Managing Revenue Uncertainty in Renewable Energy Auctions through Subsidy Design

A Real Options Approach

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Abstract

Renewable energy auctions have become a prominent policy instrument in recent years. A central issue with these auctions is that a significant number of participating projects end up not being realized. This thesis proposes a novel subsidy structure, the Moving Average Feed-in Premia, aiming to reduce revenue uncertainty of renewable energy projects and improve auction realization rates. By tying the selling price of produced electricity to a moving average price instead of the more volatile spot price, revenue uncertainty is reduced without increasing policy costs in the long run.

This thesis adds to the literature by quantifying the impact revenue uncertainty has on renewable energy outcomes. It fills a clear research gap as no previous literature has studied electricity price uncertainty within the context of renewable energy auctions. Using real option theory, non-realization of auction-winning projects is rationalised, and the role of revenue uncertainty in auction outcomes is identified. The developed model is simulated using three real-world cases based on German and Italian auction data, comparing outcomes under standard feed-in premia and moving average feed-in premia. The findings suggest that reducing revenue volatility by tying the selling price to a moving average can significantly improve auction realization rates and lead to an overall reduction in project abandonment.

Keywords: Electricity Prices, Monte Carlo, Renewable Energy Auctions, Real Options, Simulation, Uncertainty

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Abbreviations

Abbreviation	Description
GBM	Geometric Brownian Motion
FIP	Feed-in Premium
FIT	Feed-in Tariff
LSM	Least-Squares Monte Carlo
MA-FIP	Moving Average Feed-in Premium
NPV	Net Present Value
OU	Ohrnstein-Uhlenbeck
PV	Photovoltaic
RE	Renewable Energy
RO	Real Option
WACC	Weighted Average Cost of Capital

1. Introduction

Incentivising renewable energy (RE) adoption is a core component of our efforts to mitigate climate change (Gonzales et al., 2023). As a result, effective RE policy design is a central topic for policymakers worldwide. RE auctions have recently emerged as a favoured policy instrument to distribute financial support to various types of RE projects as they encourage competition among developers by incentivising them to reveal the minimum level of government support necessary to make their projects economically viable (Anatolitis, 2023; Batz Liñeiro & Müsgens, 2021; Grashof, 2021). For instance, in Germany's June 2018 auction aimed at photovoltaic (PV) projects, Enerparc AG was awarded support for several projects around Germany (Federal Network Agency, 2018). While companies like Enerparc represent larger, professional developers, smaller actors also participate in these auctions (Matthäus et al., 2021). These auctions thus not only lead to lower policy costs due to competition between project developers but also ensure, through the auction mechanism, that it is the most cost-efficient projects that receive government backing (Matthäus et al., 2021).

Despite their efficiency advantages, RE auctions frequently face the issue of project non-realization, where winning projects are abandoned due to unfavourable market conditions after the auction, limiting the effectiveness of the auctions. Non-realization directly undermines policy goals by delaying RE deployment and climate change mitigation (Matthäus et al., 2021). Developers typically have a grace period after winning an auction, during which they can delay committing fully to project construction to maximize potential profitability. However, failing to complete the project within specified timeframes ultimately leads to penalties and loss of government support. Penalties typically take the form of bonds and scale with the project's capacity, disproportionately impacting larger projects when abandoned.

A primary cause of non-realization is the inherent uncertainty developers face regarding future revenues and costs. When market conditions evolve less favourably than anticipated, developers may find their projects no longer profitable and thus choose to abandon them, despite penalties (Matthäus et al., 2021). This issue is exacerbated by bidders who strategically submit overly optimistic bids, betting on favourable future market conditions that may not materialize.

This thesis addresses this issue by proposing a subsidy structure, tying a feed-in premium (FIP) to a moving-average electricity price instead of the volatile spot price. Uncertainty faced by RE producers is thus substantially reduced. Lowering revenue volatility decreases developers' incentives to delay investments by reducing the real option (RO) value of the investment opportunity. Consequently, a moving-average feed-in premium (MA-FIP) can improve auction realization rates without increasing overall policy costs.

Previous studies on RE auctions have primarily focused on penalties and pre-qualification requirements to curb non-realization risks (Matthäus 2020; Grashof 2021; Matthäus et al., 2021). Unlike these approaches, which typically focus on penalties or pre-qualification requirements to enhance realization rates, this thesis targets the subsidy structure itself. By directly reducing price uncertainty, the proposed MA-FIP enhances project realization rates without introducing additional financial risks to developers, unlike penalty-based approaches.

To quantify the impact of this new subsidy design, this study employs a RO framework combined with Least-Squares Monte Carlo (LSM) simulations, analysing auction cases from Germany and Italy. The results demonstrate that the MA-FIP approach effectively improves project realization rates and auction efficiency.

2. Literature Review

2.1 Realization Rates and Auction Design

Developer behaviour exhibits heterogeneity across firm size and project scale. Linnerud et al. (2014) find that developers of larger, utility-scale hydropower projects behave in line with RO theory. Yet, within RE auctions, smaller actors value flexibility more highly, whereas large developers prioritize time efficiency (Côté et al., 2022). The contradicting results are explained by the findings of Fleten et al. (2016), who similarly found that RE developers claimed not to use a RO model when evaluating projects. However, when analysing the same dataset as Linnerud et al. (2014), they found that their behaviour was largely in line with that predicted by a RO framework rather than their claim of using NPV evaluation (Fleten et al., 2016).

The valuation of RE projects significantly differs when comparing traditional NPV analysis with RO approaches. Matthäus et al. (2021) present a framework showcasing the impact of bidders using RO analysis in their evaluation of projects on subsequent bids. RO developers can rationally and systematically outbid traditional NPV developers as they include the value of the flexibility that the auction gives to the developers in their project evaluation. RO bidders could therefore bid at levels lower than those the project requires in the present, hoping conditions improve later, making the project profitable if timed correctly. It is noted that this approach is positive in terms of policy cost, as the winning bids will be lower than in the NPV case, but also carries more risk as the realization of the projects is no longer guaranteed. Auctions that manage to significantly reduce policy cost by allowing flexibility will perform worse in terms of increasing adoption rates (Matthäus et al., 2021).

Matthäus et al. (2021) also evaluated the effects that prequalification requirements had on realization rates. Prequalification requires bidders to commit to the submitted project before auction participation, locking in part of the project and creating sunk costs, effectively raising the cost of abandonment (Grashof, 2021). Prequalification causes the project to lose full flexibility, as part of the project becomes locked in, which leads to a reduction in the advantage of the RO bidder, since the prequalification requirements will only affect non-realized projects (Matthäus et al., 2021). When the impact of financial prequalification on bid levels and project realization rates was simulated, they found that it was a highly effective tool in discouraging abandoning or delaying the project past the grace period.

Matthäus et al. (2021) employ two simplifying assumptions that may bias their results. First, they equate the volatile FIPs with feed-in tariffs (FITs), which guarantees a price level at which electricity can be sold at. By doing so, they effectively ignore the uncertainty stemming from electricity price evolution, thus potentially underestimating the importance of flexibility. Secondly, Matthäus et al. (2021) model investment opportunities as European options, granting only a single exercise opportunity at the end of the grace period. Consequently, there could be differences in optimal exercise strategy due to the greater temporal flexibility of American options (Longstaff & Schwartz, 2001). Using American option evaluation is therefore arguably more empirically accurate, as the developer can freely choose when to develop the project, where the grace period merely acts as a deadline before penalties are applied.

Forcing a degree of project lock-in early through prequalification may adversely affect bid volumes, decreasing the effectiveness of the auctions as an incentive to adopt RE sources (Del Río & Linares, 2014; Grashof et al., 2020). Developers' willingness to accept different types of risk was examined by Côté et al. (2022) through a survey of wind power development companies. They found prequalification measures focused on pre-securing building permits had a considerable influence on the developer's decision to participate in an auction (Côté et al., 2022). Similarly, Grashof et al. (2020) identify the cost and uncertainty regarding building permits as a contributing factor to observed decreased levels of competition. A less competitive auction impacts both the cost-efficiency and overall effectiveness of the auctions (Grashof et al., 2020). If few developers participate, there is less pressure to reveal their equilibrium level of support, driving awarded support higher. Arguably more importantly, if developers decide not to participate, adoption rates of RE will decline as they deem the support provided does not outweigh the risks stemming from the auction design.

The alternative to prequalification requirements is to impose financial penalties on non-realized projects. However, Côté et al. (2022) similarly find that bid bonds, which force participants to provide a deposit to participate in the auction, are seen as a major risk factor among developers. The required risk premia were positively correlated with the size of the bonds. Specifically, bid bonds of €5,000–30,000/MW add 0.43% to required returns, rising to 1.73% for bid bonds of €70,000/MW. Increasing financial penalties may therefore not be a viable solution to deter non-realization if policy cost is a concern.

