frac{\partial \sigma}{\partial Q} \qquad \frac{\partial d_2}{\partial Q} = \frac{\sqrt{t}}{\sigma}\frac{\partial \mu}{\partial Q} - \left(\frac{d_2}{\sigma} + \sqrt{t}\right)\frac{\partial \sigma}{\partial Q} \tag{23}$$

As another extension to the model in Farrell et al. (2017), we take into account how renewable penetration affects the probability of prices reaching a certain level instead of just analyzing how it affects the expected price.[7] As a consequence, volatility and its derivative are introduced into the optimization problem through the terms described in Eqs. (23). As shown in Eq. (22), given that d_1, d_2 and their respective derivatives depend on K_C, the equation cannot be solved for K_C explicitly. Given a certain value for ω, the above implicit equation may be solved by numerical methods. Via an iterative procedure, the solution finally converges to the optimal value K_C^*. Conversely, given a value of K_C, we repeat the procedure and obtain an optimal value for ω^*. Eq. (22) describes a unique locus of efficient pairs of K_C and ω, with a single efficient ω for each value of K_C and a single efficient K_C for each value of ω. Moreover, there is an inverse relationship between the optimal values of ω and K_C.

3.3.5. Cap & floor

The payoffs that an investor receives at $(t \le T_1)$ are described by:

$$P_{D,t}(S_t) = \max\{K_D, \min\{S_t, \overline{C}\}\} = \begin{cases} K_D & S_t < K_D \\ S_t & K_D \le S_t < \overline{C} \\ \overline{C} & \overline{C} \le S_t \end{cases} \tag{24}$$

where K_D and $\overline{C}$, $(K_D \le \overline{C})$, represent the price floor and cap, respectively. Under this scheme, the policymaker's costs are:

$$F_{D,t}(S_t) = \max\{K_D - S_t, 0\} + \max\{\overline{C} - S_t, 0\} = \begin{cases} K_D - S_t & S_t < K_D \\ 0 & K_D \le S_t < \overline{C} \\ \overline{C} - S_t & \overline{C} \le S_t \end{cases} \tag{25}$$

The expected profits and costs in each period are as follows:

$$E[P_{D,t}] = K_D\left(1 - \Phi(d_2)\right) + S_0 e^{\mu t}\left(\Phi(d_1) - \Phi(d_3)\right) + \overline{C}\Phi(d_4) \tag{26}$$

$$E[F_{D,t}] = K_D\left(1 - \Phi(d_2)\right) - S_0 e^{\mu t}\left(1 - \Phi(d_1) - \Phi(d_3)\right) + \overline{C}\Phi(d_4) \tag{27}$$

[7] In solving the investors' optimization problem, we take into account the derivatives of the terms $\Phi(d_i)$ with respect to the installed power.

where d_3 and d_4 are defined as follows:

$$d_3(\overline{C},t) = \frac{\log\left(\frac{S_0}{\overline{C}}\right) + \left(\mu + \frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}} \qquad d_4(\overline{C},t) = \frac{\log\left(\frac{S_0}{\overline{C}}\right) + \left(\mu - \frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}} \tag{28}$$

Proceeding as in the previous case and considering the extensions proposed and discussed above, the condition for a feasible optimal combination of K_D and $\overline{C}$ is as follows:

$$\begin{aligned}
&\sum_{t=1}^{T_1} e^{-rt}\left\{\left[K_D^*\left(1-\Phi(d_2(K_D^*,t))\right) + S_0e^{\mu t}\left(\Phi(d_1(K_D^*,t)) - \Phi(d_3(\overline{C},t))\right) + \overline{C}\Phi(d_4(\overline{C},t))\right]\frac{\partial G}{\partial Q} + \right.\\
&\left[S_0e^{\mu t}\left(t\frac{\partial \mu}{\partial Q}\left(\Phi(d_1(K_D^*,t)) - \Phi(d_3(\overline{C},t))\right) + \phi(d_1(K_D^*,t))\frac{\partial d_1(K_D^*,t)}{\partial Q} - \phi(d_3(\overline{C},t))\frac{\partial d_3(\overline{C},t)}{\partial Q}\right) + \right.\\
&\left.\left.\overline{C}\phi(d_4(\overline{C},t))\frac{\partial d_4(\overline{C},t)}{\partial Q} - K_D^*\phi(d_2(K_D^*,t))\frac{\partial d_2(K_D^*,t)}{\partial Q}\right]G\right\}\Bigg|_{Q=Q_I} + \\
&\sum_{t=T_1+1}^{T_F} S_0e^{(\mu-r)t}\left(t\frac{\partial \mu}{\partial Q}G + \frac{\partial G}{\partial Q}\right)\Bigg|_{Q=Q_I} - C = 0
\end{aligned} \tag{29}$$

where

$$\frac{\partial d_3}{\partial Q} = \frac{\sqrt{t}}{\sigma}\frac{\partial \mu}{\partial Q} - \left(\frac{d_3}{\sigma} - \sqrt{t}\right)\frac{\partial \sigma}{\partial Q} \qquad \frac{\partial d_4}{\partial Q} = \frac{\sqrt{t}}{\sigma}\frac{\partial \mu}{\partial Q} - \left(\frac{d_4}{\sigma} + \sqrt{t}\right)\frac{\partial \sigma}{\partial Q} \tag{30}$$

Again, it is not possible to explicitly solve the previous equation for K_D. Instead, for a given value of the cap $\overline{C}$, the implicit Eq. (29) can be solved iteratively until it converges to the optimal solution K_D^*. Conversely, given a value for K_D, it can be solved to obtain an optimal value of $\overline{C}^*$. In any case, Eq. (29) describes the locus of efficient combinations of floor and cap. As in the shared upside scheme, there is an inverse relationship between these two policy parameters. A lower floor implies a higher efficient cap, and vice versa. As a consequence, there is an inverse relationship between the investor's and policymaker's exposure to market price variability.

3.3.6. *Other incentive schemes*

Other incentive schemes are possible, but they could be analyzed as combinations of the previous ones. For example, in our model investors are assumed to accept or decline the incentive scheme and stay committed to their decision until the end of the game. If investors were allowed to decline the incentive scheme in favor of the market price whenever the latter is higher, this would amount to a guaranteed minimum price with no upside constraint. Note, however, that such a policy could also be described by our model, since it would be equivalent to the limit case of a Shared Upside where all the upside is received by the investor, or to a Cap & Floor where the cap imposed is infinite.

4. Empirical application: Calibration

After the theoretical analysis we now empirically compare the risk exposure for investors and policymakers in each of the schemes under consideration. We thus perform a numerical analysis to determine how these schemes would work in a case study for wind energy deployment. We calibrate the model for the Spanish electricity market for two years: 2013 (the last year with an active FiT/FiP scheme) and 2019 (after the FiT/FiP regulation had been phased out).[8]

As a result of optimization problem (3), an installed quantity equal to the target quantity (Q_I) is achieved for both years studied and for each policy. The installation target is taken as the difference between the objective set by the Spanish government and the total power installed up to that year (Q_0). In 2011, the wind target was 35.75 GW for 2020 in the "Plan de Energías Renovables" document (IDAE, 2011), and 50.33 GW for 2030 in the "Plan Nacional Integrado de Energía *y* Clima" document (MITECO, 2020). The average operational lifetime of a wind turbine is 20 years (IDAE, 2010). The duration of the Fixed Tariff and Constant Premium given by the Spanish government was also 20 years (BOE, 2007).[9]

We obtained the VWAP for the initial year (S_0) with data from the Spanish TSO (Red Eléctrica de España, REE) and market operator (Operador del Mercado Ibérico de Energía, OMIE). For a given year, we match the hourly wind energy generation (REE, 2021) with the hourly market matching price. Then each hour's price (s_h) is weighted according to the amount of wind electricity (y_h) generated in that same hour (OMIE, 2023), that is: $S_t = \frac{\sum_{h\in t} s_h y_h}{\sum_{h\in t} y_h}$. In the calibration process we take advantage of the fact that in the approximate period from 2012 to 2018 the amount of operative wind capacity remained virtually constant in Spain. We denote by $\overline{Q}_1$ the average value of the capacity in that window. The parameter γ is calibrated to find the best match between the historical annual wind electricity generation and penetration of wind energy, with annual generation and capacity data provided

[8] See Ciarreta et al. (2017a,b) and Espinosa and Pizarro-Irizar (2018).

[9] Even though in this application $T_1 = T_F$, there are other applications where it would be useful to have the more general version $T_1 \le T_F$. Some recent examples of this in Europe can be found in the Netherlands, UK, Poland, Portugal, Hungary, etc.

Table 1
Calibrated parameters and sources for variable parameters.

Parameter	Value 2013	Sources 2013	Value 2019	Sources 2019
Q_0 (MW)	22,960	AEE (2021a)	25,704	AEE (2021a)
Q_I (MW)	12,790		24,626	
κ (eq.h)	2150	IDAE (2011)	2355	MITECO (2020)
A (€/MW)	1,400,000		1,150,000	
r	0.10	Noothout et al. (2016)	0.052	Roth et al. (2021)
S_0 (€/MWh)	39.80	Own calculations (data: REE, 2021 & OMIE, 2023)	45.63	Own calculations (data: REE, 2021 & OMIE, 2023)

Table 2
Calibrated parameters and sources for constant parameters.

