Measuring The Effectiveness of Hedging Strategies: The Case of Energy Retailers

Paola Fernandez[1] and Javier Orlando Pantoja-Robayo[2*]

Abstract

In a climate emergency context, energy retailers are essential in transitioning to low-carbon energy as they engage with producers and consumers. However, providing a low-carbon energy mix in compliance with low-carbon emissions targets requires hedging portfolios that improve financial performance. In this sense, we present a solution to the problem of hedging price and quantity risks using financial instruments based on price and weather indexes. We propose an optimal hedging strategy consisting of a portfolio of price and weather derivatives, allowing to transfer risk exposures to financial markets. We also find a vector of optimal quantities of each energy source according to expected demand. We evaluate the hedging efficiency by comparing the distribution of the retailer's payoffs before and after hedging. Our results provide energy retailers with evidence and tools to manage risks by defining appropriate hedging methods. We evaluate these solutions in various scenarios that include different combinations of energy generation sources. Our findings underline the significance of weather derivatives in optimizing energy portfolios, with implications for risk reduction and profit enhancement.

Keywords: Energy retailers, Hedging efficiency, Weather derivatives, Renewable Energy Sources

[1] School of Economics and Finance, EAFIT, Cra. 49 #7S - 50, Medellin, 050022, Antioquia, Colombia; E-mail: pfernan4@eafit.edu.co; ORCID: 0009-0001-4008-5841

[2] Business School, EAFIT, Cra 49 #7S - 50, Medellín, 050022, Antioquia, Colombia; E-mail(s): jpantoja@eafit.edu.co ; ORCID: 0000-0002-3881-3811. *Corresponding author(s).

1. Introduction

Over the last decades, power markets around the globe have evolved into deregulated markets, and in many countries, electricity is now traded under competitive rules (Mayer and Truck, 2018). Producers, traders, and large consumers can buy or sell power in organized markets as part of this deregulation. Energy retailers buy electricity from producers in a competitive wholesale market for (re)sale in the retail market (Boroumandet al., 2015). As a result of these dynamics, they face price and volumetric risks.

Price risks are caused by high volatility in wholesale power prices, which directly affects retailers' net earnings. Volumetric risk, associated with uncertainty in the electricity load, also affects retailers' net earnings as they must meet varying customer demands at fixed market rates (Oum et al., 2006). Also, the inelasticity and the rigidity of supply caused by non-storability and plant outages expose retailers' net profits (Stoft, 2002). Moreover, growing distributed renewable generation and self-consumption increases the hedging needs of retailers, who are more exposed to higher demand uncertainty (Russo et al., 2022). Such risks have raised awareness of the importance and necessity of risk management in the competitive electricity market.

The risk hedging problem of energy retailers has been studied from various perspectives in the literature. Most of them attempt to find an optimal portfolio of financial derivatives to mitigate losses that retailers may incur due to changes in energy prices and volume. These studies differ in the financial instruments, the objective function, the model, or the assumptions used to solve the problem. Recent works have included renewable energy sources (Fernandez et al. 2023); however, no research has been conducted on how these sources impact retailers' payoffs.

While including renewable energy sources (RES) contributes to the literature from a risk management and environmental perspective, it is worth considering whether it contributes to financial performance. That is if considering cleaner energy generation sources in an energy retailer's hedging problem adds value in financial terms. The relevance of this question is related to the correlation that RES exhibit with weather indices1, but also because its increasing use is pertinent to the current environmental context.

Our society faces an energy challenge: The energy demand worldwide has reached levels that cannot be sustained in the future. At the same time, fossil fuels are limited, and their widespread use has severe environmental consequences (Michaelides, 2012). The world must transition to cleaner energy sources to reduce the planet's carbon footprint and ensure sustainable living conditions. Consequently, evidence that including these sources has both an environmental and a financial benefit to retailers is essential.

As market intermediaries, energy retailers play an essential role in transitioning to low-carbon energy as they engage with producers and consumers. However, providing a low-carbon energy mix in compliance with low-carbon emissions targets requires hedge portfolios that improve financial performance. This paper aims to provide evidence that renewable energy sources combined with an appropriate hedging strategy can be as efficient as nonrenewable ones. This would incentivize retailers and producers to use renewable sources, thereby motivating further study of the problem and generating solutions that will benefit society.