2.2 Revenue Uncertainty

Electricity price is the most common source of uncertainty cited among papers analysing RE investments through the lens of RO (Kozlova, 2017; Lazo & Watts, 2023). Electricity markets typically use supply and demand-based pricing, allowing electricity price uncertainty to be mitigated through support schemes that promise long-term stability and predictability of the electricity price. A traditional FIT scheme guarantees the price at which produced electricity can be sold, thus eliminating revenue uncertainty stemming from electricity price volatility altogether. However, eliminating the revenue uncertainty of RE projects does not remove the underlying price uncertainty (Alcorta et al., 2023). FITs instead move all uncertainty to the issuer of the subsidy, as any price deviations away from the FIT-level must be covered (Alcorta et al., 2023; Grashof, 2021).

In a RO analysis of the effects of different support schemes aimed at RE investment, Boomsma et al. (2012) found that FITs tended to encourage earlier investment compared to other types of subsidies. When compared to FIPs, it was found to have a slight adverse impact on overall project value, but with a significantly lower waiting option value. The waiting option value is the monetary benefit of being allowed to wait and see how conditions develop, and limiting it is key to accelerating RE adoption. These findings are in line with other literature on the subject, such as Cheng et al. (2017) where it was also found that FITs accelerated investment in RE production. Additionally, they found that the effects of the respective support schemes were time-dependent, with the more uncertain FIP scheme greatly increasing option value in the short term and the FIT scheme being more impactful in long-term scenarios (Cheng et al., 2017).

Empirically, the main concern among auction participants is regarding the support scheme on offer in the auction (Côté et al., 2022). Auction outcomes are not only theoretically sensitive to the type of support scheme on offer but also confirmed by empirical findings. Similarly, Egli (2020) finds that price uncertainty has become the most important risk factor for PV and onshore wind power investments. The introduction of RE auctions in combination with exposing developers to price risk uncertainty was identified to be the main driver behind this rise (Egli, 2020).

2.3 Summary and Research Gap

Accounting for RO developers is found to be highly relevant when designing effective auctions. There are measures aimed at guaranteeing the realization of participating projects by targeting the waiting option value. However, current measures put in place to mitigate the reduced realization rates stemming from

RO-type developers come with drawbacks that adversely affects both participation and bid levels.

Price uncertainty is found to be a major concern among developers as it makes the profitability of their project highly unpredictable. Yet, no identified literature has incorporated price uncertainty within the context of RE auctions. This study will fill this gap by putting the role of price uncertainty into practice through the MA-FIP policy instrument. Using case analysis, investment timing will be simulated under different levels of revenue uncertainty, giving new insight into how realization rates can be improved.

3. Theoretical Framework

3.1 Stochastic Processes

The profitability of a RE project is based on two variables: the price (*P*) at which a unit of generated electricity can be sold at and the cost (*C*) of production for that unit. Over long timeframes, a simple Geometric Brownian Motion (GBM) process is adequate to model the development of electricity prices (Pindyck, 1999). The production costs of energy are unknown to the prospective producer at the time of the auction, as future technological progress could affect the cost and efficiency of RE projects. Following the work of Torani et al. (2016), the technological progress and the resulting cost variation is also modelled as a GBM process. The two variables are thus modelled as a pair of stochastic differential equations:

$$dP_t = \mu_P P_t dt + \sigma_P P_t dW_t,$$
$$dC_t = \mu_C C_t dt + \sigma_C C_t dW_t$$

(1)

Each step of these processes is made up of two components. The deterministic long-term drift (μ) of the process as well as a stochastic component, comprised of volatility (σ) and the increment of a Wiener process (dW_t). The Wiener process is the driving noise of a GBM process, as it is a random variable that takes a new value at each timestep, with an expected value of 0. A convenient trait of the Wiener process is its Markovian property, meaning it has independent, memoryless increments, meaning the value it takes at time $t - 1$ does not influence its value at time t. This is convenient when forecasting paths since the only value necessary to create forecasts for time *t* is the level at time 0 and the long-term drift (Dixit & Pindyck, 2012):

$$E[P_t] = P_0 e^{\mu_P t}$$

$$E[C_t] = C_0 e^{\mu_C t}$$

(2)

In the case of RE auctions, the values at time 0 are the price and cost levels when the auction takes place.

3.2 The Net Present Value Case

The net present value (NPV) of a RE project investment subject to feed-in premiums (FIP) can be formalized as:

$$V^{NPV}(0) = Q \int_0^T e^{-rs}(P_0 e^{\mu_P s} + FIP - C_0)\, ds$$

(3)

Q represents the quantity of electricity produced, and C is the production cost of said energy. P is the price, and FIP is the agreed-upon level of government support. Changes in price affect the revenue generated from the project throughout its lifespan, so the developer will consider the expected growth rate of these prices. Cost, on the other hand, is treated as constant, as it is assumed that the NPV developer would start construction immediately. Furthermore, as most costs associated with RE sources come from capital expenditure, rather than operation and management (IRENA, 2024), developments in terms of cost after the project has been constructed become irrelevant, meaning costs are locked in at the start date. Once a specific technology is adopted, further technology-related improvements in efficiency also become irrelevant since these improvements cannot be applied to already built projects.

The goal of the reverse auction scheme typically employed in RE auctions is to force prospective developers to disclose their minimum required support to make the project feasible. Assuming the auction is successfully competitive, the winning bid would be a level of FIP that results in the expected payoff of the project being zero (Matthäus et al., 2021). In other words, the level of support corresponds to the developer being indifferent between developing the project or not. By setting the NPV of the project to 0 and solving for FIP, the truth-telling equilibrium for a NPV developer, denoted as FIP^{NPV} below, becomes:

$$FIP^{NPV} = C_0 - \underbrace{\frac{r}{1 - e^{-rT}}}_{\text{Annuity factor}} \underbrace{P_0 \frac{e^{(\mu_P - r)T} - 1}{\mu_P - r}}_{\substack{\text{Discounted price} \\ \text{growth factor}}}$$

(4)

The equilibrium level of FIP fills the gap between the production cost of each unit of energy and the discounted cash flows generated from selling the energy. Under this subsidy, building at $t = 0$ yields 0 profit on average. In other words, it is the level of subsidy that corresponds to the NPV developer's indifference point.

Under sufficiently lopsided initial conditions, a negative FIP^{NPV} is theoretically possible. However, the bids in actual auctions will be positive, as bidding for negative support is irrational.

3.3 Real Option Developers

RO developers extend the NPV framework by comparing the expected profit from immediate exercise with the expected value of the project if it were to be developed at some point in the future. This is possible as the auction gives the developer the right, but without strict obligation, to develop the project. The developer thus has the flexibility to choose when to develop the project at the time most advantageous to them. In contrast to the NPV case, a RO developer will factor in the possibility of deferring the investment. By waiting for more favourable conditions, the developer can maximize the value generated by the project. As in the NPV case, the unit production cost is frozen at the level of the project date, t, while the evolution of electricity prices affects the revenue of the investment throughout its lifespan.

The immediate exercise value, $V(t)$, is the value the project would generate if developed at time t and is derived from the project value function of (3), with s denoting time since exercise:

$$V(\mathrm{t}) = Q\int_0^T e^{-rs}(\mathrm{P}(\mathrm{t}+\mathrm{s}) + FIP - \mathrm{C}(\mathrm{t}))\,ds \tag{5}$$

The investment is no longer a now-or-never opportunity, as the developer can freely choose the optimal time to develop the project. It can therefore be viewed as an American option, as the developer is not constrained to a specific point in time where development must be commenced.

There is value in increased flexibility. At time t, the developer will compare the immediate exercise value, $V(t)$, and the continuation value, $F(t)$, given the current market conditions, which in this case is the price and production cost of electricity. If the immediate exercise value is greater, the project is developed. At times where the continuation value is greater, meaning the expected value from waiting is higher than the immediate exercise value, the project is delayed. The value of the option to develop the project can thus be expressed as:

$$ROV(t) = \max\bigl(V(t), F(t)\bigr) \tag{6}$$

The RO Value, $ROV(t)$, of the project is the maximum of the immediate exercise value and the continuation value. As the RO developer is bidding for the option to develop a project, instead of the project itself, the truth-telling equilibrium also differs. In the NPV case, the FIP equilibrium is at a level where the immediate exercise value at time 0 would be 0. The RO developer factors in the value of waiting, which at time 0 is defined as the difference between the RO value and the immediate exercise value. Since the immediate exercise value is equal to the NPV at time 0, $V(0)$, the waiting option value, denoted below as WOV, is therefore:

$$WOV(0) = ROV(0) - V(0) \tag{7}$$

WOV is the additional value RO developers are bidding for compared to the NPV developer, who only considers project value and can be interpreted as the value of flexibility. When FIP is set to the level where the NPV of the project is 0, the above expression becomes:

$$WOV(0)^{NPV=0} = ROV(0)^{NPV=0} \tag{8}$$

Assuming uncertainty in the underlying market variables, this value will be positive, resulting in waiting potentially being beneficial. Furthermore, neither WOV nor ROV can be negative, as the option simply would not be exercised in that case, giving a payoff of 0. In other words, when the FIP is set at a level where the NPV developer is indifferent or opposed to developing the project, the RO developer will evaluate it at least equally to the NPV developer, but in cases where waiting is beneficial, they will deem the project to have positive value. This allows the RO developer to outbid the NPV developer, to the point where $ROV(0)$ is minimized, becoming the RO truth-telling equilibrium.