Parameter	Value	Sources
T_F (years)	20	IDAE (2010)
T_1 (years)	20	BOE (2007)
O (€/MW)	$0.03A$	IDAE (2011)
Q_{max} (MW)	332,000	Aymamí et al. (2011)
γ	$3.4 \cdot 10^{-6}$	Own calculations (data: CNMC, 2022b)
a	0.045	
b	0.0049	
c	10^{-4}	Own calculations (data: REE, 2021, AEE, 2022a, OMIE, 2023, Ciarreta et al., 2014a)
α	1.50	
β	1.33	
δ	$2.55 \cdot 10^{-6}$	

by the Spanish competition regulator (CNMC). Thus, we calibrate γ such that $G(\overline{Q}_1) = \overline{G}_1$, where $\overline{G}_1$ denotes the average annual production of electricity from wind in that window. The parameters defining the drift and volatility functions are calibrated using estimators described in Wilmott (2013). σ_0 is found using annual prices that would have resulted in the market from 2008 to 2018 in the absence of wind power (zero penetration scenario), provided by the Spanish Wind Energy Association (AEE, 2022a; Ciarreta et al., 2014a). If these prices are denoted by Sc_t, then, $\sigma_0 = sd(\log Sc_{t+1} - \log Sc_t)$. Likewise, σ_1 is estimated using annual market prices in the window from 2012 to 2018 where penetration remained almost unchanged: $\sigma_1 = sd(\log S_{t+1} - \log S_t)$. From Eq. (7), it is possible to approximate $\sigma(Q) \approx \alpha_1 + \alpha_2 Q$, where $\alpha_1 = \alpha - \beta$ and $\alpha_2 = \beta\delta$. We calibrate α_1 and α_2 such that $\sigma(0) = \sigma_0$, and such $\sigma(\overline{Q}_1) = \sigma_1$. Setting α then, $\beta = \alpha - \alpha_1$, and $\delta = \frac{\alpha_2}{\beta}$. Similarly, for the drift we require $\mu(Q_1) = \mu_1$ and $\mu(0) = \mu_0$, where μ_1 denotes the average value of $\left(\frac{S_{t+1}-S_t}{S_t} + \log\left(\frac{S_{t+1}}{S_t}\right)\right)/2$ in the window from 2012 to 2018, and μ_0 is found from the series of counterfactual prices: Starting from a point where wind capacity was very low with average annual prices denoted by $\overline{S}_0$, the expected evolution of counterfactual prices after a time Δt is given by $\overline{S}_0 e^{\mu_0 \Delta t}$. Thus μ_0 is found by requiring $\overline{S}_0 e^{\mu_0 \Delta t} = \overline{Sc}_1$, where $\overline{Sc}_1$ is the average counterfactual price in the constant penetration window described. Then c is set and we solve for b and a. Capital and operating costs for onshore and offshore wind energy are different: In general, offshore wind farms are much more expensive both to build and to maintain than onshore ones. For that reason, we estimate A as a weighted average of the onshore and offshore wind capital costs, weighted according to the respective shares of onshore and offshore deployment in the installation target Q_I.

We follow the same procedure for estimating operating costs. For the discount rate (r), we use the Weighted Average Cost of Capital (WACC). Generally, the risk associated with energy projects subsidized by the government is considerably lower than for those which are promoted entirely by the private sector. Thus, the discount rate used in each case is usually different. The WACC, which is a weighted average cost of a firm's equity and debt (Steffen, 2020), does not directly consider the risk involved in investment. This is why publicly subsidized RES projects often use this method to discount future cash flows and consider the financial feasibility of the investment (Haar and Haar, 2017). All the parameters that do not vary from year to year and their respective sources are outlined in Table 1, while those that do change are shown in Table 2.

5. Results

This section simulates the potential evolution of electricity prices in Spain under the different proposals for two years with different regulatory schemes: 2013 (Section 5.1) and 2019 (Section 5.2). We also perform a sensitivity analysis, changing several parameters and measuring the impact of those changes on the relevant results (Section 5.3).

Table 3
Results for the two pure schemes & benchmark case (2013).

	Optimal incentive (€/MWh)	Expected profits (€M)	Expected costs (€M)
No Subsidy	–	−9,102.8	0
Fixed Tariff	$K_A^* = 98.8$	492.5	9,595.3
Constant Premium	$\Delta^* = 41.6$	513.1	9,615.9

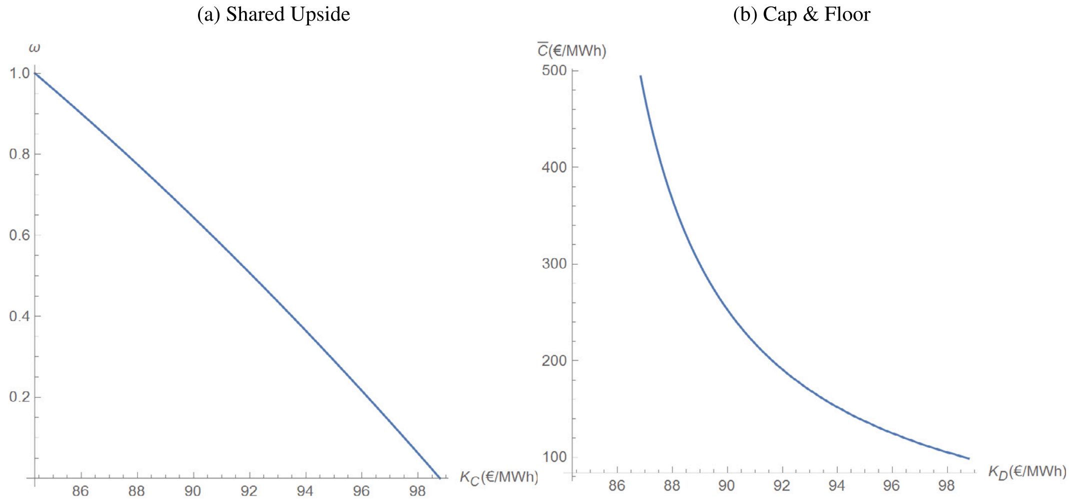

Fig. 2. Optimal Locus (2013).

5.1. Results for 2013

This section presents the results for the different incentive schemes with the parameter values for 2013.[10]

Pure Schemes & Benchmark: No subsidy (NS), Fixed Tariff (FT), and Constant Premium (CP). The results under the three pure schemes (those with only one degree of freedom for the investment of Q_I units) are summarized in Table 3. Under no subsidy, the profits that investors deploying the objective target Q_I expect to make according to Eq. (10) are €−9,102M. That is, investors are expected to lose more than 9 billion Euros if their only revenue is the market price. In the case of FT, the decision maker finds it optimal to invest in the deployment of exactly Q_I units of wind energy if, according to the solution given by Eq. (13), the policymaker sets an FT of $K_A^* =$ €98.8/MWh, leading to expected profits for investors of 492 million Euros and expected costs of more than 9,595 million Euros for the regulator. Finally, under the CP scheme, according to Eq. (16), the policymaker sets a premium of $\Delta^* =$ €41.6/MWh, leading to expected profits of 513 million Euros and costs of 9,615 million.

Hybrid Schemes: Shared Upside (SU) and Cap & Floor (C&F). In these two cases there are two degrees of freedom in the design of each FiT, so the optimal configuration is now defined by a locus of efficient combinations (K_C, ω) for the SU, and $(K_D, \overline{C})$ for the C&F schemes. These loci are represented in Fig. 2. In both cases, there is an optimal value of the other parameter for each possible value of a price floor K. For any point in this locus, under the corresponding FiT scheme, the investor will find it optimal to invest in the installation of exactly Q_I new units.

As shown in Figs. 2(a) and 2(b), there is a negative relationship between K_C and ω, as well as between K_D and $\overline{C}$. This is an expected result, and it corresponds to the following trade-off from the policymaker's perspective: If the regulator is willing to offer a higher guaranteed minimum price to the investor, then the latter can be expected to demand a higher share of the potential upside $(1-\omega)$ for the SU regime and a lower cap $\overline{C}$ for the C&F, which would mean more frequent remuneration (as everything exceeding the cap goes to the regulator). For the given values of the parameters, the feasible values for the price floor range from approximately €85 to €99 per MWh under the two schemes.[11]

It is noteworthy that if the price floor is set at €98.8/MWh in both cases, under the SU scheme the value of ω (the efficient share that the investor would receive of the upside exceeding the floor) becomes zero, and under the C&F the efficient cap $\overline{C}$ becomes €98.8/MWh too. That is, the efficient FT is obtained in both cases, which supports the consistency of our model.

Next we calculate the expected profits and costs for the four schemes discussed, along with the risk exposure. In the case of SU and C&F, the expected profits and costs depend on the price floor K chosen (because setting the value of K uniquely determines

[10] We have checked that the singular points defined by Eqs. (13), (16), (22), and (29) satisfy the second order conditions of the investor's problem in Eq. (3) for each tariff for the given installation target Q_I. Further constraints can also be added to the optimization problem, for example an upper bound to the policymaker's budget.

[11] The feasible values are those that correspond to maximum points. In addition they must fulfill $(0 < \omega < 1)$ for the SU tariff and $(K < \overline{C})$ for the C&F scheme.

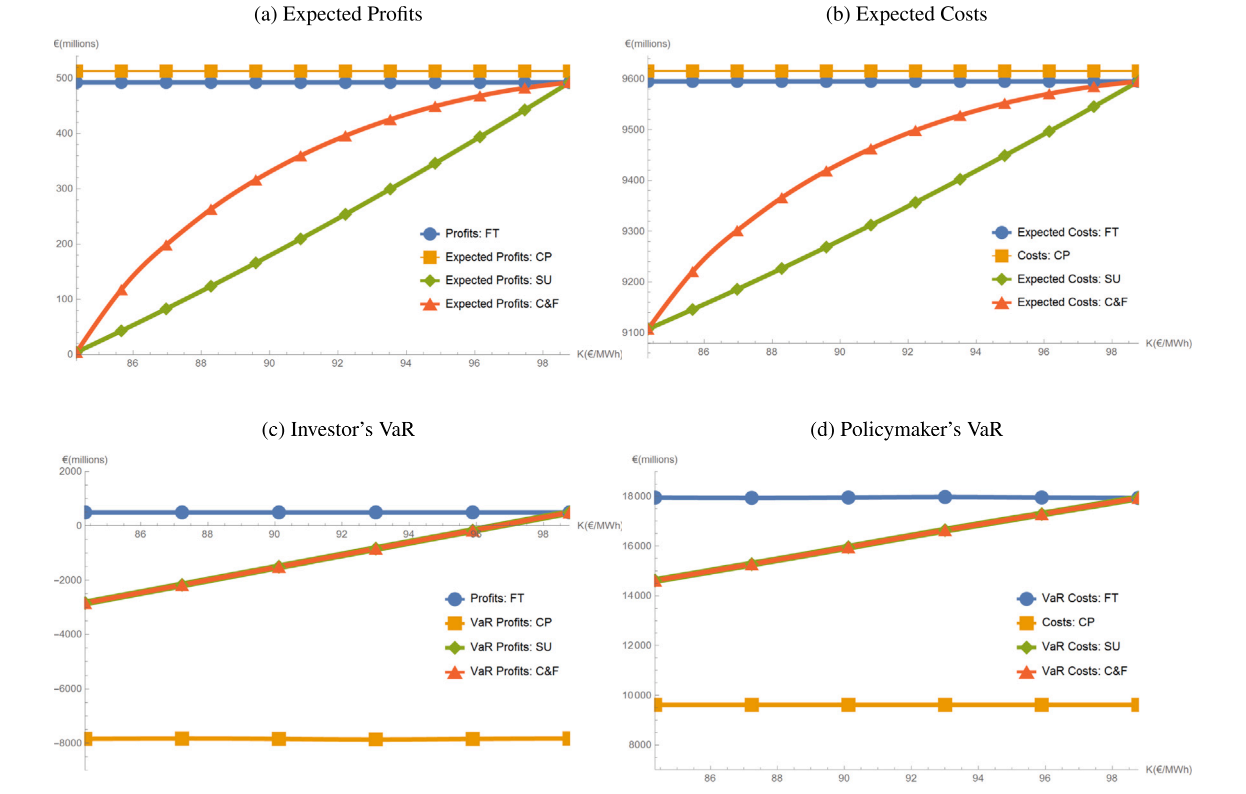

Fig. 3. Results under each tariff (2013).

the efficient paired parameter $\omega/\overline{C}$). To quantify the different risk exposures for each tariff, we define the Value at Risk (VaR) as a percentile of the distribution of potential profits (costs) that investors (policymakers) may obtain (incur) under the uncertain evolution of electricity prices. In our case, we set the VaR at the 10th percentile of the investor's profits as a measure of exposure to under-remuneration, and at the 90th percentile of the regulator's costs as a measure of exposure to cost overrun. Investors are exposed to risk if their VaR is lower than their expected profits. In the same way, regulators are exposed to risk when their VaR is higher than the expected costs.