In this work, we evaluate the hedging efficiency of renewable hedging strategies by comparing the financial benefits of the retailer's hedging solution using renewable vs. non-renewable energy sources. Specifically, we evaluate the performance of the hedging strategies by comparing the distribution of the retailer's payoffs before and after hedging. We evaluate these solutions in various scenarios that include different combinations of energy generation sources. As the basis of the analysis, we use a multi-commodity model in which the mean variance of the retailer's profits is optimized. As a result, a price and weather hedging portfolio are obtained, as well as the optimal distribution of energy generation sources. We use data from the German electricity market, the largest and the primary daily reference market for wholesale power in Europe, which is also strongly influenced by wind and solar production. Thus, with our work, we want to encourage future research on renewable energy sources from the retailer's perspective, as we believe the electricity sector is crucial to achieving an energy and ecological transition. The rest of the document is organized as follows. After a brief literature review in Section 2, we present the methodology in Section 3. Then in Section 4, we present the results for the hedging strategies. Finally, in Section 6, we discuss the main conclusions of the work.

2. Literature Review

The energy deregulation process has resulted in several technical papers discussing methods of managing the multiple sources of uncertainty that affect the trade of energy. Regarding price hedging, Vehviläinen and Keppo (2003) develop an integrated framework for optimal price risk management using a portfolio of electricity derivatives. They use Monte Carlo simulation to obtain the optimal portfolio that maximizes the expected utility of terminal wealth. Näsäkkälä and Keppo (2005) develop a hedging strategy of cash flows using forward contracts based on an optimal hedge ratio. Datong P. Zhou et al. (2017) construct hedging strategies by profit maximizing forward contracts and call options portfolios as a function of uncertain aggregate user demand and wholesale prices. Other works about price hedging in electricity markets can be found in Deng and Oren (2006); Tegnér et al. (2017); Souhir et al. (2019); Xiang et al. (2019); Niromandfam et al. (2020) and the references therein.

The retailer's hedging problem of joint price and volumetric risks under an expected utility maximization criterion was addressed by Oum et al. (2006). They propose a hedging methodology using electricity derivatives with any payoff functions that can be replicated by a series of standardized derivatives (as in Carr and Madan (2001)). Some variants of this hedging problem using the VaR criterion have been addressed by Woo et al. (2004), Kleindorfer and Li (2005), and Oum and Oren (2009). Later, Oum and Oren (2010) extend their method by optimizing the portfolio and the timing of hedge contracts. Similarly, Id-Brik and Roncoroni (2016) derive a closed-form solution to the static hedging problem of price and volumetric risk, using any index that exhibits statistical correlation to volumetric load.

Although weather derivatives have gained traction in recent years and exhibit high correlation with RES, few studies have considered the inclusion of these sources in the retailers' risk hedging problem. Brigatto and Fanzeres (2022) propose a risk-and ambiguity-constrained portfolio allocation model for backing a supply contract with the optimal combination of call/put options and renewable sources. Following this work, we are interested in proposing an optimal hedging strategy that consists of a hedging portfolio composed of price and weather derivatives for a retailer that has access to diverse sources of renewable energy. As well as investigating the impact of the inclusion of RES on the retailers' hedging problem.

3. Methodology

In this section, we provide a detailed description of the methodology. We begin by introducing the hedging problem and the formulation of the optimization problem. Additionally, we present a proposition that enables a numerical solution to this problem. Finally, we present the performance metrics to be used in measuring the effectiveness of the hedging strategies.

3.1 Optimal hedging

In this section, we formulate the optimization problem so that the retailer maximizes its expected profits by choosing adequate hedging portfolios and weights for each energy source.

Consider an energy retailer who needs to serve an uncertain electricity demand q at a fixed price r. The retailer produces electricity from the wholesale market at the spot price. Electricity can be generated from various sources: hydro, wind, solar, and so on. As a result, their returns might be exposed not only to price risks but also to volumetric (weather) risks. To protect against those risks, the retailer can construct hedging portfolios composed of hedging instruments such as options and forwards with weather indices and energy prices as underlying.