As the RO value is derived from the maximum of the immediate exercise value and the continuation value, projects with a high waiting option value are synonymous with projects having a high continuation value. A high waiting option value is therefore suboptimal in terms of adoption rates. As the optimal exercise time is defined as the time when the continuation value equals the immediate exercise value, it leads to the adoption being slow (Dixit & Pindyck, 2012). Developers seeing great value in waiting will act accordingly, and adoption of RE sources might therefore occur later than socially optimal.

3.4 Auction Design

The waiting option value cannot reasonably be eliminated due to its dependence on the behaviour of underlying stochastic market variables. However, it can be decreased through policy design. In the context of RE auctions, the act of waiting is discouraged through non-realization penalties, aiming to make delaying the project riskier and more expensive. By denoting the cost of the non-realization, which includes the penalty as well as the sum of the total discounted payoffs generated from the FIP (which is revoked if the grace period is violated), as L, the continuation value for projects subject to non-realization measures can be formulated as:

$$F(t) = E_t[e^{-r(\tau-t)}V(\tau) - e^{-r(T_g-t)}L1_{\{\boldsymbol{\tau}>\boldsymbol{T_g}\}}] \tag{9}$$

Here, $1_{\{\tau>T_g\}}$ is an indicator function, taking the value of 1 if the optimal exercise time, τ, is after the grace period has run out. If exercise occurs within the grace period, the indicator function is 0, meaning the penalty is not applied. As the penalty is paid at the expiration of the grace period, the penalty is discounted back to the expiration of the grace period, while the project value is discounted back to the development point. A higher L will lead to a lower continuation value, as a portion of the evaluated scenarios will give a lower payoff. This effect will become stronger as t approaches T_g, as a larger proportion of the potential exercise times will violate the grace period, meaning postponement past this point becomes more likely.

A lower continuation value makes it more likely that the investment threshold condition, $V(t) = F(t)$, is fulfilled, leading to the projects being developed. Non-realization penalties will increase the probability of exercise being within the grace period. Projects deferred past the grace period are unlikely to be developed soon after the grace period has ended, as the cash flows generated from the projects are now without government support. Additionally, the penalties incurred for non-realization would further harm the profitability of these projects. Project development would still be possible in these cases, but would require the market variables to develop considerably in a favourable direction.

Alternatively, the underlying uncertainty could be removed, which is what is done to price uncertainty with FITs. The issue with removing electricity price uncertainty through FITs is that the risk is then fully placed on the issuer of the subsidy, leading to the cost of the policy potentially becoming very high depending on fluctuations in price.

A high volatility leads to a greater spread, with some paths being highly favourable (high price, low cost) and some being equally unfavourable (low price, high cost). But the unfavourable paths become irrelevant in the RO framework, as the project will not be developed if conditions are poor, giving the continuation value a lower bound of 0. The severity of the bad paths is therefore inconsequential, and only the ratio of good-to-bad paths is relevant. On the other hand, positive paths do not have an upper ceiling, meaning the increased volatility leads to a higher continuation value.

Lowering the volatility will compress the range of possible future prices around current levels. Consequently, there will be fewer high-payoff scenarios, and the continuation value will therefore be lower. This has the benefit of making the evaluation at time 0 more predictable. As volatility is lower, the continuation value will be lower, potentially increasing realization rates as bids will more strongly be rooted in current project needs, rather than the speculative continuation value. Simply put, the value of waiting will be lower, leading to earlier exercise times.

4. Methodology

To evaluate the effects of electricity price volatility on RE auction realization rates, the underlying market variables will be simulated using Monte Carlo simulations. Both variables must therefore first be mapped to their respective stochastic processes. In the interest of ensuring empirical relevance, this calibration is done using real-world data. These processes are then used as a foundation to simulate the auctions and their outcomes in terms of realization rates and exercise times. Four calibrations for the price will be performed. One uses the observed electricity price, and three that simulate the behaviour of price curves under MA-FIPs that are 3-months, 6-months, and 1-year long, respectively.

4.1 Stochastic Process Calibration

To calibrate the parameters of the two underlying stochastic processes, electricity price and cost, Itô's Lemma is applied to the stochastic differential equations presented in (1), giving:

$$d(\ln P_t) = \left(\mu_P - \frac{1}{2}\sigma_P^2\right)dt + \sigma_P dW_t \tag{10}$$

The estimation of cost parameters is analogous to the price case as both variables are modelled as GBM processes. As any increment of the Wiener process is normally distributed, the log returns (R_t) of the stochastic process for any time interval $[t, t + \Delta t]$ becomes normally distributed (Cheng et al., 2017; Dixit & Pindyck, 2012):

$$\mathrm{R_t} = \ln\left(\frac{P_{t+\Delta t}}{P_t}\right) \sim N\left(\left(\mu_P - \frac{1}{2}\sigma_P^2\right)\Delta t, \sigma^2 \Delta t\right) \tag{11}$$

The drift and volatility of the process are then calculated as the mean and variance of the computed log-returns. As these are parameters of a differential equation, the mean is the average change at each timestep, and the volatility is the variance of these changes:

$$\hat{\mu} = \frac{1}{N}\sum_t R_t\,, \qquad \hat{\sigma} = \sqrt{\frac{1}{N-1}\sum_t (R_t - \bar{R})^2} \tag{12}$$

4.1.1 Price Data and Parameter Calibration

The drift and volatility of the price processes are estimated using monthly index data of German producer electricity prices from Destatis (2023), covering the years 2005 through to 2022. As the variable of interest is the relative change between periods, there is no need to convert the index values to absolute terms. The values are adjusted for inflation using consumer price index data, meaning all subsequent estimates of drift and volatility refer to real changes in electricity price (Destatis, 2025).

Electricity prices exhibit significant seasonal variance. While the volatility stemming from seasonal factors is real, it is deterministic. Seasonal variance can be planned and accounted for and is therefore not uncertain. The data is consequently deseasonalized by applying STL decomposition in R, improving the accuracy of the resulting parameters (Cleveland et al., 1990; Janczura et al., 2013; Lucia & Schwartz, 2002). By removing it from the raw index data, a volatility term composed of truly random price shocks is calibrated.

Observing Figure 1, the result of the deseasonalization is a slightly smoothed-out curve, while still following the same general trend as the original observations. The minor differences between the two curves indicate that only a minor portion of the total variance can be explained by seasonal factors.

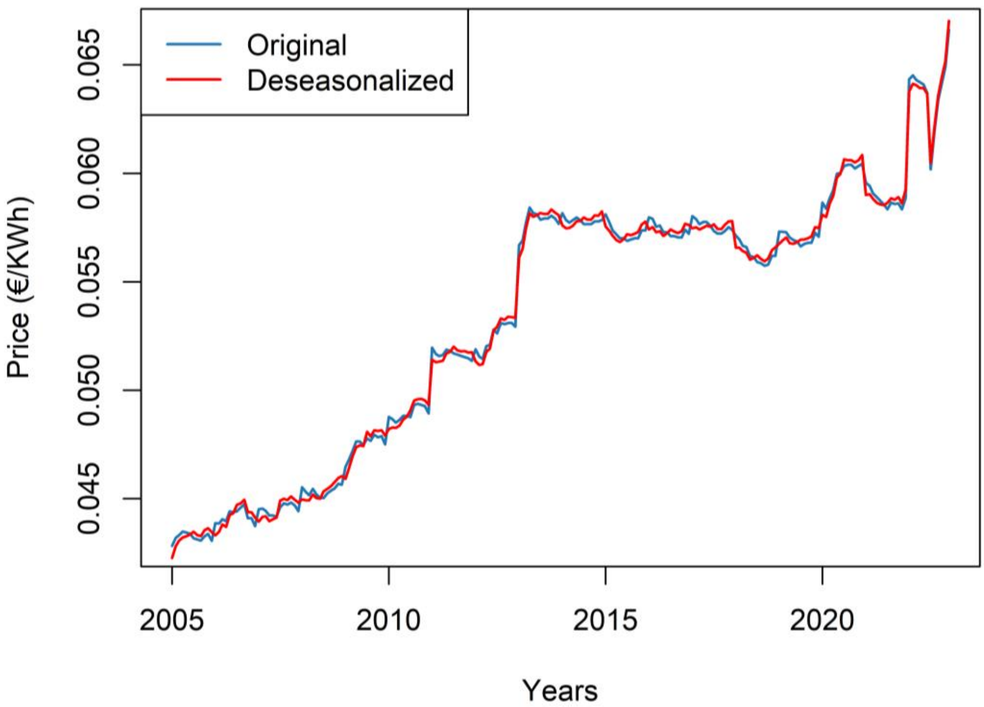

Figure 1. Observed electricity prices pre- and post-deseasonalization.