To obtain a value for the VaR, we first estimate the probability distribution for each tariff of potential profits and costs. With the parameters given in Tables 1 and 2, we simulate the stochastic GBM described in Eq. (1) many times (100,000 in our particular case). For each trial, we obtain a particular stochastic evolution of the VWAP (S_t), then use that value to calculate the profits and costs that result from each FiT. In the case of SU and C&F, we do this for every feasible price floor. Finally, with the sample of the results and the frequency of each result, we estimate the VaR for the investor's profits and policymaker's costs. For each tariff, we show the expected profits (Fig. 3(a)), the expected costs (Fig. 3(b)), the investor's VaR (Fig. 3(c)), and the policymaker's VaR (Fig. 3(d)), as a function of the price floor of the two hybrid schemes ($K = K_C = K_D$).[12]

First of all, it is worth noting that if enough trials are performed the mean values of the simulation eventually converge to the expected values already determined analytically. As shown in Figs. 3(a) and 3(b), the expected profits and costs of the CP scheme are higher than those of the other tariffs. In turn, for both SU and C&F schemes, the higher the floor K, the higher the expected profits and costs. Finally, it should be noted that the C&F schemes provide higher expected profits and costs than the SU for all values of K. For pure schemes, if it is assumed that both participants base their decisions on expected profits (costs) then investors would prefer a CP, whereas policymakers would prefer an FT. Focusing on the two hybrid schemes, the regulator prefers to set the floor (K) as low as possible, whereas the investor prefers it to be as high as possible. In the particular case of Spain, the main mechanism used to incentivize wind energy investment was a constant premium scheme. As can be seen, it is possible to design schemes that incentivize the same level of investment in renewables with different costs for the regulator. The fact that the main reason why these schemes were abandoned in 2013 was their high regulatory cost means that these results are highly significant.

As already discussed, in the case of FT the investor's profits are deterministic. Thus, there is no risk exposure for investors under this scheme, so the investor's VaR coincides with the expected profits (€492.5M). By contrast, under a CP policy regulators are not exposed to risk, and the policymaker's VaR coincides with the expected costs (€9,615.9M). As can be seen, there is no significant

[12] The lines representing FT and CP schemes are plotted for visual reference, as they do not depend on K.

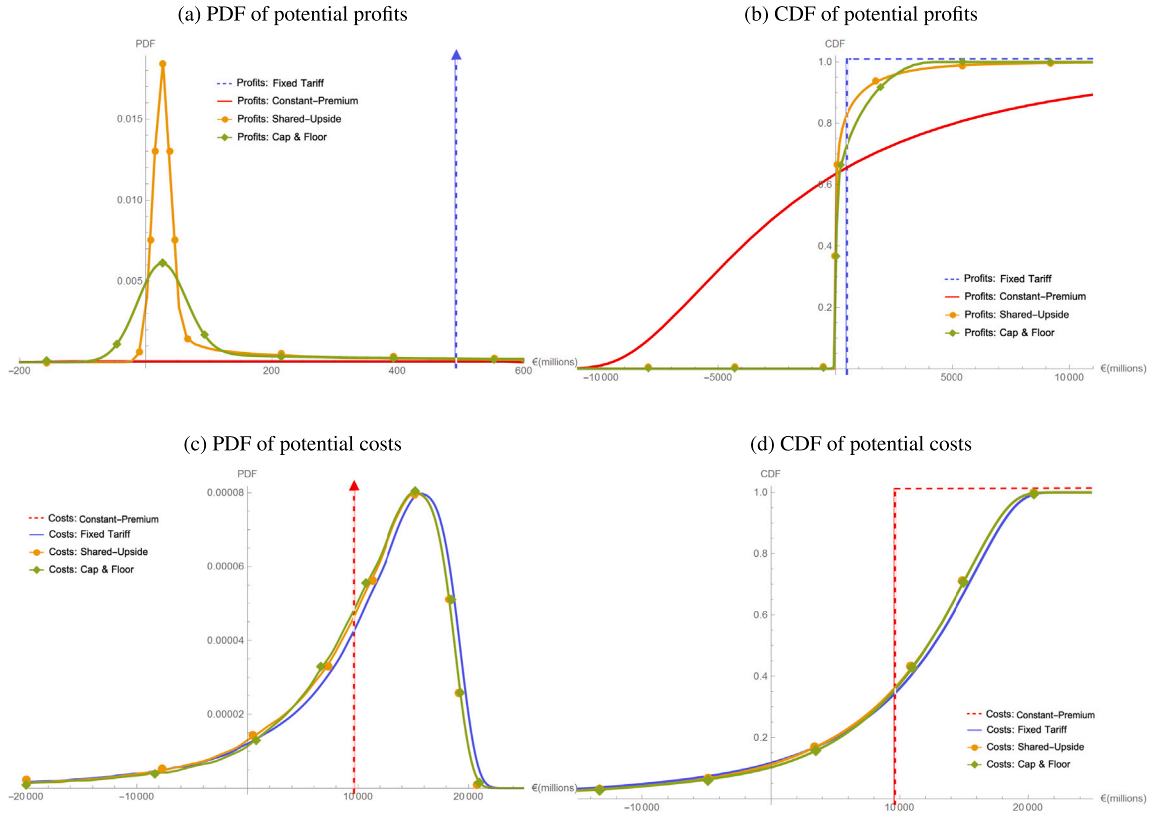

Fig. 4. Distributions of profits and costs (2013).

difference in the VaR between the two hybrid subsidies. Investors face lower risk with a higher K, while regulators face lower risk with lower price floors. On the one hand, the investor is more protected against under-remuneration under either hybrid scheme than under the CP scheme. On the other hand, the policymaker is more protected against cost overruns than under the FT policy.

Given that the effectiveness of Feed-in Tariffs has been attributed to the reduced risk that they entail for investors, transferring all the risk to them might be counterproductive. We analyze in greater detail some hybrid schemes that share out the risk between the two parties. For example, we examine Shared Upside and Cap & Floor schemes with an arbitrarily chosen price floor of €96.7/MWh which, according to the above figures, seems to be close enough to the FT scheme while offering an intermediate solution to the opposing interests of the two parties. Thus, the value of the efficient parameters turns out to be $\omega = 0.16$, and $\overline{C}$ = €116.7/MWh. Now we represent the distribution of potential profits and costs obtained from the simulations. Figs. 4(a) and 4(b) represent the PDF and CDF, respectively, of the distribution of profits. Figs. 4(c) and 4(d) do the same for the resulting distribution of costs. Finally, Table 4 shows the different percentiles of the distributions and the sample means.

It is no coincidence that the PDFs of the distributions of both profits and costs resemble a skewed Gaussian distribution. At a fixed time t, any GBM process described as in Eq. (1) follows a log-normal distribution (similar to a skewed normal distribution). Thus, S_t is log-normally distributed. Profits and costs are functions of the stochastic variable S_t, so they follow a similar pattern for every support scheme. As shown in Fig. 4(a), the mode of the distribution for FT, SU, and C&F subsidy schemes is positive.[13] By contrast, the CP distribution is so flat that no insight can be obtained by inspecting the PDF. The CDFs in Fig. 4(b) and the information in Table 4 show that, except for the CP scheme, investors are more likely to make profits than losses. With the floor selected, there is less than a 1% chance that they will suffer investment losses under SU and C&F schemes, compared to almost a 60% chance if they receive a CP type subsidy. But despite the high probabilities of investment losses, the possibility of high potential returns (albeit unlikely) outweighs the contribution of the negative earnings when computing the expected values (unlike the left-hand side tail of the distribution, the right-hand tail of the profit PDF is unbounded).

The preferred option for the policymaker is likely to be the Shared Upside scheme. However, as shown in Table 4, the differences in expected costs between the four schemes are almost negligible. Furthermore, as can be seen in Figs. 4(c) and 4(d), the distribution of costs under FT, SU and C&F schemes is almost identical. Under these schemes, there is approximately a 10% chance of the regulator having negative costs (earnings) whereas for the CP, as discussed above, the costs are fixed.

[13] The FT distribution is represented by a Dirac delta distribution (Riley et al., 2006).

Table 4
Percentiles of total potential profits and costs in 2013 (€M).

	Investor's profits				Policymaker's costs			
	FT	CP	SU	C&F	FT	CP	SU	C&F
Mean	492.5	508.1	415.4	475.0	9,600.2	9,615.9	9,523.2	9,582.8
1th %ile	492.5	−9,831.3	24.5	24.5	−32,346.8	9,615.9	−27,237.9	−29,869.7
5th %ile	492.5	−8,685.2	24.5	24.5	−9,469.3	9,615.9	−7,756.3	−7,588.5
10th %ile	492.5	−7,846.4	24.5	24.5	−1500,6	9,615.9	−937.8	−204.4
25th %ile	492.5	−5,892.6	24.5	24.5	6,983.7	9,615.9	6,704.6	7,022.6
50th %ile	492.5	−2,521.3	24.5	24.5	12,629.8	9,615.9	12,173.8	12,208.0
75th %ile	492.5	3,124.3	204.8	598.1	16,000.8	9,615.9	15,533.4	15,536.0
90th %ile	492.5	11,608.6	1,106.5	1,700.0	17,954.6	9,615.9	17,486.8	17,486.8
95th %ile	492.5	19,576.5	2,196.3	2,404.7	18,793.6	9,615.9	18,325.6	18,325.6
99th %ile	492.5	42,438.3	5,683.3	3,349.6	19,938.6	9,615.9	19,470.6	19,470.6

Table 5
Results for the two pure schemes & benchmark case (2019).