The retailer's profit is $(r - p^T\omega)q$ where p is the price vector for m energy sources, and ω is the weight vector contains the proportion (percentage) of the total quantity to purchase from each source. The retail price r is known, while demand q and spot prices vector p are random. We construct separately the payoffs of the price hedging portfolio and the weather hedging portfolio. Let M_p and M_h be the matrices containing the payoffs of each portfolio. Following the put-call parity[3], in both portfolios there are put options, a forward and a treasury risk-free bond. Without losing generality, we will assume that in both portfolios, there are n put options, one forward and one bond for each underlying. In the price hedging portfolio, the underlying assets are the prices of m sources of generation $p_1, p_2, \cdots, p_m$ and in the volumetric hedging portfolio, the underlying assets are l weather indices $h_1, h_2, \cdots, h_l$. Then the matrices M_p and M_h are:

$$M_p = \begin{pmatrix} \left(k_{p_1}^1 - p_1\right)^+ & \left(k_{p_2}^1 - p_2\right)^+ & \cdots & \left(k_{p_m}^1 - p_m\right)^+ \\ \left(k_{p_1}^2 - p_1\right)^+ & \left(k_{p_2}^2 - p_2\right)^+ & \cdots & \left(k_{p_m}^2 - p_m\right)^+ \\ \vdots & \vdots & \ddots & \vdots \\ \left(k_{p_1}^n - p_1\right)^+ & \left(k_{p_2}^n - p_2\right)^+ & \cdots & \left(k_{p_m}^n - p_m\right)^+ \\ p_1 - f_{p_1} & p_2 - f_{p_2} & \cdots & p_m - f_{p_m} \\ 1 & 1 & \cdots & 1 \end{pmatrix}$$

$$M_h = \begin{pmatrix} \left(k_{h_1}^1 - h_1\right)^+ & \left(k_{h_2}^1 - h_2\right)^+ & \cdots & \left(k_{h_l}^1 - h_l\right)^+ \\ \left(k_{h_1}^2 - h_1\right)^+ & \left(k_{h_2}^2 - h_2\right)^+ & \cdots & \left(k_{h_l}^2 - h_l\right)^+ \\ \vdots & \vdots & \ddots & \vdots \\ \left(k_{h_1}^n - h_1\right)^+ & \left(k_{h_2}^n - h_2\right)^+ & \cdots & \left(k_{h_l}^n - h_h\right)^+ \\ h_1 - f_{h_1} & h_2 - f_{h_2} & \cdots & h_l - f_{h_l} \\ 1 & 1 & \cdots & 1 \end{pmatrix}$$

[3] The put–call parity shows that the value of a European call can be deduced from the value of a European put with the same strike price and maturity date, a zero-coupon bond, and a share (or a forward).

where $\left(k_{p_i}^j - p_i\right)^+ = \max\{\mathrm{k}_{\mathrm{p_i}}^{\mathrm{j}} - \mathrm{p_i}, 0\}$ and $k_{p_i}^j$ is the strike price of the j_{th} put option whose underlying is the price p_i (energy generation source i). Similarly, $k_{h_i}^j$ is the strike price of the j_{th} put option underlying is weather index i. Also, f_{p_i} is the contractual fixed price of the forward to be paid for one MWh of energy with price p_i and f_{h_i} is the contractual fixed price of the forward for weather index h_i. The total payoff of each portfolio can be calculated with matrices of weights (proportions) for each instrument.

Let Γ, Λ be the proportion matrices for each portfolio respectively, i.e., the amount of each instrument in the hedging portfolios. Matrix Γ has the same dimensions as M_p and Λ the same as M_h. If we use the Frobenius inner product $\langle \cdot,\cdot \rangle_F$, then the payoff of the price hedging portfolio is $\left\langle M_p, \Gamma \right\rangle_F$ and the payoff of the weather hedging portfolio is $\langle M_h, \Lambda \rangle_F$ .Then the total retailer's profit is $(r - p^T\omega)q + \langle Mp, \Gamma \rangle_F + \langle M_h, \Lambda \rangle_F$.