The deseasonalized data set of real electricity prices, as seen in Figure 1, will serve as the foundation for the calibration of the mean and variance as specified in (12). The resulting parameters represent the baseline case for the empirical analysis.

To model the moving average price curves, new GBM parameters must be calibrated. A consequence of having to compute the moving averages is that the first datapoints will not have valid values. For example, the 1-year moving average will start at the twelfth data point, as the first eleven months of 2005 do not have enough prior data to construct a 1-year moving average. Each subsequent month is calculated as the average value of the current deseasonalized real electricity price and the previous 11 months. The general case of an *n*-month moving average (MA_t) thus becomes:

$$MA_t = \frac{1}{n}\sum_{i=0}^{n} P_{t-i}, \qquad t = n, \dots, T$$

(13)

The log returns of this newly constructed dataset will be heavily serially correlated, as adjacent values MA_n and MA_{n+1} would share $n - 1$ constructing datapoints. As mentioned in the previous section, GBM is a Markov process, meaning each increment should be independent. If this condition is not met, the estimated volatility would be biased downwards, as the serial correlation causes the process to be artificially slow-moving. To mitigate this, the calibration of the volatility will be performed using non-overlapping, year-on-year log returns:

$$R_t = ln\frac{MA_t}{MA_{t-n}}, \qquad t = n, \dots, T$$

(14)

An important note here is that it is only the volatility that changes depending on the length of the moving average; the drift of all calibrated processes will be identical, fixed to the $\hat{\mu}$ of the baseline process. The reasoning behind this assumption is that MA_t should, on average, grow at the same exponential rate as its underlying variable P_t. The moving average will never outgrow or fall behind the spot price on which it is based on in the long term.

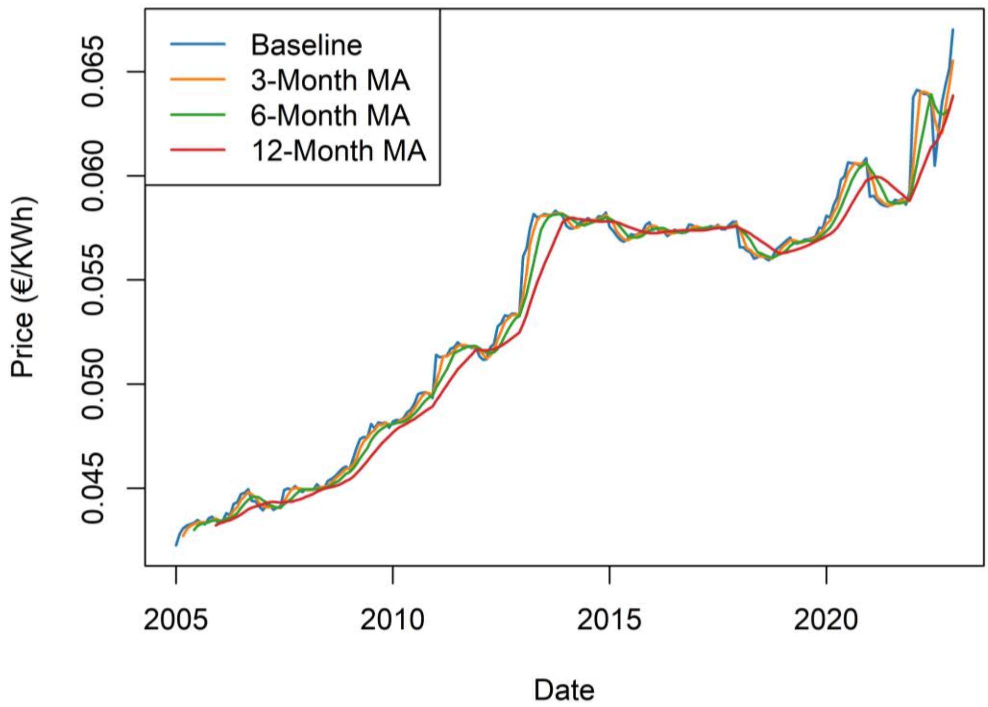

Figure 2. Observed Baseline, 3, 6, and 12-Month MA Electricity Prices.

The resulting data sets, which are used for the calibration of their respective GBM process, are presented in Figure 2. Each dataset follows the same long-term trend but differs in the short term due to the varying levels of price-smoothing applied. Additionally, the delayed starting points for the moving average-based process are visible, with longer moving averages having a later first value.

4.1.2 Cost Data and Parameter Calibration

Cost is measured by the levelized cost of electricity, which is the sum of the discounted expenditures related to the project divided by the electricity generated over the project's lifespan. In practice, this value is equal to the required price that the produced electricity would have to be sold at for the project to break even (IRENA, 2024).

The GBM model for cost is estimated following the same process, based on annual data from IRENA (2024). Due to data limitations, with only annual data being available and only covering years 2010 to 2023, the estimated parameters of the cost model become less robust than their price counterpart.

4.2 Least-Squares Monte Carlo

The key to determining exercise times is estimating the continuation value and comparing it to the immediate exercise value. The immediate exercise value can be calculated at each timestep as the total present value of future cash flows the project would generate if it were to be developed at that point in time. In contrast, the continuation value, representing the expected benefit of waiting, is more complex to compute. This is especially true for the RO examined in this paper, as it depends on multiple stochastic processes as well as being American-style, allowing for early exercise (Longstaff & Schwartz, 2001).

A viable method to estimate American option value is through LSM simulation, which combines simulations and regression techniques to estimate the optimal exercise times and option value (Lazo & Watts, 2023; Longstaff & Schwartz, 2001). To start, multiple paths of the underlying state variables, in this case, the price and cost of electricity, are simulated in discrete time with each timestep denoted by k. Each simulated path, indexed by i, represents a possible evolution of market conditions, capturing the uncertainty in future prices and costs.

These simulations are then used to calculate the immediate exercise payoff for each timestep k and path i, which is the sum of the discounted future cash flows that would be generated if the project were developed at that point in time. This involves freezing the cost at its current value and calculating future profits based on the cost level at exercise compared to a simulated price path and the awarded FIP. A penalty will be deducted from the immediate exercise value of any project that is exercised after the given grace period, consistent with (9.

The LSM algorithm proceeds by working backwards in time, starting from the final timestep, K. At this endpoint, both the continuation value and the immediate exercise value are 0, since no future cash flows remain, and investment cannot be delayed further. The continuation value is 0 since the option to further delay investment is no longer available, as we are at the end of the simulated time space. Likewise, the immediate exercise payoff is 0 as it is a function of the state variables, which become 0 for timesteps outside the simulated period. In this case, the terminal condition is therefore:

$$V_K^{(i)} = F_K^{(i)} = 0$$

(15)

At each timestep before the terminal period, the option value is defined as the maximum of the immediate exercise value and the estimated continuation value:

$$ROV_k^{(i)} = max\left(V_k^{(i)}, \hat{F}_k^{(i)}\right)$$

(16)

This decision rule reflects the flexibility embedded in the option as the holder will develop the project if immediate exercise is more valuable. If the continuation value is greater, the project is deferred.

By using multiple linear regressions, a fitted model is created, that maps continuation values for each path based on the current state variable values and its combinations. This is achieved in two steps. First, the continuation value is regressed on the current state variables:

$$
\begin{aligned}
e^{-r\Delta t}\left(ROV_{k+1}^{(i)}\right) \\
&= \beta_0 + \beta_1 P_k^{(i)} + \beta_2 LCOE_k^{(i)} + \beta_3\left(P_k^{(i)} \times LCOE_k^{(i)}\right) + \beta_4\left(P_k^{(i)}\right)^2 \\
&+ \beta_5\left(P_k^{(i)}\right)^2 + \varepsilon_k^{(i)}
\end{aligned}
\tag{17}
$$

The linear terms provide estimates for the direct proportional relationship between state variables and continuation value. The interaction term is included as the evolution of the state variables in proportion to each other will influence the continuation value. For example, a scenario where prices are high while costs are low will affect the continuation value differently from a scenario where both prices and costs are high, as project value is dependent on the difference between the two variables. Lastly, the quadratic terms allow for non-linear relationships between state variables and continuation value.