	Optimal incentive (€/MWh)	Expected profits (€M)	Expected costs (€M)
No Subsidy	–	10,284.0	0
Fixed Tariff	$K_A^* = 57.8$	1,662.5	−8,621.5
Constant Premium	$\Delta^* = -12.3$	1,703.5	−8,580.5

5.2. *Results for 2019*

This section presents the results of the different incentive schemes with the parameter values for 2019.[14]

Pure Schemes & Benchmark: No subsidy, Fixed Tariff, and Constant Premium. The results under the three pure schemes for the investment of Q_I units are summarized in Table 5. With no subsidy the expected profits for investors according to Eq. (10) are €10,284M. That is, investors are expected to make more than 10 billion Euros if they only receive the market price. In the case of an FT, the decision-maker finds it optimal to invest in the deployment of Q_I units of wind energy if the policymaker sets an FT of $K_A^* =$ €57.8/MWh, leading to expected profits for investors of €1,662.5 million and entailing expected costs of €−8,621.5 million for the regulator. That is, regulators are expected to get a surplus. Finally, under the CP scheme, according to Eq. (16), the policymaker sets a premium of $\Delta^* =$ €−12.3/MWh, leading to expected profits of approximately €1,703M and costs of €−8,580M. A negative optimal incentive value might seem counter-intuitive, but given the investment environment and the projected electricity prices, the only way to "coerce" the investor into investing in the deployment of just Q_I units, and not more, is by reducing the price that the generator will receive by exactly Δ^*. Even with no subsidy (which is the same as offering a premium with zero value) the expected profits are much higher than those of the FT and are without cost for the regulator, so it makes no sense to establish a negative premium as an incentive mechanism. Hence, we do not discuss the CP scheme any further. Instead, we look at the No Subsidy regime.

Hybrid Schemes: Shared Upside and Cap & Floor. The loci of efficient combinations for SU and C&F schemes are represented in Figs. 5(a) and 5(b), respectively. As shown in both figures, there is a negative relationship between K_C and ω, as well as between K_D and $\overline{C}$, pointing to the same type of trade-off as discussed for 2013. As can be seen, the feasible values of the price floor extend to approximately €58/MWh under both Shared Upside and Cap & Floor tariffs. Moreover, if the price floor is set at €57.8/MWh, under the SU scheme the value of ω becomes zero, and under the C&F the efficient cap $\overline{C}$ turns out to be €57.8/MWh too. Thus, both schemes degenerate to the efficient FT. This finding supports the consistency of the model.

We now represent the expected profits (Fig. 6(a)), the expected costs (Fig. 6(b)), the investor's VaR (Fig. 6(c)), and the policymaker's VaR (Fig. 6(d)). Recalling the results for No Subsidy from Table 5, if investors receive no subsidy their expected profits are much higher than under any support scheme for any value of the floor. At the same time, for any subsidy policy the regulator is expected to have negative costs (i.e. profits), whereas with no subsidy the regulation costs are obviously zero. As can be seen, the C&F tariff yields higher profits and costs than the FT and SU for any value of the floor. By contrast, the SU scheme yields lower profits and costs than any other tariff.

In the case of FT, the investor's profits are completely deterministic. As a consequence, under a Fixed Tariff scheme, the investor's VaR coincides with the expected profits (more than €1.6 billion). If the policymaker does not care about risk, the preferred option is the SU, which entails the lowest expected costs, as was the case for 2013. Under the C&F scheme the investor (regulator) prefers the price floor to be as low (high) as possible. As shown in Figs. 6(c) and 6(d), the investor's and regulator's VaR under SU and C&F schemes are almost identical for most floor values. It can be observed that the higher the price floor K, the higher the VaR, and hence the higher (lower) the risk exposure of the policymaker (investor). For example, in the case of Shared Upside and Cap & Floor schemes with an arbitrarily chosen price floor of €55.5/MWh (close to the FT scheme while allowing some flexibility), the

[14] For all schemes, the singular points defined by Eqs. (13), (16), (22), and (29) satisfy the second order conditions of the investor's problem in Eq. (3) for the given installation target.

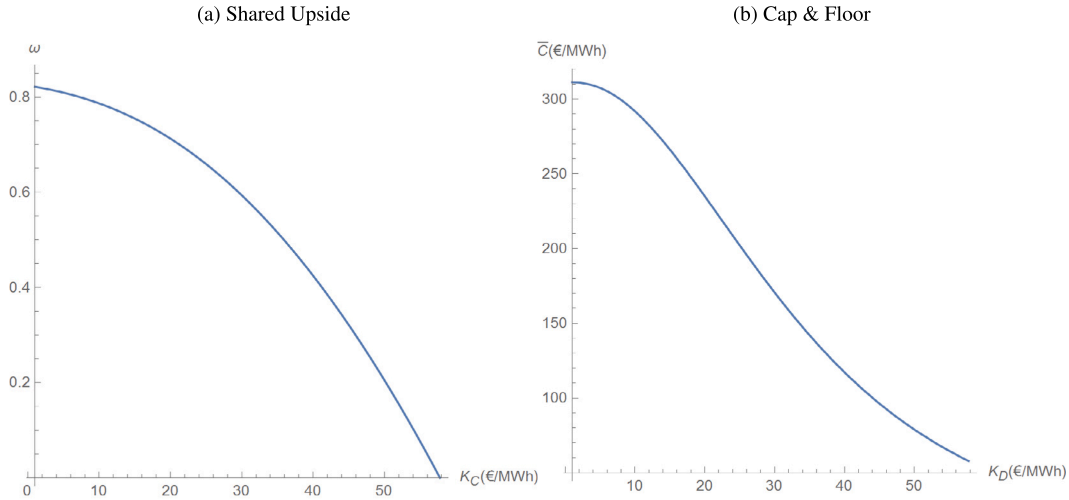

Fig. 5. Optimal Locus (2019).

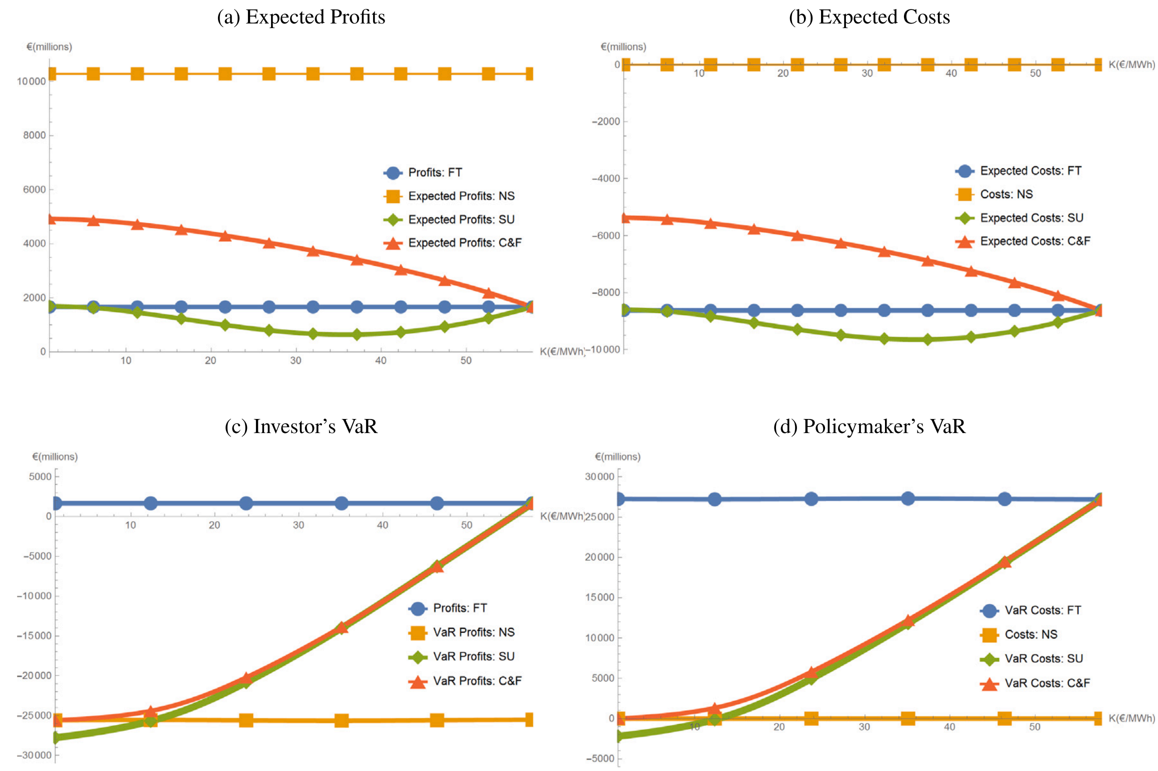

Fig. 6. Results under each tariff (2019).

values of the efficient parameters turn out to be $\omega = 0.06$ (for the SU) and $\overline{C} = 63.3$ (for the C&F). We show the distribution of potential profits and costs obtained after the simulations for this value of the floor; Figs. 7(a) and 7(b) show the PDF and CDF of the distribution of profits. Figs. 7(c) and 7(d) show the distribution of costs. Finally, Table 6 presents different percentiles of the distributions and the average profits and costs.

As shown in Fig. 7(a), the mode is positive (except for the NS scheme, whose PDF is so flat that it cannot be interpreted from the figure). The CDF in Fig. 7(b) shows that with the floor selected for the hybrid schemes there is approximately a 60% chance that investors will make losses on their investment under a no-subsidy scheme. But that substantially high probability of losses on investment is outweighed by the possibility of high potential returns (fat-tailed distributions).