To find an optimal hedging strategy, we propose the following optimization problem using the mean-variance utility function.

$$\max_{\omega,\Gamma,\Lambda} \mathbb{E}^{\Psi}\left[(r - p^T\omega)q + \left\langle M_p, \Gamma \right\rangle_F + \langle M_h, \Lambda \rangle_F\right] - aVar^{\Psi}\left[(r - p^T\omega)q + \left\langle M_p, \Gamma \right\rangle_F + \langle M_h, \Lambda \rangle_F\right]$$

$$\begin{aligned} \text{s.t} \quad & \mathbb{E}^{\Phi}\langle Mp, \Gamma \rangle_F = 0 && (1)\\ & \mathbb{E}^{\Phi}\langle M_h, \Lambda \rangle_F = 0 && (2)\\ & \omega \mathbb{E}^{\Psi}[q] \leq c && (3)\\ & l \leq \omega \leq u && (4)\\ & e^T\omega = 1, \omega_i \geq 0 && (5) \end{aligned}$$

In this model, Ψ is a probability measure that represents the ER beliefs on the real distribution of the realization of p, q and h, and Φ is a risk-neutral probability measure (not unique since the market is incomplete). Constraints 1 and 2 indicate that the portfolios with payoffs $\left\langle M_p, \Gamma \right\rangle_F$ and $\langle M_h, \Lambda \rangle_F$ are self-financed. Constraint 3 is related to the limits of installed generation capacity by energy source defined in vector c. Constraint 4 represents political and/or environmental restrictions of maximum and minimum consumption of each of the generation sources, and finally, Constraint 5 indicates that the weights of each energy source must be non-negative and add up to 100%.

3.2 Optimal solution

In this section, we present an approach to solve the optimization model introduced previously. We assume a discrete setting with M prices for each generation source, L values for each weather index, and N values for quantity. That is, we have sets $P = \{p_1^i, \cdots, p_m^i : i = 1, \cdots, M\}, H = \{h_1^i, \cdots, h_l^i : i = 1, \cdots, L\}\ and\ Q = \{q_i : i = 1, \cdots, N\}$ which contain possible prices, weather indices and quantities respectively. In this setting, the retailer's beliefs distribution Ψ is a probability measure supported on $P \times H \times Q$ and the risk-free distribution Φ is a probability measure supported on $P \times H$.

Proposition 1. Let: 1 $\mu_{pq} = \mathbb{E}^{\Psi}[pq]$ the expected vector of prices multiplied by quantity for each generation source. 2. $\mu_q = \mathbb{E}^{\Psi}[q]$ the expected quantity. 3. $\mu_p = \mathbb{E}^{\Psi}[p]$ the expected matrix of price-hedging portfolio payoffs. 4. $\mu_h = \mathbb{E}^{\Psi}[M_h]$ the expected matrix of weather-hedging portfolio payoffs. 5. $\mu_p^{\Phi} = \mathbb{E}^{\Phi}[M_p]$ the expected matrix of price-hedging portfolio payoffs under risk-neutral probability. 6. $\mu_h^{\Phi} = \mathbb{E}^{\Phi}[M_h]$ the expected matrix of weather-hedging portfolio payoffs under risk-neutral probability. 7. $\sigma_q^2 = Var^{\Psi}[q]$ the variance of the quantity. 8. $\Sigma_{pq} = Var^{\Psi}[pq]$ the variance of the product between the vector of prices and the quantity. 9. $\Sigma_{pq,q} = Cov^{\Psi}[pq, q]$ the covariance vector between quantity and the product of prices and quantity. 10. $\Sigma M_p = Var^{\Psi}[M_p]$ the variance tensor of random matrix M_p. 11. $\Sigma M_h = Var^{\Psi}[M_h]$ the variance tensor of random matrix M_h. 12. $\Sigma M_p, M_h = Cov^{\Psi}[M_p, M_h]$ the covariance tensor of random matrices M_p and M_h. 13. $\Sigma M_{p,q} = Cov^{\Psi}[M_{p,q}]$ the covariance tensor of random matrix M_p and random variable q. 14. $\Sigma M_{h,q} = Cov^{\Psi}[M_{h,q}]$ the covariance tensor of random matrix M_h and random variable q. 15. $\Sigma M_{p,pq} = Cov^{\Psi}[M_{p,pq}]$ the covariance tensor of random matrix M_p and random vector $p^T q$. 16. $\Sigma M_{h,pq} = Cov^{\Psi}[M_{h,pq}]$ the covariance tensor of random matrix M_h and random vector $p^T q$.