Once the regression coefficients have been estimated, the state variables for a path are then put into the same regression again, but now with already estimated coefficients. The function will then output the future option value. It is this value that is used as the continuation value for the given path and timestep, expressed below using $b_1, \ldots, b_5$ to denote the coefficients previously estimated in (17:

$$
\begin{aligned}
\hat{F}_k^{(i)} \approx \hat{E}\left[e^{-r\Delta t}\left(ROV_{k+1}^{(i)}\right)\middle| P_k^{(i)}, LCOE_k^{(i)}\right] \\
&= b_0 + b_1 P_k^{(i)} + b_2 LCOE_k^{(i)} + b_3\left(P_k^{(i)} \times LCOE_k^{(i)}\right) + b_4\left(P_k^{(i)}\right)^2 \\
&+ b_5\left(P_k^{(i)}\right)^2
\end{aligned}
\tag{18}
$$

The above regression model provides an estimate of the conditional expected value of waiting, based on the current values of price and cost. This approach allows the decision of whether to exercise or defer at each point in time to be made using only present information, not relying on knowledge of future outcomes. The estimated continuation value is then compared to the precalculated immediate exercise value for the same path and timestep, with the greater of the two becoming the option value used to fit the regression for the next (chronologically earlier) step.

To exemplify this process, the penultimate timestep, $K-1$, is considered. This timestep is simplified due to the continuation value in the following timestep, *K*, being zero as per the terminal condition. The project will therefore be developed if the market conditions are such that the immediate exercise payoff of the project is above zero. The option value at time $K-1$ thus becomes:

$$ROV_K^{(i)} = max\left(V_{K-1}^{(i)}, 0\right)$$

(19)

These option values, across all paths, are discounted and used as the dependent variables in a regression against the corresponding state variables at $K-1$. This regression yields a set of coefficients that describe how the continuation value depends on the current values of the state variables.

As the investment decision at $K-1$ cannot be based on future information, as it is unknown in the present, the simulated values of the state variables for each path must be plugged into this fitted regression model to estimate the expected conditional continuation value, $\hat{F}_{K-1}^{(i)}$. This estimate represents the expected value of waiting one more timestep, given the current market conditions in path *i*.

Each path then compares this estimated continuation value to its previously calculated immediate exercise value at *K−1*. The greater of the two is recorded as the option value for that timestep and path, and this updated option value becomes the input for the regression at *K-2*, and so forth.

Finally, the RO value at time 0 is an estimate of the average option value across all paths at time 0:

$$ROV_0 = \frac{1}{N}\sum_{i=1}^{N} ROV_0^{(i)}$$

(20)

To summarize, the LSM algorithm estimates the option value at time 0 by first simulating multiple paths for the state variables over discrete time. Then it computes the immediate exercise values for all paths and timesteps. Once the terminal condition is set, it maps current state variables to discounted option values. The resulting fitted model is then used to estimate the continuation value based on current state variables. Those estimates are then compared to the corresponding immediate exercise values, with the greater of the two being recorded as the option value. The recorded option value is then used in the next (earlier) step. Once this is done for all timesteps back to time 0, the average option value of each path becomes the overall option value.

Optimal exercise times for each path are a valuable byproduct of using LSM to estimate the option value. As the immediate exercise value and continuation value are calculated for each timestep, the point where the investment threshold is reached, $V(t) = F(t)$, can be logged and becomes the optimal exercise time of the project.

5. Empirical Applications

This section analyses three distinct real-world RE auctions using the theoretical framework and methodology developed in the preceding sections. All three cases will be technology-specific to PV systems, allowing disregard of the complexities arising from inter-technology auctions (Matthäus et al., 2021). All data relating to auction design are sourced from the AURES II Project database (AURES II Project, 2022).

To ensure consistency and allow clear comparisons, all scenarios assume a standardized project capacity of 1,500 KW. The annual electricity production of the projects in each case is adjusted using capacity factors obtained from IRENA (2024). Different capacity factors are applied to account for variations in PV system efficiency, which are influenced by technological advancements and geographic location, as climate conditions significantly affect electricity generation.

Once the yearly production of the projects is calculated, the revenue of the projects is the difference between the simulated price and cost, as well as the average awarded FIP for the auction (AURES II Project, 2022). The auction date is treated as the starting point for each variable, with a starting electricity price based on bi-annual data of price for non-household consumers, taxes excluded (Eurostat, 2025). Initial production costs taken from IRENA's annual cost assessments (IRENA, 2024). These two market variables are then simulated over a 30-year horizon, reflecting the duration of the investment opportunity. Due to computational constraints, the model operates with a monthly timestep, implying that developers face one investment opportunity per month.

Once the project is developed, it will generate revenue for 20 years, thus allowing developers the flexibility to exceed the provided grace period without part of the project lifespan immediately falling outside of the simulated time range. The cash flows of the project are discounted using a composite of the risk-free rate, approximated as the 15-year domestic bond yields (Matthäus et al., 2021; Trading Economics, 2025a; 2025b), and weighted average cost of capital (WACC) markups, following the estimations of Steffen (2020).

The first case considers an auction conducted in Germany under relatively unfavourable initial market conditions. The second case study is also a German auction, conducted almost three years later. The auction design mirrors that of the first case, and the stochastic processes for price and cost remain. However, the starting market conditions are more favourable. Specifically, the initial electricity price exceeds the production cost, resulting in strong initial project profitability.

Additionally, this scenario stands out by having a negative risk-free rate, reducing the discount rate applied to cash flows.

The third and final auction took place in Italy, meaning different process parameters. The stochastic process for cost is country-specific and is therefore recalibrated using Italian cost data (IRENA, 2024). Italian PV project costs decline at a slower rate and exhibit higher volatility compared to Germany, thus presenting higher uncertainty for developers. The discount rate in this scenario is higher due to increased domestic bond yields and a larger WACC markup, reflecting greater perceived market risk. The auction design is similar to previous cases, except that the non-realization penalty is 100 €/KW compared to 50 €/KW in the German auctions.

Table 1. Case Parameters.

Category	**Parameter**	**Case 1**	**Case 2**	**Case 3**
Auction	Country	Germany	Germany	Italy
	Date	2018-06-01	2021-03-01	2019-10-01
	Grace Period	2 years	2 years	2 years
	Penalty	50 €/KW	50 €/KW	100 €/KW
	Average FIP	0.0459 €/KWh	0.0503 €/KWh	0.0600 €/KWh
Price	Drift	0.0255	0.0255	0.0255
	Volatility (Baseline)	0.0336	0.0336	0.0336
	Volatility (3-month MA)	0.0295	0.0295	0.0295
	Volatility (6-month MA)	0.0278	0.0278	0.0278
	Volatility (1-year MA)	0.0256	0.0256	0.0256
	Starting point	0.0457 €/KWh	0.0520 €/KWh	0.0779 €/KWh
Cost	Drift	-0.1358	-0.1358	-0.1201
	Volatility	0.1388	0.1388	0.2026
	Starting point	0.0693 €/KWh	0.0473 €/KWh	0.0497 €/KWh
Discount rate	Risk-free rate	0.69%	-0.034%	1.409%
	WACC Markup	2.9%	2.9%	3.02%
Simulation	Paths	3,000	3,000	3,000
	Years	30	30	30
	Timestep	1 month	1 month	1 month
	Project Lifespan	20 years	20 years	20 years
	Capacity	1,500 KW	1,500 KW	1,500 KW
	Capacity Factor	0.1790	0.1721	0.1751

Each case will be run four times, each with a different length MA-FIP. The baseline scenario follows the real-world FIP subsidy, with developers being exposed to the raw spot price of electricity. Scenarios two through four will use the adjusted price volatility parameters as specified in Table 1, mirroring the price behaviour of MA-FIPs with lengths of 3 months, 6 months, and 1 year, respectively.

5.1 Case 1 Results

Table 2 shows the results of the simulations using the parameters of case 1. The RO evaluation grants a substantial increase in value, indicated by the waiting option value, $WOV(0)$, making up a substantial portion of the RO value ($ROV(0)$ at the time of the auction. As per (7), $WOV(0)$ is the difference in project value between NPV and RO valuations.

As predicted, using moving average price curves has a positive impact on realization rates and overall exercise time. A clear positive relationship between the length of the MA-FIP and the realization rate, $P(\tau < T)$, is observed, indicating that the MA-FIP is an effective tool to mitigate the propensity to delay past the grace period in this case.

Table 2. Case 1 simulation results.