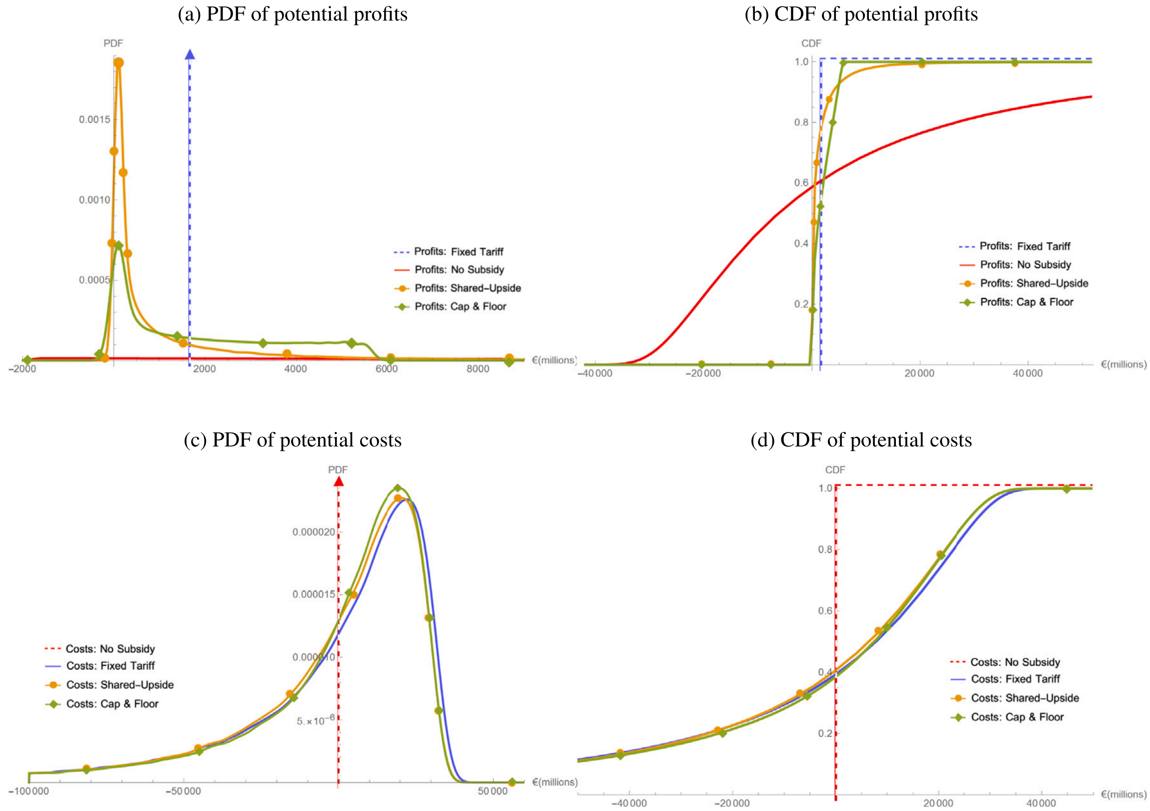

Fig. 7. Distributions of profits and costs (2019).

Table 6
Percentiles of total potential profits and costs in 2019 (€M).

	Investor's profits				Policymaker's costs			
	FT	NS	SU	C&F	FT	NS	SU	C&F
Mean	1,662.5	10,246.0	1,464.9	1,905.2	−8,583.5	0	−8,781.1	−8,340.8
1th %ile	1,662.5	−31,672.8	73.7	73.7	−233,714.0	0	−220,418.0	−230,314.0
5th %ile	1,662.5	−28,247.3	73.7	73.7	−98,942.0	0	−94,131.3	−95,811.1
10th %ile	1,662.5	−25,616.2	73.7	73.7	−57,049.2	0	−54,858.7	−54,241.0
25th %ile	1,662.5	−19,001.3	76.1	111.9	−15,937.8	0	−16,229.3	−14,007.2
50th %ile	1,662.5	−6,254.9	301.1	1,379.6	7,916.3	0	6,564.4	7,620.5
75th %ile	1,662.5	17,599.9	1,397.1	3,383.3	20,663.2	0	19,089.9	19,253.0
90th %ile	1,662.5	58,710.7	3,868.2	4,735.6	27,278.2	0	25,692.9	25,724.7
95th %ile	1,662.5	100,597.0	6,489.3	5,148.6	29,908.7	0	28,319.9	28,328.3
99th %ile	1,662.5	235,195.0	14,948.3	5,528.9	33,335.1	0	31,746.2	31,746.2

The policymaker prefers to offer the SU scheme. Moreover, as shown in Fig. 7(d), there is a 40% chance that the regulator may incur negative costs (i.e. earnings) under the FT, SU, and C&F regimes. The expected profits associated with all three tariffs are much lower than for no subsidy, but so are the potential losses on investment. As can be noted in the figures, in the worst possible scenario for investors under SU or C&F, they do not lose money. By contrast, with no subsidy they could potentially lose most of their investment (€38.6 billion).

5.3. Sensitivity analysis

Given the estimated values of the parameters, the solutions that we obtain for the profits and costs under each subsidy scheme are optimal in expectation. However, the possibility should be considered that some parameters that depend on the market might not evolve as expected. Moreover, the sensitivity of the expected profits and costs of each policy to deviations in the values of these market-dependent parameters may be an important consideration for both investors and regulators when designing their optimal decisions.

Table 7
Elasticities of expected profits and costs with respect to different parameters.

2013		FT	CP	SU			C&F		
				(K = 89)	(K = 92)	(K = 95)	(K = 89)	(K = 92)	(K = 95)
Profits	$E_{\Pi,\mu}$	0	10.18	3.28	1.56	0.37	1.99	1.04	0.27
	$E_{\Pi,\sigma}$	0	0	4.11	1.98	0.47	1.00	0.43	0.09
	$E_{\Pi,r}$	−33.99	−36.07	−54.27	−43.74	−36.31	−39.45	−36.40	−34.50
	$E_{\Pi,C}$	−45.33	−43.51	−70.63	−57.50	−48.23	−51.36	−47.89	−45.84
	$E_{\Pi,G}$	46.33	44.51	71.63	58.50	49.23	52.36	48.89	46.84
Costs	$E_{\Gamma,\mu}$	−0.54	0	−0.44	−0.49	−0.53	−0.46	−0.50	−0.53
	$E_{\Gamma,\sigma}$	0	0	0.14	0.08	0.02	0.05	0.02	0.00
	$E_{\Gamma,r}$	−0.55	−0.73	−0.61	−0.58	−0.56	−0.60	−0.58	−0.56
	$E_{\Gamma,C}$	0	0	0	0	0	0	0	0
	$E_{\Gamma,G}$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2019		**FT**	**NS**	**SU**			**C&F**		
				(K = 25)	(K = 45)	(K = 65)	(K = 25)	(K = 45)	(K = 65)
Profits	$E_{\Pi,\mu}$	0	2.21	8.61	3.63	0.60	1.67	1.10	0.32
	$E_{\Pi,\sigma}$	0	0	5.00	2.43	0.45	−1.87	−1.37	−0.45
	$E_{\Pi,r}$	−11.05	−2.53	−24.86	−17.69	−12.28	−6.67	−7.82	−9.98
	$E_{\Pi,C}$	−23.22	−3.75	−49.37	−35.97	−25.60	−13.22	−15.90	−20.83
	$E_{\Pi,G}$	24.22	4.75	50.37	36.97	26.20	14.22	16.90	21.83
Costs	$E_{\Gamma,\mu}$	2.64	–	1.68	2.04	2.49	2.42	2.55	2.63
	$E_{\Gamma,\sigma}$	0	–	−0.41	−0.28	−0.08	0.74	0.42	0.10
	$E_{\Gamma,r}$	−0.89	–	−0.69	−0.76	−0.86	−0.89	−0.90	−0.89
	$E_{\Gamma,C}$	0	–	0	0	0	0	0	0
	$E_{\Gamma,G}$	1.00	–	1.00	1.00	1.00	1.00	1.00	1.00

Assume that each tariff is designed with the policy set $(K, \Delta, \omega, \overline{C})$, but some of the model parameters do not change over time as anticipated. The expected profits and costs will thus be compromised. We show below in Table 7 the elasticities (E) of expected profits (Π) and costs (Γ) with respect to some market-dependent parameters. The values reported correspond to the parameter settings for each of the two years studied. For the SU and C&F schemes we show how the choice of the minimum price K can affect the value of the elasticities. Specifically, we analyze deviations in the drift (μ) and volatility (σ) of the GBM, the discount rate (r), the total investment cost per installed MW (C), and electricity generation in each period (G). The elasticity of a variable Λ with respect to another variable λ is defined as $E_{\Lambda,\lambda} = \frac{\partial\Lambda/\Lambda}{\partial\lambda/\lambda}$, so if λ increases by 1%, then Λ increases by approximately $E_{\Lambda,\lambda}$%. Therefore, lower exposure to unexpected changes in a given parameter is obtained with elasticities which are lower in absolute value. Thus, regulators may perceive policies that are overly responsive to market conditions as too risky.[15]

For unexpected changes in μ, investors under a Constant Premium bear all the uncertainty, unlike those under a Fixed Tariff. For the hybrid schemes, the higher the value of K, the lower the elasticities of profits with respect to the drift. By contrast, policy costs are insensitive to such changes under CP schemes, and under FT it is the regulator who bears the risk, while for the SU and C&F schemes, the higher the price floor, the greater the sensitivity of costs to changes in μ. Expected profits and policy costs are insensitive to changes in volatility under both FT and CP, as the expected value of the GBM ($S_0 e^{\mu t}$) does not depend on σ. Under SU and C&F schemes, a higher value of K (and thus a lower value of ω or $\overline{C}$) decreases both the investor's and the regulator's sensitivity to changes in the value of σ. As expected, regulators are insensitive to changes in total installation costs per MW (C). The profit elasticities with respect to G and C differ by exactly one unit, but have opposite signs. For both parameters, the higher the value of K, the higher the investor's confidence under SU or C&F regimes with respect to variations in generation or costs. For any policy, regulators share the same exposure to changes in the electricity generation in each period.

From a regulatory perspective, two key conclusions can be drawn. Firstly, an increase in the guaranteed price K of hybrid policies would increase the risk associated with potential market fluctuations. Secondly, sensitivity analysis can be used as a tool when designing incentive policies. For instance, if the regulator lacks certainty about the discount rate r, a C&F scheme may be preferred over a SU scheme due to the lower risk involved.

6. Discussion

Our methodology relies on the assumption that investors seek to maximize expected returns on their investment decisions. This assumption may be justified if investors can diversify their risks with investments in other sectors, which in the best-case scenario are negatively correlated with the investment in renewable sources under consideration. This assumption enables us to obtain analytical solutions for the optimal expected profits and policy costs associated with each subsidy scheme. Nevertheless, we do not exclude the possibility that investors may take risks into consideration.

[15] Hereafter, we refer to elasticities in absolute value, without considering their sign.

From the results obtained in Section 5.1, it can be concluded that without public subsidy support, investors in 2013 would have been unlikely to decide to install the wind capacity required to meet the government's target set in 2011 for 2020. The fact that wind energy investment was frozen after the elimination of subsidies in 2013 strongly supports this finding. According to our results, the necessary investment environment in 2013 required either a Constant Premium support scheme or a Shared-Upside or Cap & Floor scheme (to permit some risk-sharing between the regulator and the investor) with the floor K being as high as possible (i.e. ensuring a higher guaranteed price). As shown in Figs. 3(a) and 3(c), the higher the price floor, the higher the expected profits and, by the same token, the lower the investors' risk exposure to under-remuneration. If investors have to choose between the two hybrid schemes, they prefer the Cap & Floor scheme with the highest possible price floor. From the policymaker's perspective, the policy configuration that leads to the lowest expected policy costs is the Shared-Upside with the floor as low as possible, leading also to lower exposure to cost overrun. It is under a Constant-Premium scheme that the regulator faces the lowest risk of cost overruns.

The main incentive mechanism for wind energy deployment in Spain during that period was the Constant Premium. Our results suggest that not only the Fixed-Tariff but also the other two hybrid schemes provide better expected results for the policymaker than the more widespread mechanism of a Constant Premium. Our findings could also help to determine the optimal level of incentives for reaching the desired installation target. It is possible to design schemes more efficiently, leading to the same level of investment but involving lower expected regulatory costs. Furthermore, some of these new mechanisms may also enable risk exposure to be shared between regulators and investors, which is also a relevant consideration if they cannot perfectly diversify risk.

In regard to the results reported in Section 5.2, we conclude that with no public subsidy market incentives in 2019 were sufficient for firms to invest in wind capacity so as to meet the government's target for 2030. Our analysis suggests that in 2019 an investor seeking to maximize expected profits preferred to receive the market price rather than the supporting policies we consider, by contrast with what happened in 2013. This finding is consistent with the fact that the average price in all the energy auctions held in 2016 and 2017, which led to the new installed capacity in 2019, was zero (AURES II, 2021b). That is, the participants were willing to invest in the installation of wind energy with the market price alone as payment. There are three main reasons for this. First, the costs associated with the installation of a wind farm were far lower than in 2013. Second, the price for the initial period (S_0) was considerably higher in 2019 than in 2013. Finally, in recent years the WACC has been decreasing, so future payments to investors are discounted at a lower rate.

All the schemes analyzed involve negative expected policy costs (earnings for the regulator) for 2019 due to the high market prices. This is not a problem because the participation of companies in the incentive system is voluntary. If a firm were offered a negative subsidy, it would simply reject it. In mathematical terms, there is a corner solution outside the feasible set where the policy costs are negative. This is not a problem for our initial purpose, since our objective is to compare how each scheme behaves with respect to the others. As in 2013, the policymaker's expected policy costs in the hybrid schemes are lower than those for the FiP or for no subsidy. It should be noted that if the FiP is taken into account, its expected policy costs in 2019 (−8,580M) would be higher than those of either the FT or the SU scheme. Therefore, the same level of investment (Q_I new units of wind power) is encouraged more efficiently. This is evidence of an indisputable gain compared to both the FiP and the no-subsidy case. Our results show that for the year 2019, the optimal regulation is not to provide incentives to investors. Note that providing incentives is different from providing insurance. The regulator may still want to provide insurance to investors (to ease the financial conditions for investment, for example) offering a price that (on average) is not more advantageous than the market price (insurance, but not a premium over the market price).

We have shown how the interests of the policymaker and those of the investor tend to be opposed. Both parties not only have to consider protecting themselves against the risk of low/high electricity market prices but must also consider the risk that the market-dependent parameters for which public subsidies are designed may not change over time as expected. Thus, there is a trade-off between greater protection against market prices and higher (lower) expected profits (policy costs) that investors (the regulator) must face.

Finally, we show that the set of new assumptions (i.e. endogenous σ and d_i to the investors' optimization problem) can lead to results which are significantly different from those in Farrell et al. (2017), not only quantitatively but also, more importantly, qualitatively. As a result, policy recommendations in each case may differ considerably. This can be observed in Appendix B, where we compare the results obtained under the two sets of assumptions.

7. Conclusions

Until they were eliminated in 2013, Feed-in Tariffs were the main instrument for supporting investment in renewable energy in Spain. After that time, wind energy investment slowed down for several years. A major drawback of typical FiT schemes is that only one of the parties assumes all the risk. Building on the work by Farrell et al. (2017), we design and simulate hybrid incentive schemes that have two degrees of freedom in their design, making them more flexible than traditional tariffs. This flexibility thus introduced into policy design may result in efficiency gains or the possibility of risk-sharing between investors and governments.

In this paper, we extend the original model in Farrell et al. (2017) in different directions. First, we consider that volatility depends on penetration, so volatility and its variation with respect to installed capacity are endogenous to the investor's optimization problem. Second, we take into account how installed capacity affects the probability of prices reaching a certain level. Finally, we discuss non-zero initial wind capacity. The adoption of these new assumptions can yield results that differ significantly, not just quantitatively but also, more importantly, qualitatively. Consequently, the policy recommendations of each model may differ significantly.

We present an empirical application for wind power in Spain for 2013, the final year in which the Feed-in Tariff scheme was in force, and for 2019, when Feed-in Tariffs had been completely phased out but before the demand shock caused by COVID-19, the restructuring of market price limits, and the recent energy price crisis in Europe. We run stochastic simulations to determine how these schemes would behave in a scenario that seeks to approximate the Spanish environment for 2013 and 2019. We fully characterize the distribution of potential investment profits and policy costs under each scheme. Finally, we carry out a sensitivity analysis to determine the effects of each policy on expected profits from investment and policy costs if different market-dependent parameters do not evolve as expected.

The methodology described enables different incentive mechanisms to be designed, each of which entails different expected policy costs for the regulator while resulting in the same level of investment in renewable sources. Furthermore, two of the mechanisms that we study (Shared-Upside and Cap & Floor) permit risk-sharing between investor and regulator and, more importantly, might be more efficient than the traditional schemes: These two tariffs entail lower expected policy costs than constant-FiP, which is the main mechanism used to date to foster the penetration of wind energy in Spain. These intermediate or hybrid schemes can be adapted to modify the value of the expected policy costs and investment profits and the risk that each party has to bear. Our results also show that there is an unavoidable conflict between the interests of investors and the regulator. Each party faces its own trade-off: Investors might have to choose between higher expected profits and lower risk of low remuneration, while regulators might be forced to choose between lower expected policy costs and lower risk of public cost overruns (as occurred for C&F in 2019). We further show that sensitivity analysis can offer some interesting insights for both investors and regulators when each policy is designed.

Our methodology includes certain assumptions and approximations that may limit its accuracy. First, the calibration carried out is intended to credibly align with the investment environment at the aggregate level. For a more accurate application of the methodology, a more precise calibration of specific projects would be required. Second, it must be borne in mind that the assumption that electricity prices follow a Geometric Brownian Motion is justified but it must be remembered that it is an approximation for analytical convenience. Real-world processes may be more complex. The model for electricity prices could be generalized to include more variables that affect electricity prices, but this would mean giving up on analytical tractability. The GBM process should not be considered as a forecasting model, but as a tool to incorporate uncertainty in a way that can be managed by analytical methods. Finally, the various approximations made to obtain closed-form solutions, such as assuming identical costs per MW (C) for the entire project and constant wind generation (G) over time, could compromise the accuracy of the results in real applications. However, this is not a problem: As already pointed out, our purpose is not to characterize or predict the precise financial results of a particular policy but rather to see how each incentive scheme behaves compared to the rest. Therefore, the method followed is valid and has significant implications. Most of the parameters needed to calibrate the model come from official sources (government, system operator, market operator), so the practical implementation of the model is feasible from the regulator's point of view.

We show that the design of the FiT schemes used in Spain until 2013 can be improved in several ways. This contribution is relevant because at the end of 2020, FiT/FiP mechanisms continued to promote different RES technologies in 83 jurisdictions at national and subnational levels. In addition, our model can provide valuable insights into the minimum expectations that regulators consider when conducting auctions, as it is reasonable to assume that the regulator expects the outcome of the auction to be at least as efficient as the FiT/FiP it would offer beforehand. Furthermore, the model presented can also be a useful tool for designing auctions with no maximum price, since it enables the performance of different payment systems to be compared, even if their incentive levels are awarded in auctions. Therefore, the model described can aid in setting the maximum bidding price for auctions with a reserve price. This is not a trivial issue, as demonstrated by the case of Spain in 2022, where miscalculating the limit price resulted in the auction failing.

As discussed above, green energy promotion policies often involve very high regulatory costs. Therefore, any contribution to a more efficient design of these policies may be useful and of interest at global level. Moreover, according to Dijkgraaf et al. (2018), the literature underestimates the potential impact of these incentives, as the specific design of policies turns out to be crucial. Indeed, they show that the effect of a well-designed regulation is far greater than the average effect of the schemes currently applied.

For further research, we propose to study the possibility of relaxing some of the approaches and further extending the model in various directions. The most noteworthy improvement could be to characterize investors' preferences by a constant relative risk aversion (CRRA) utility function instead of simply via expected profits, which would make our analysis more general. Another substantial improvement would be to consider random generation. Such extensions may require greater use of computational methods in the methodology. Finally, the optimal scheme found numerically under this extended methodology could be compared to other public support systems for renewable sources, such as Tradable Green Certificates and Energy Auctions (Ciarreta et al., 2014b). These open questions are left for future research.

Declaration of competing interest

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Data availability

Data will be made available on request.

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Appendix A. Detailed derivation of the model solution under each regulation

In this appendix, we provide a detailed description of the procedure followed to derive expressions (13), (16), (22), and (29) in the text.