Scenario	ROV(0)	P(τ < T)	WOV(0)	E[τ]	FIP^{NPV}
Baseline	1850967.0848 (15.7155)	0.6577 (0.0087)	699665.5570 (2957.6542)	8.4064 (0.1734)	0.0116
3-month MA-FIP	1821031.1904 (0.0000)	0.7067 (0.0083)	669661.9099 (2611.2031)	7.2247 (0.1592)	0.0116
6-month MA-FIP	1807607.2879 (0.0000)	0.7293 (0.0081)	656039.1898 (2484.1244)	6.6733 (0.1516)	0.0116
1-year MA-FIP	1794875.5185 (0.0000)	0.7460 (0.0079)	643288.4304 (2293.9283)	6.3536 (0.1473)	0.0116

Monte Carlo standard errors in parentheses.

The mean optimal exercise times ($E[\tau]$) of all scenarios are still outside the grace period of 2 years. A developer who chooses to exceed the grace period and pay the penalties would, at that point, be expected to develop their project quite some time after the grace period has ended, as the immediate exercise value is now much lower, as there is no longer a FIP. As the penalty is deducted at the expiration of the grace period, the immediate payoff decreases, whereas the continuation value remains the same since it treats the penalty as a sunk cost past this point.

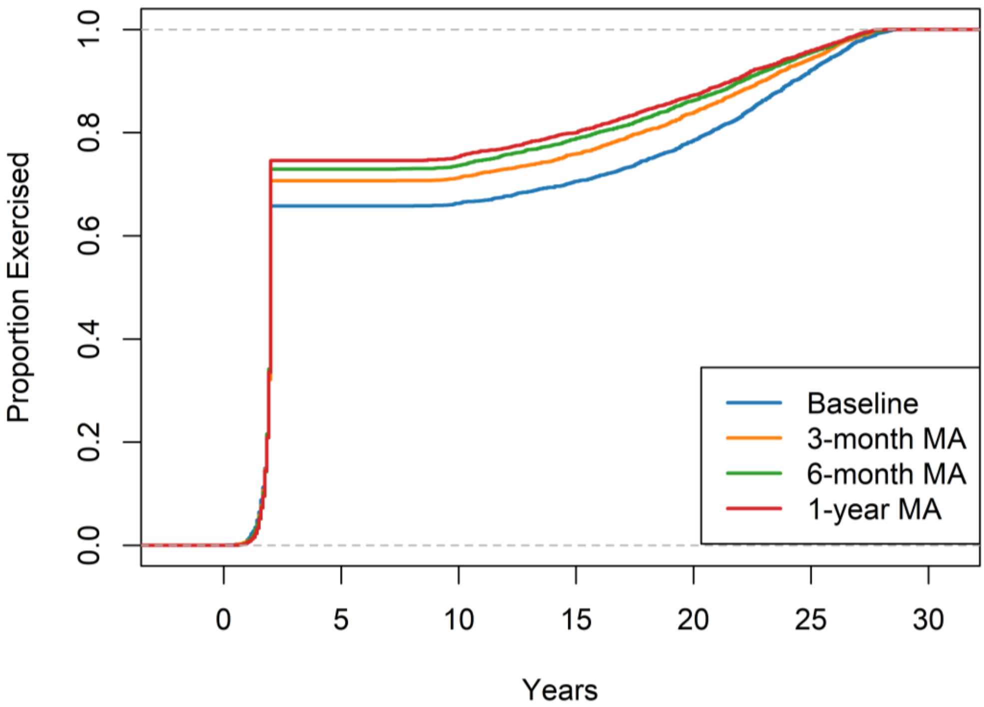

Figure 3. Cumulative distribution function of optimal exercise times.

When considering Figure 3, the mean exercise time sits at a point where no projects are developed. This is a consequence of the simulation parameters, specifically total simulation time and project lifespan. The market variables are simulated 30 years into the future, and the project lifespan is 20 years, meaning the project loses one time step worth of profit for each step the project is deferred after the 10-year mark. Once the grace period is exceeded, waiting essentially becomes free. However, once the project lifespan bleeds out into non-simulated time, waiting comes at a cost of one timestep worth of profit.

The end-of-simulation dynamics become especially clear when looking at a single path. Figure 4 shows one of the paths of the baseline scenario where the project was not realized within the grace period. The steeper decline of the continuation value due to a decreasing amount of cash flows eventually leads to the project finally being developed, albeit late into the simulation. Additionally, the impact of the non-realization penalties is demonstrated, as they result in a sharp decrease in immediate exercise value, leading to the optimal exercise time being pushed further into the future.

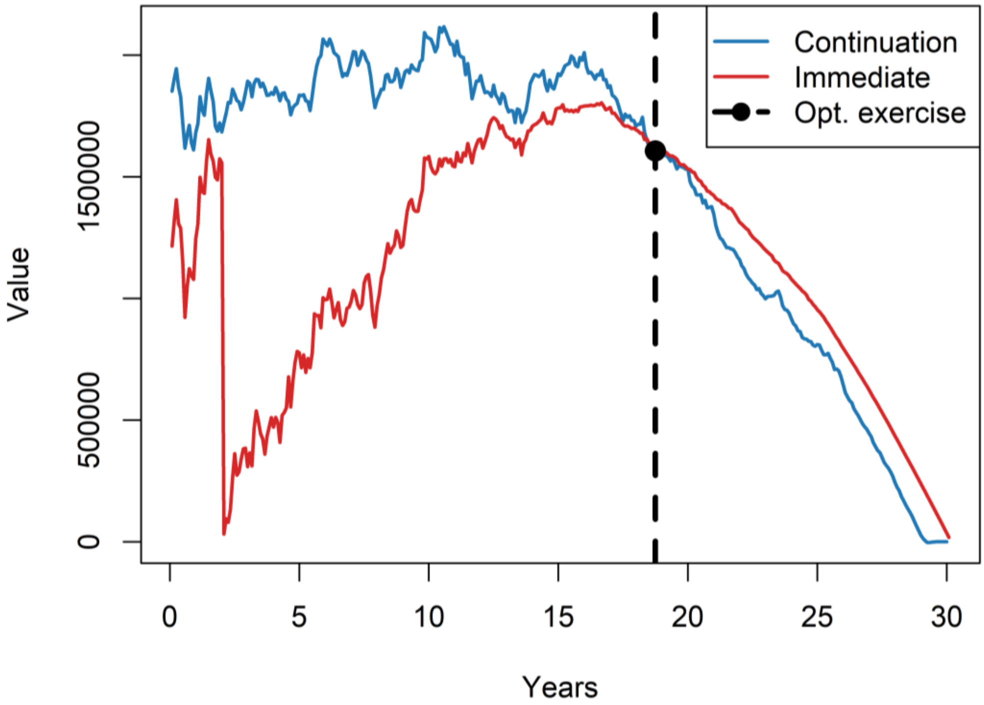

Figure 4. Immediate exercise value and continuation value evolution of a single path.

Poor simulated conditions partly explain the tendency to exercise later than 10 years into the simulation. If price and cost evolve in such a way that results in small or even negative cash flows, the rational choice is to wait for conditions to improve. Projects with an immediate exercise value close to or below 0 will not be adversely affected by forgone profit, as the project in question will not be profitable.

5.2 Case 2 Results

Table 3. Case 2 simulation results.

Scenario	**ROV(0)**	**P(τ < T)**	**WOV(0)**	**E[τ]**	**FIP^{NPV}**
Baseline	2955147.0678 (189.3443)	0.9700 (0.0031)	571735.1571 (3555.6455)	2.3910 (0.0597)	-0.0189
3-month MA-FIP	2908016.6858 (69.9553)	0.9910 (0.0017)	524982.5100 (3108.2438)	2.0183 (0.0345)	-0.0189
6-month MA-FIP	2909725.1835 (101.5427)	0.9920 (0.0016)	526125.2888 (3055.8165)	1.9818 (0.0284)	-0.0189
1-year MA-FIP	2868385.6769 (8.5588)	0.9943 (0.0014)	485691.5704 (2616.3337)	1.9713 (0.0280)	-0.0189

Monte Carlo standard errors in parentheses.

The starting conditions for this auction were much more favourable to the developers compared to the first case. The NPV truth-telling equilibrium (FIP^{NPV}) is negative, implying projects developed at this time would not require support to turn a profit. The option value is also higher compared to the first case due to the improved initial project economics.

The value of flexibility is lower compared to the first case, yet the option value is higher. This indicates that flexibility becomes more valuable in adverse conditions like the ones in the first case, and less valuable when conditions are better and the project is instantly profitable.

The positive relationship between MA-FIP length and realization rate is still present here. Favourable starting conditions resulted in the baseline case being highly successful, leading to the introduction of MA-FIPs having a smaller impact compared to the first case. Interestingly, even though the baseline case had a high realization rate, none of the MA-FIP scenarios resulted in a perfect realization rate.

5.3 Case 3 Results

Table 4. Case 3 simulation results.