The strategic interaction between policymaker and investors in the design of a FiT is modeled as a leader-follower game, where the policymaker selects the policy remuneration first (decision variable K) and investors respond with their investment decisions (Q). Thus, the policymaker must consider the strategic response of investors and select K to implement the desired level of investment. To solve this problem, the optimal response function of investors is first calculated and then incorporated into the policy maker's decision function. As described in Section 3.2 in the main text, the desired level of investment Q_I is achieved when

$$\left.\frac{\partial \Pi}{\partial Q}\right|_{Q=Q_I} = \sum_{t=1}^{T_F} e^{-rt} \left(E[P_t]\frac{\partial G}{\partial Q} + \frac{\partial E[P_t]}{\partial Q} G \right)\Big|_{Q=Q_I} - C = 0 \tag{A.1}$$

For each policy, we denote by P_t the benefits obtained in each period t, which depend on the market price in that period. Given that the regulation, in general, may be in force for a time T_1 shorter than the operative lifetime of the utility (T_F), we differentiate the revenues ($P_t = P_t^*$) obtained under the incentive policy in $t \le T_1$ from those received after the subsidy has ended at $T_1 < t \le T_F$, where suppliers are paid at market price ($P_t = S_t$).

$$P_t = \begin{cases} P_t^* & ; 1 < t \le T_1 \\ S_t & ; T_1 < t \le T_F \end{cases} \tag{A.2}$$

In Eq. (A.1) we separate the terms corresponding to $t \le T_1$ and the others:

$$\left[\sum_{t=1}^{T_1} e^{-rt} \left(E[P_t^*]\frac{\partial G}{\partial Q} + \frac{\partial E[P_t^*]}{\partial Q} G \right) + \sum_{t=T_1+1}^{T_F} e^{-rt} \left(E[S_t]\frac{\partial G}{\partial Q} + \frac{\partial E[S_t]}{\partial Q} G \right) \right] \Big|_{Q=Q_I} - C = 0 \tag{A.3}$$

We now replace the relevant expressions in the preceding equation. The expected revenue received in each period depends directly on the market price, which in turn will depend on the installed quantity Q (as μ and σ depend on Q). The expectations are found by integrating the probability density of the Geometric Brownian Motion process defined in Eq. (8) in the main text:

$$E[P_t] = \begin{cases} E[P_t^*] = \dfrac{1}{\sigma\sqrt{2\pi T}} \displaystyle\int_0^\infty \frac{P_t^*(\xi)}{\xi} \exp\left(-\frac{\left(\log\left(\frac{\xi}{S_0}\right) - (\mu - \frac{\sigma^2}{2})T \right)^2}{2\sigma^2 T} \right) d\xi \\[2ex] E[S_t] = \dfrac{1}{\sigma\sqrt{2\pi T}} \displaystyle\int_0^\infty \exp\left(-\frac{\left(\log\left(\frac{\xi}{S_0}\right) - (\mu - \frac{\sigma^2}{2})T \right)^2}{2\sigma^2 T} \right) d\xi = S_0 e^{\mu t} \end{cases} \tag{A.4}$$

As shown, $E[S_t] = S_0 e^{\mu t}$. $E[P_t^*]$ and its derivative will differ for each policy.

$$\frac{\partial E[P_t]}{\partial Q} = \begin{cases} \dfrac{\partial E[P_t^*]}{\partial Q} & ; 1 < t \le T_1 \\[2ex] S_0 e^{\mu t} t \dfrac{\partial \mu}{\partial Q} & ; T_1 < t \le T_F \end{cases} \tag{A.5}$$

As discussed in the main text:

$$G(Q) = Q_{max}\kappa(e^{-\gamma Q_0} - e^{-\gamma(Q_0+Q)}) \tag{A.6}$$

hence:

$$\frac{\partial G(Q)}{\partial Q} = Q_{max}\kappa\gamma e^{-\gamma(Q_0+Q)} \tag{A.7}$$

Therefore, Eqs. (13), (16), (22), and (29) are obtained by introducing the values of $E[P_t^*]$ and $\frac{\partial E[P_t^*]}{\partial Q}$ that correspond to the policy under consideration. The detailed calculations for each incentive scheme are shown below.

Fixed tariff

For the Fixed Tariff regulation, $P_t^* = K_A$, hence

$$E[P_t^*] = K_A \tag{A.8}$$

$$\frac{\partial E[P_t^*]}{\partial Q} = 0 \tag{A.9}$$

Substituting (A.8) and (A.9) in Eq. (A.3), we characterize the optimal point $K_A = K_A^*$:

$$\left[\sum_{t=1}^{T_1} e^{-rt}\left(K_A^* \frac{\partial G}{\partial Q}\right) + \sum_{t=T_1+1}^{T_F} e^{-rt}\left(S_0 e^{\mu t} t \frac{\partial G}{\partial Q} + S_0 e^{\mu t} t \frac{\partial \mu}{\partial Q} G\right)\right]\Bigg|_{Q=Q_I} - C = 0 \tag{A.10}$$

Note that the optimal level of the incentive, K_A^*, is such that investors maximize profits by choosing the targeted level $Q = Q_I$. Finally, from (A.10) a closed-form solution is obtained for K_A^*.

$$K_A^* = \frac{C - \sum_{t=T_1+1}^{T_F}\left[S_0 e^{(\mu-r)t}\left(t\frac{\partial \mu}{\partial Q}G + \frac{\partial G}{\partial Q}\right)\right]\Big|_{Q=Q_I}}{\sum_{t=1}^{T_1} e^{-rt}\frac{\partial G}{\partial Q}\Big|_{Q=Q_I}} \tag{A.11}$$

For the rest of the tariffs the procedure is identical. For the Shared Upside and the Cap & Floor schemes it is not possible to obtain a closed-form solution, so the solution must be found by numerical methods.

Constant premium

For a constant premium tariff, the payment that investors receive is based on a constant premium (Δ) offered on top of the market price: $P_t^* = \Delta + S_t$:

$$E[P_t^*] = \Delta + S_0 e^{\mu t} \tag{A.12}$$

$$\frac{\partial E[P_t^*]}{\partial Q} = S_0 e^{\mu t} t \frac{\partial \mu}{\partial Q} \tag{A.13}$$

leading to:

$$\Delta^* = \frac{C - \sum_{t=1}^{T_F}\left[S_0 e^{(\mu-r)t}\left(t\frac{\partial \mu}{\partial Q}G + \frac{\partial G}{\partial Q}\right)\right]\Big|_{Q=Q_I}}{\sum_{t=1}^{T_1} e^{-rt}\frac{\partial G}{\partial Q}\Big|_{Q=Q_I}} \tag{A.14}$$

Shared upside

The payoffs that an investor receives at $(t \le T_1)$ under the Shared Upside scheme are described by:

$$P_t^* = \max\{K_C, \omega(S_t - K_C) + K_C\} = \begin{cases} K_C & S_t < K_C \\ \omega(S_t - K_C) + K_C & K_C \le S_t \end{cases} \tag{A.15}$$

hence:

$$E[P_t^*] = K_C(1 - \omega\Phi(d_2)) + \omega S_0 e^{\mu t}\Phi(d_1) \tag{A.16}$$

$$d_1 = \frac{\log\left(\frac{S_0}{K}\right) + \left(\mu + \frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}} \qquad d_2 = \frac{\log\left(\frac{S_0}{K}\right) + \left(\mu - \frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}} \tag{A.17}$$

$$\frac{\partial E[P_t^*]}{\partial Q} = -K_C\omega\phi(d_2)\frac{\partial d_2}{\partial Q} + \omega S_0 e^{\mu t}\left(t\frac{\partial \mu}{\partial Q}\Phi(d_1) + \phi(d_1)\frac{\partial d_1}{\partial Q}\right) \tag{A.18}$$

$$\frac{\partial d_1}{\partial Q} = \frac{\sqrt{t}}{\sigma}\frac{\partial \mu}{\partial Q} - \left(\frac{d_1}{\sigma} - \sqrt{t}\right)\frac{\partial \sigma}{\partial Q} \qquad \frac{\partial d_2}{\partial Q} = \frac{\sqrt{t}}{\sigma}\frac{\partial \mu}{\partial Q} - \left(\frac{d_2}{\sigma} + \sqrt{t}\right)\frac{\partial \sigma}{\partial Q} \tag{A.19}$$

finally leading to:

$$\begin{aligned}&\sum_{t=1}^{T_1} e^{-rt}\left\{\left[K_C^*\left(1-\omega\Phi(d_2(K_C^*,t))\right)+\omega S_0 e^{\mu t}\Phi(d_1(K_C^*,t))\right]\frac{\partial G}{\partial Q}+\right.\\&\left.\left[\omega S_0 e^{\mu t}\left(t\frac{\partial \mu}{\partial Q}\Phi(d_1(K_C^*,t))+\phi(d_1(K_C^*,t))\frac{\partial d_1(K_C^*,t)}{\partial Q}\right)-K_C^*\omega\phi(d_2(K_C^*,t))\frac{\partial d_2(K_C^*,t)}{\partial Q}\right]G\right\}\Bigg|_{Q=Q_I}+\\&\sum_{t=T_1+1}^{T_F} S_0 e^{(\mu-r)t}\left(t\frac{\partial \mu}{\partial Q}G+\frac{\partial G}{\partial Q}\right)\Bigg|_{Q=Q_I}-C=0\end{aligned}\tag{A.20}$$

Cap and floor

The payoffs that an investor receives at $(t \leq T_1)$ under a Cap&Floor are described by:

$$P_t^* = \max\{K_D, \min\{S_t, \overline{C}\}\} = \begin{cases} K_D & S_t < K_D \\ S_t & K_D \leq S_t < \overline{C} \\ \overline{C} & \overline{C} \leq S_t \end{cases}\tag{A.21}$$

hence:

$$E[P_t^*] = K_D\left(1-\Phi(d_2)\right)+S_0e^{\mu t}\left(\Phi(d_1)-\Phi(d_3)\right)+\overline{C}\Phi(d_4)\tag{A.22}$$

where

$$d_3 = \frac{\log\left(\frac{S_0}{\overline{C}}\right)+\left(\mu+\frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}} \qquad d_4 = \frac{\log\left(\frac{S_0}{\overline{C}}\right)+\left(\mu-\frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}}\tag{A.23}$$

$$\frac{\partial E[P_t^*]}{\partial Q} = -K_D\phi(d_2)\frac{\partial d_2}{\partial Q}+S_0e^{\mu t}\left(t\frac{\partial \mu}{\partial Q}\Phi(d_1)+\phi(d_1)\frac{\partial d_1}{\partial Q}\right)-S_0e^{\mu t}\left(t\frac{\partial \mu}{\partial Q}\Phi(d_3)+\phi(d_3)\frac{\partial d_3}{\partial Q}\right)+\overline{C}\phi(d_4)\frac{\partial d_4}{\partial Q}\tag{A.24}$$