Scenario	ROV(0)	P(τ < T)	WOV(0)	E[τ]	FIP^{NPV}
Baseline	3909363.3223 (506.0406)	0.9867 (0.0021)	606323.2935 (5119.6346)	2.0535 (0.0450)	-0.0481
3-month MA-FIP	3778911.9865 (294.1809)	0.9993 (0.0005)	475022.8869 (3881.9505)	1.7974 (0.0140)	-0.0481
6-month MA-FIP	3937110.2777 (678.3879)	0.9890 (0.0019)	633293.3426 (5214.3599)	1.9896 (0.0395)	-0.0481
1-year MA-FIP	3716078.2803 (235.1339)	0.9993 (0.0005)	412550.2321 (3294.9935)	1.8037 (0.0094)	-0.0481

Monte Carlo standard errors in parentheses.

The results of Case 3 resemble those of Case 2. The main difference between the two lies in the overall valuation metrics of the projects. Because of the higher starting electricity price, the equilibrium FIP for NPV projects is strongly negative. The flatter cost process of the Italian market does not influence the equilibrium FIP since it only considers immediate exercise, making future evolution of cost irrelevant.

A relevant factor is instead the higher discount rate. The truth-telling equilibrium is partly determined by the expected price growth relative to the discount rate. A higher discount rate will therefore mean that the effective revenue growth throughout the project lifespan decreases. However, the benefit of a favourable starting point outweighs the more conservative revenue growth forecast, resulting in a low truth-telling equilibrium FIP.

The introduction of MA-FIPs has a small but positive effect on realization rates. The baseline scenario saw a very high realization rate, which resulted in a marginal impact of the introduction of MA-FIPs. Interestingly, the 6-month MA-FIP scenario had slightly worse outcomes compared to its more volatile counterparts. Upon closer inspection of the data, the inconsistency can be attributed to a larger fraction of paths ending in non-exercise, meaning the exercise did not occur until the final timestep. Exercise at this point results in a project without revenue or cost; these paths must therefore have experienced unlikely, but not impossible, market variable evolution, leading to non-exercise. Outlier paths explain both the inconsistent realization rates and optimal exercise time across scenarios, as well as the larger standard errors seen in the 6-month MA-FIP scenario.

6. Robustness Checks

6.1 Bid Levels

The overall effect of the MA-FIP is limited by the baseline realization rate. Auctions with high baseline realization rates will have little room for improvement. A high baseline realization rate is not only dependent on market conditions being favourable, but also that the awarded FIP is sufficient. It is therefore of interest to see how a hypothetical case with a lower FIP would play out. To investigate how a lower FIP affects the baseline realization rate and the effects MA-FIPs would have, case 2 is re-simulated but with an awarded FIP that is 75% of its original value. This test can thus be treated as a hypothetical high-competition scenario, where competition between developers has driven down bid levels towards the truth-telling equilibrium.

Table 5. Case 2 results when using a lower FIP.

Scenario	**ROV(0)**	**P(τ < T)**	**WOV(0)**	**E[τ]**	**FIP^{NPV}**
Baseline	2546572.7300 (127.5847)	0.6637 (0.0086)	597003.4212 (3521.5722)	8.2816 (0.1740)	-0.0189
3-month MA	2507083.4173 (49.1293)	0.7513 (0.0079)	557435.4277 (3116.0410)	6.3305 (0.1502)	-0.0189
6-month MA	2485680.8152 (53.5724)	0.8003 (0.0073)	535788.5343 (2966.1998)	5.4180 (0.1372)	-0.0189
1-year MA	2875358.1456 (31.2238)	0.9910 (0.0017)	492064.9556 (2739.9401)	2.0120 (0.0310)	-0.0189

Monte Carlo standard errors in parentheses.

The results of the modified case differ significantly from the original. The baseline results here are more in line with the Case 1. As expected, the introduction of a MA-FIP leads to significantly better realization rates. However, when the lower awarded FIP sits closer to the truth-telling equilibrium, the improvement between different degrees of price-smoothing becomes more pronounced. The 1-year MA-FIP stands out, with a 99.1% realization rate, a substantial jump from the baseline realization rate of 66.37%, but shorter MA-FIPs still have considerable benefits. Again, the realization rate improvements are heavily correlated with reduced initial waiting option values.

An additional contributing factor to the larger outcome gaps between different length MA-FIPs is the discount rate. Case 2 has a lower discount rate compared to Case 1, meaning future cash flows become more valuable. Additional price-smoothing therefore has a larger effect on overall developer behaviour, as the uncertainty stemming from volatility becomes greater the further into the future the project economics are forecasted. As a low discount rate means future cash flows are valued more, decreases in long-term volatility have a larger effect. The effects of the MA-FIP thus become more apparent in cases where the discount rate is low.

6.2 Model Specification

An alternative way to model electricity prices is by using an Ohrnstein-Uhlenbeck (OU) process:

$$dlnP_t = \kappa(\theta - lnP_t) + \sigma dW_t \tag{21}$$

By including a mean-reversion component, κ, prices following an OU process are subject to random price shocks but will eventually revert to their mean value θ. Compared to a GBM process with drift, which will diverge to infinity given enough time, an OU process will converge to its mean. When replacing the previous GBM process with an OU process, the value of waiting will decrease as there is no longer any price growth, only short-term fluctuations.

To test the overall findings of previous cases, the price process is re-modelled as an OU process. Case 1 is then re-simulated using the new OU process to establish if the results still hold under this alternate model specification. Focusing on Case 1 specifically, it becomes easier to evaluate the effects of the model choice as the results were distant from the realization rates limits.

Table 6. Case 1 with OU-process simulation results.

Scenario	**ROV(0)**	**P(τ < T)**	**WOV(0)**	**E[τ]**	**FIP^{NPV}**
Baseline	1776891.7535 (0.0000)	0.8327 (0.0068)	624017.5414 (2349.7071)	4.9638 (0.1304)	0.0116
3-month MA-FIP	1699430.9270 (0.0000)	0.8883 (0.0058)	570382.1164 (1557.8075)	3.7785 (0.1006)	0.0116
6-month MA-FIP	1625438.8221 (0.0000)	0.9273 (0.0047)	530160.7336 (963.8032)	3.0842 (0.0782)	0.0116
1-year MA-FIP	1627793.1583 (0.0000)	0.9323 (0.0046)	523593.0864 (715.7837)	2.9601 (0.0713)	0.0116

Monte Carlo standard errors in parentheses.

The results presented in Table 6 are in line with expectations. When compared to the original results, modelling price as an OU process has shifted the results towards realization. Considering the more stable price evolution model, it is a natural result.

In the original framework, both GBM processes had drift, benefiting the profitability of the projects. The price of electricity rose while costs declined. The long-term benefit of waiting is therefore mitigated when using an OU process for price, as it stabilizes long-term. In this case, only the cost will provide a long-term deterministic incentive to wait, effectively mitigating the overall value of waiting. Despite this change, the benefits of an MA-FIP are still present, indicating that the results are not overly dependent on which electricity price model is used.

7. Discussion

The MA-FIP is shown to be a potentially effective tool to improve realization rates of RE auctions. It can partly save auctions that would otherwise have poor realization rates and does not harm auctions that would have been successful even without the MA-FIP. Case 1 and the low-FIP Case 2 saw substantially improved realization rates and exercise timings when MA-FIPs were introduced. On the other hand, Cases 2 and 3 both fall into the latter category, having high baseline realization rates. These auctions not only had superior initial market conditions compared to Case 1, but also a higher average awarded FIP.

The above truth-telling equilibrium FIPs concur with the literature on the risk preferences of RE project developers. The truth-telling equilibrium does not incorporate the required risk premia discussed in previous literature and above-equilibrium FIPs and could therefore be due to developers adapting their bids based on previous auctions and their outcomes (Côté et al., 2022). The underlying risk of auction participation could have been underestimated in Case 1, with bids not properly accounting for uncertain market conditions. The higher awarded FIPs of the later auctions analysed in Cases 2 and 3 could thus reflect developers taking note of earlier auction results and adjusting their bids accordingly. This explanation is in line with the findings of Egli (2020). Market variable uncertainty, especially in regard to revenue, thus became a major concern for developers, and the above-equilibrium winning bids reflect this development (Egli, 2020).

The MA-FIPs' effect on realization rates and overall exercise timings are in line with the arguments proposed by Boomsma et al. (2012) and Cheng et al. (2017), where it was found that less volatile support schemes, such as FITs, promote earlier adoption times. The MA-FIP support scheme is a hybrid between the static FIT and the volatile FIP. There is still revenue uncertainty under the MA-FIP scheme, but it is reduced through price-smoothing. As such, if the analysis of Boomsma et al. (2012) were to incorporate MA-FIPs, the result would likely be somewhere between the FIT and the FIP in terms of exercise timing.