$$\frac{\partial d_3}{\partial Q} = \frac{\sqrt{t}}{\sigma}\frac{\partial \mu}{\partial Q}-\left(\frac{d_3}{\sigma}-\sqrt{t}\right)\frac{\partial \sigma}{\partial Q} \qquad \frac{\partial d_4}{\partial Q} = \frac{\sqrt{t}}{\sigma}\frac{\partial \mu}{\partial Q}-\left(\frac{d_4}{\sigma}+\sqrt{t}\right)\frac{\partial \sigma}{\partial Q}\tag{A.25}$$

finally leading to:

$$\begin{aligned}&\sum_{t=1}^{T_1} e^{-rt}\left\{\left[K_D^*\left(1-\Phi(d_2(K_D^*,t))\right)+S_0e^{\mu t}\left(\Phi(d_1(K_D^*,t))-\Phi(d_3(\overline{C},t))\right)+\overline{C}\Phi(d_4(\overline{C},t))\right]\frac{\partial G}{\partial Q}+\right.\\&\left[S_0e^{\mu t}\left(t\frac{\partial \mu}{\partial Q}\left(\Phi(d_1(K_D^*,t))-\Phi(d_3(\overline{C},t))\right)+\phi(d_1(K_D^*,t))\frac{\partial d_1(K_D^*,t)}{\partial Q}-\phi(d_3(\overline{C},t))\frac{\partial d_3(\overline{C},t)}{\partial Q}\right)+\right.\\&\left.\left.\overline{C}\phi(d_4(\overline{C},t))\frac{\partial d_4(\overline{C},t)}{\partial Q}-K_D^*\phi(d_2(K_D^*,t))\frac{\partial d_2(K_D^*,t)}{\partial Q}\right]G\right\}\Bigg|_{Q=Q_I}+\\&\sum_{t=T_1+1}^{T_F} S_0e^{(\mu-r)t}\left(t\frac{\partial \mu}{\partial Q}G+\frac{\partial G}{\partial Q}\right)\Bigg|_{Q=Q_I}-C=0\end{aligned}\tag{A.26}$$

Appendix B

Our analysis builds on the approach by Farrell et al. (2017) to model the interaction between the regulator and investors. We extend their model to consider an additional type of policy mechanism (fixed prices) and, more importantly, we allow both the volatility and the price drift to depend endogenously on renewable energy penetration. The idea that volatility and price levels may change with renewable penetration is supported by data from actual markets, and it is a more realistic assumption (Ballester and Furió, 2015). However, assuming they are constant could be a reasonable simplifying assumption. We check in this appendix whether the assumption of fixed volatility and drift (as in Farrell et al. 2017) is innocuous for the results or not. It turns out that when both are endogenously dependent on the penetration of renewable sources, the results are qualitatively different, which leads to significant changes in the predictions of the model and the policy implications.

To assess the effects of our extension ($\sigma(Q)$ and $\mu(Q)$ depend on renewable penetration) we solve the model by fixing both parameters throughout the optimization process (Farrell et al. 2017) to compare the results to the case where they are not fixed (our extension). We present a comparison of the main results, expected benefits, and costs obtained from each model for the two years under study.

As shown in Figs. A.1 and A.2, the results obtained for 2013 differ significantly from one model to the other. In our model, the expected benefits and costs of both intermediate schemes are lower than for the conventional FT and CP schemes. Moreover, of the two intermediate schemes, the C&F scheme offers higher values than the SU scheme. Finally, for both hybrid schemes the expected benefits and costs increase as the incentive level K increases. On the other hand, when solving the model without taking

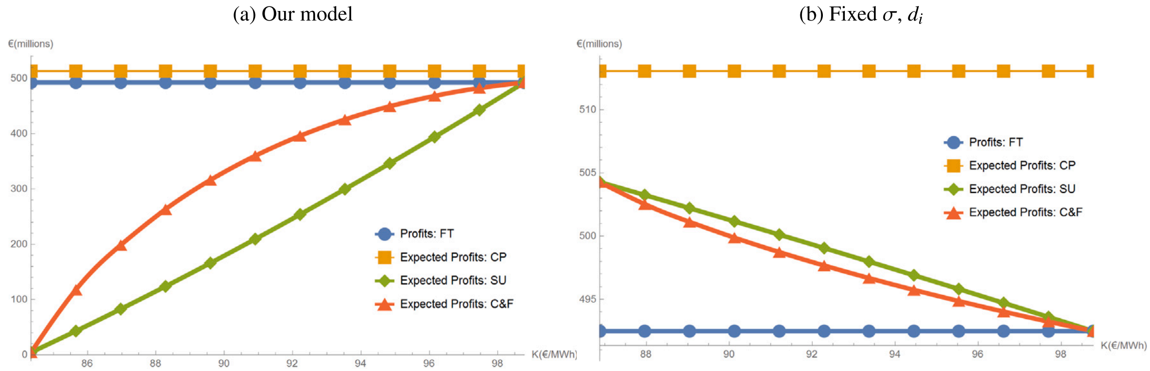

Fig. A.1. Expected profits (2013).

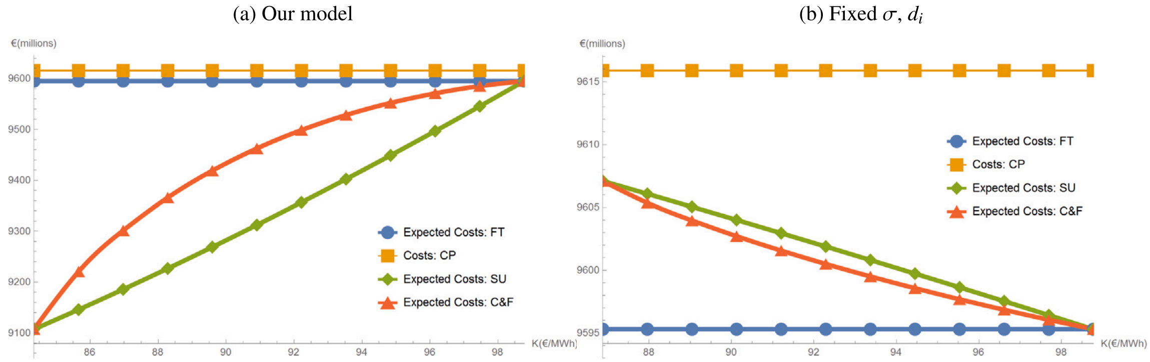

Fig. A.2. Expected costs (2013).

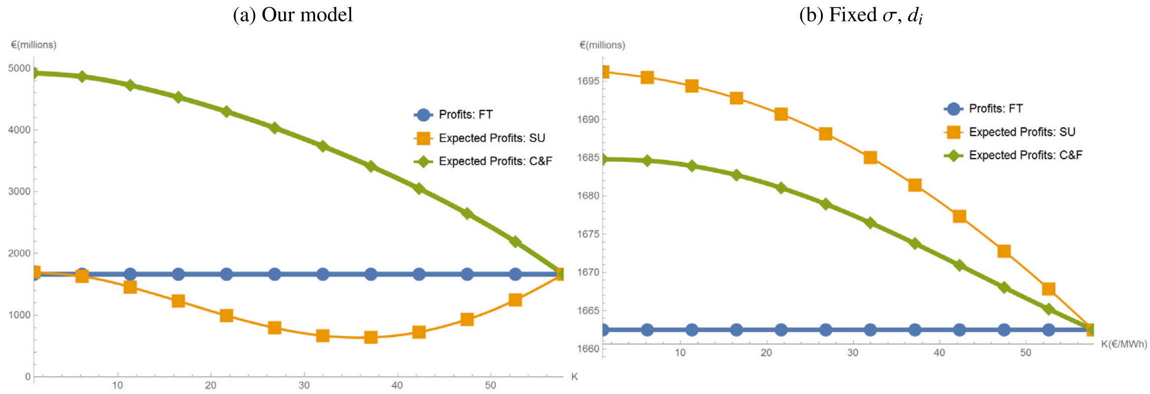

Fig. A.3. Expected profits (2019).

into account the dependence of σ and d_i on Q in the optimization problem, it is found that the CP scheme offers higher expected costs and benefits than any other regulation, while the FT scheme implies lower values. Furthermore, the ordering of the intermediate schemes is opposite to the previous case and, more importantly, as the incentive price increases the expected costs and benefits decrease.

Likewise, we compare the results obtained from the two models for 2019, where we ignore the benchmark case of no subsidy since both models give identical results for that case. Generally, the differences between the two models will depend on the parameters used in the specific application. As can be seen in Figs. A.3 and A.4, there are not only quantitative differences, but also significant qualitative differences between the two models.

We conclude that the assumption that σ and μ are fixed is not innocuous for the results. It affects the relative expected benefits and costs of the different incentive schemes, potentially leading to different policy recommendations. As a representative example, under our model it is convenient for the regulator to establish an SU regulation with the lowest possible minimum price in 2013

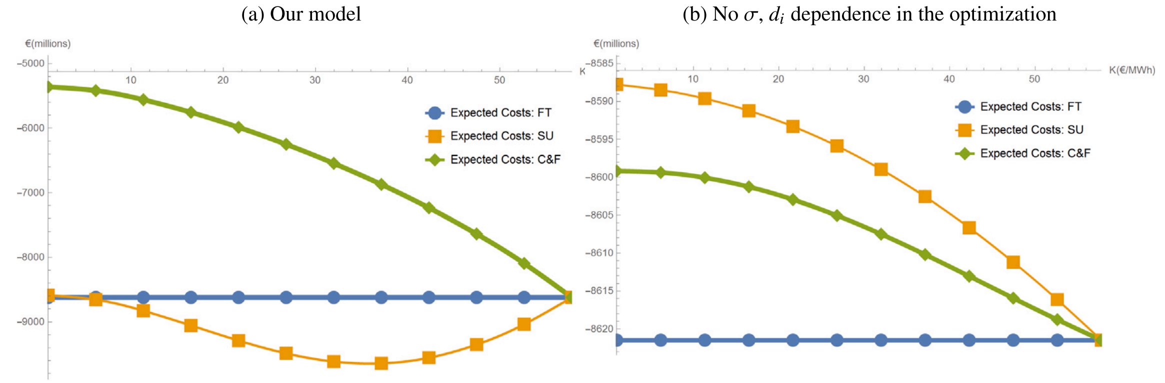

Fig. A.4. Expected costs (2019).

and an FT regulation for 2019. However, when the two parameters are assumed to be fixed, and therefore independent of renewable penetration, it is optimal for the regulator to establish an FT regulation in both years.

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