The choice of the smoothing window length of the MA-FIP should consider the financial conditions of RE projects. A longer window leads to better outcomes across all cases, but the benefit of longer windows is found to be highly dependent on discount rates. Long-term price-smoothing is found to have a larger effect on overall developer behaviour in cases where discount rates are low, as the uncertainty stemming from volatility is greater further into the future. This pattern is displayed when comparing the results of Case 1 and the low-FIP version of

Case 2. The latter had a lower risk-free rate at the time of the auction, leading to the overall discount rate being lower. The additional benefit of longer MA-FIPs then becomes more significant, meaning longer windows should be used when interest rates are low. Combining MA-FIPs with favourable financing of RE projects could thereby lead to significant improvements in RE auction effectiveness. As seen in Case 2, if competition is high and winning bids are lower as a result, a low risk-free rate or WACC markup leads to a substantial jump in realization rate, especially if a longer price-smoothing window is applied. Ultimately, the introduction of a MA-FIP is synonymous with a re-distribution of project risk between the subsidy-issuer and the developer. Longer MA-FIPs mean the subsidy-issuer takes on more of the project risk (Grashof, 2021). It can be argued that this is a more effective distribution of risk, as governments typically are more resilient to risk compared to individual RE project developers. Fluctuations in cash flows can significantly affect the financial stability of RE developers, while having a relatively minimal impact on government budgets (Arrow & Lind, 1970; Chang, 2013).

The results of this study highlight the penalty-amplifying property of the MA-FIP. As penalties gain effectiveness when combined with a MA-FIP, it allows penalties to be adjusted depending on which outcome is preferable to the auction designer. Utilising MA-FIPs gives the auction designer an additional tool to reach a preferred auction outcome, as volatility reduction can be balanced with other methods of ensuring realization rates. Based on the findings of Matthäus (2020) and Matthäus et al. (2021), auctions without any non-realization measures are highly unlikely to experience adequate realization rates. Proposing MA-FIPs as a replacement for these measures is therefore not reasonable, and MA-FIPs should instead be treated as a complement to current non-realization measures. However, as seen in the single path analysis of Case 1, the application of non-realization measures to a project further delays its development, and reducing these measures could move overall exercise timings forward.

Revenue uncertainty and non-realization measures weigh heavily in developers' risk analyses, and if they could be minimized, while still allowing auctions to effectively boost RE adoption, it could lead to auctions becoming a more cost-efficient policy (Côté et al., 2022; Grashof et al., 2020). The main reason behind the introduction of RE auctions was their superior cost-efficiency compared to previous policies, showing that the cost of a policy is of especially high importance to policymakers today (Del Río & Linares, 2014; Grashof, 2021; Matthäus et al., 2021). Existing literature suggests that minimizing these factors could lead to auctions becoming significantly more favoured among developers, as well as improving the auction outcomes. Decreasing revenue volatility through a MA-FIP could mitigate the current reliance on measures like fines or pre-qualification requirements while also reducing overall revenue uncertainty.

The overall effect that lower volatility would have on bid levels is ambiguous. Contrary to the literature focused on risk preferences, bid levels would increase because of MA-FIPs in accordance with the theoretical framework of this thesis, as well as Matthäus et al. (2021). As uncertainty is reduced, so is the waiting option value. The competitive advantage RO developers gain from incorporating temporal flexibility into their evaluation is thus diminished by the introduction of the MA-FIP (Matthäus et al., 2021). The truth-telling bid equilibrium of RO developers would thus be brought closer to the comparatively higher truth-telling equilibrium of the NPV developers. Higher bids would boost realization rates further, at the cost of the policy becoming more expensive.

Whether the bid-decreasing risk premia effect or the bid-increasing truth-telling equilibrium effect would take precedence is determined by developer behaviour. If developers are predominantly of the NPV type, the risk premia effect should dominate, and bids will decrease, as the truth-telling equilibrium for these developers will remain unchanged, as the NPV equilibrium is not affected by price uncertainty. If the opposite is true, and most developers behave in line with RO theory, the truth-telling equilibrium effect will likely win out, leading to higher bids.

As discussed in Linnerud et al. (2014) and Fleten et al. (2016), there are often contradictions and an overall lack of clarity regarding whether RE developers behave according to NPV or RO. This lack of clarity extends to the developer's perception of their behaviour, as it was discovered that self-proclaimed NPV developers often exhibit behaviour more in line with RO theory. An empirical ratio between NPV and RO developer behaviour is therefore difficult to estimate. Matthäus et al. (2021) account for behaviour heterogeneity by assigning a ratio of RO to NPV preference to developers in their framework. However, this ratio is endogenously decided in their model, based on the bid levels of the auction, and not directly based on empirical data. As such, the behaviour ratios have internal validity but come without external validation.

Any potential effects the introduction of MA-FIP would have on bid dynamics are not incorporated into the simulations. However, previous literature suggests reductions in investment risk should lead to lower bids as the required risk premia would decrease (Côté et al., 2022). While lower bids would be beneficial in reducing overall policy cost, it could adversely affect realization rates as it would result in lower initial immediate exercise values, making it less likely that the investment threshold is reached within the grace period.

It is important to note that the applied method and the underlying assumptions on which it is built have limitations. While the simulations are based on empirical data, it is not an infallible prediction of outcomes if a MA-FIP policy were to be put in place. Instead, it showcases how previous auctions could have benefited from MA-FIPs. As suggested by previous literature on the subject, auction participants may not fully conform to RO theory, and as discussed, the resulting bid dynamics are therefore unknown.

Autocorrelation issues were mitigated in the calibration process by using non-overlapping data points. However, the inherent serial correlation of an actual moving average process is ignored by modelling it as a memoryless GBM process (Dixit & Pindyck, 2012). Instead, it only captures the volatility-reducing effect of MA-FIPs, as the full extent of price shocks is smoothed out by pre-shock prices. Despite this abstraction, the results still hold empirical relevance. Isolating the volatility-reducing effect of MA-FIPs gives insights into how RE project developers using RO valuation could respond to less erratic conditions.

Future research can build upon the methodology and results of this study by incorporating more sophisticated stochastic processes for electricity prices and cost (Deng, 2000; Farmer & Lafond, 2016). Furthermore, multi-technology auctions could be considered, allowing the capture of potential effects of volatility reduction on inter-technology competition scenarios, thus providing more nuanced insights into auction design (Matthäus et al., 2021).

8. Conclusion

This study has proposed and investigated a novel subsidy structure, the MA-FIP, using a combination of stochastic process modelling and Monte Carlo simulations. The utilised framework is rooted in RO theory, where the investment is treated as an American call option rather than a now-or-never investment. The increased flexibility stemming from this investment valuation framework is not only shown to give a competitive advantage but also leads to socially sub-optimal outcomes where bid-winning projects are being deferred far into the future.

The proposed MA-FIP is found to improve RE auction outcomes by decreasing the revenue volatility of participating projects. Simulations show that it could be especially effective in cases where market conditions are poor, but can still be beneficial in more favourable conditions. Robustness checks show the positive effect becoming stronger when winning bids are low, indicating that the non-realization boosting effect would hold as auctions grow more competitive. The positive effect of the MA-FIP is also shown to hold when an OU process is used to simulate the electricity price, further highlighting its robustness.

As the MA-FIP does not result in additional long-term policy costs compared to the common FIP, it can be seen as a safety measure. The outcome of any given auction is not known until years later, and any tool with the potential to improve the effectiveness of policy in a cost-efficient way should therefore be valuable to policymakers. If current non-realization penalties can be reduced while still being effective, it should have a positive effect on developers' risk assessment of auction participation.

This thesis contributes to a subject that, to this point, has only been sparsely researched. It is only in recent years that RE auctions have gained popularity, and as such, the field is still developing. The existing literature on auction design has focused on de-incentivising excessive deferral of projects through penalisation. This study will hopefully serve as a stepping-stone to further research on the impact of revenue uncertainty mitigation within the context of RE auctions.

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Popular science summary

Renewable energy projects, such as solar power plants, are essential for reducing climate change. To encourage the development of these projects, governments often use auctions where companies bid to build renewable energy facilities at the lowest possible subsidy cost. However, a common issue in these auctions is that some winning projects are never completed. This happens because developers face uncertainty about future electricity prices, making projects risky or potentially unprofitable.

This study examines how project uncertainty may be reduced, thus increasing the likelihood of projects being completed by proposing a new subsidy structure. This subsidy links the financial support companies receive to a stable, averaged electricity price rather than a highly fluctuating spot price. By doing so, it lowers the risk developers face, making them less likely to delay or abandon projects.

Using simulations based on real-world data, this thesis evaluates renewable energy auctions from Germany and Italy. Results show that using this more stable subsidy may significantly improve the number of completed renewable energy projects, especially in auctions facing tough market conditions or intense competition.

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