Then the optimization model is equivalent to

$$r\mu_q - ar^2\sigma_q^2 + \max_{\omega,\Gamma,\Lambda} - \mu_{pq}^T\omega + \langle\mu_p,\Gamma\rangle_F + \langle\mu_h,\Lambda\rangle_F - a\Big\{\omega^T\Sigma_{pq}\omega - 2r\Sigma_{pq,q}^T\omega + \left\langle\Sigma_{\mathrm{M_p}},\Gamma\otimes\Gamma\right\rangle_F + \langle\Sigma_{\mathrm{M_h}},\Lambda\otimes\Lambda\rangle_F + 2r\left\langle\Sigma_{\mathrm{M_p},q},\Gamma\right\rangle_F - 2\left\langle\Sigma_{\mathrm{M_p},pq},\omega\otimes\Gamma\right\rangle_F + 2r\langle\Sigma_{\mathrm{M_h},q},\Lambda\rangle_F - 2\langle\Sigma_{h,pq},\omega\otimes\Lambda\rangle_F + 2\left\langle\Sigma_{\mathrm{M_p},M_h},\Gamma\otimes\Lambda\right\rangle_F\Big\}$$

$$\text{s.t} \quad \langle\mu_p^\Phi,\Gamma\rangle_F = 0 \qquad (1)$$
$$\langle\mu_h^\Phi,\Lambda\rangle_F = 0 \qquad (2)$$
$$\omega\mu_q \le c \qquad (3)$$
$$l \le \omega \le u \qquad (4)$$
$$e^T\omega = 1, \omega_i \ge 0 \qquad (5)$$

Using Proposition 1. and a quadratic optimization solver we can then find a numerical solution to the problem. To check if the numerical solution is indeed optimal, we use the KKT conditions that allow us to verify if the necessary conditions are met.

3.3 Performance metrics

This section describes the different metrics we will use to measure hedging performance. This methodology is particularly useful when there are several commodities or derivative instruments to consider. In these cases, examining the hedge ratio or correlation between the underlying and the asset/ commodity to be hedged is insufficient. In fact, the strategy should be evaluated as a whole, considering the correlations and interactions between all the portfolio elements. Thus, we analyze the payoff distributions before and after hedging to measure the impact of hedging.

Following Ederington (1979) we define the hedging effectiveness as the percent reduction in the variance.

$$e = 1 - \frac{Var[Payoff\ after\ hedging]}{Var[Payoff\ before\ hedging]} = 1 - \frac{Var\left[(r - p^T\omega)q + \langle M_p,\Gamma\rangle_F + \langle M_h,\Lambda\rangle_F\right]}{Var[(r - p^T\omega)q]} \qquad (12)$$

So $0 < e \leq 1$ measures the amount of variance in payoffs that is reduced by hedging.

We calculate the VaR and ES for the distribution of the payoffs after hedging. Value at Risk is defined as the loss level that will not be exceeded with a specified probability α, while Expected Shortfall is the expected loss given that the loss is greater than the VaR level. Mathematically, where F_X is the cumulative distribution function of the payoffs, we empirically estimate the VaR and the ES using the percentile estimates of the historical payoff of the retailers.

$$VaR_\alpha(X) = -\inf\{x \in \mathbb{R}: F_X(x) > \alpha\} \tag{12}$$

$$ES_\alpha(X) = -\frac{1}{\alpha}\int_0^\alpha VaR_\gamma(X)d\gamma \tag{13}$$

We will present the percent reduction after hedging for both the Value at Risk and Expected Shortfall as:

$$\%VaR_\alpha = 1 - \frac{VaR_\alpha^{after\ hedging}}{VaR_\alpha^{before\ hedging}}; \%ES_\alpha = 1 - \frac{ES_\alpha^{after\ hedging}}{ES_\alpha^{before\ hedging}}$$

We define the risk-adjusted payoffs as

$$\eta^* = -\frac{E[Payoff\ after\ hedging] - E[Payoff\ before\ hedging]}{\sqrt{Var[Payoff\ after\ hedging]} - \sqrt{Var[Payoff\ before\ hedging]}}$$

$$= -\frac{E\langle M_p, \Gamma\rangle_F + \langle M_h, \Lambda\rangle_F}{\sqrt{Var\left[(r - p^T\omega)q + \langle M_p, \Gamma\rangle_F + \langle M_h, \Lambda\rangle_F\right]} - \sqrt{Var[(r - p^T\omega)q]}}$$

which is equivalent to calculating the slope of the line between the risk adjusted payoffs before and after hedging (see Fig 1).. In this case, the higher the value, the better the strategy, as it allows us to achieve a higher risk adjusted payoff after hedging.

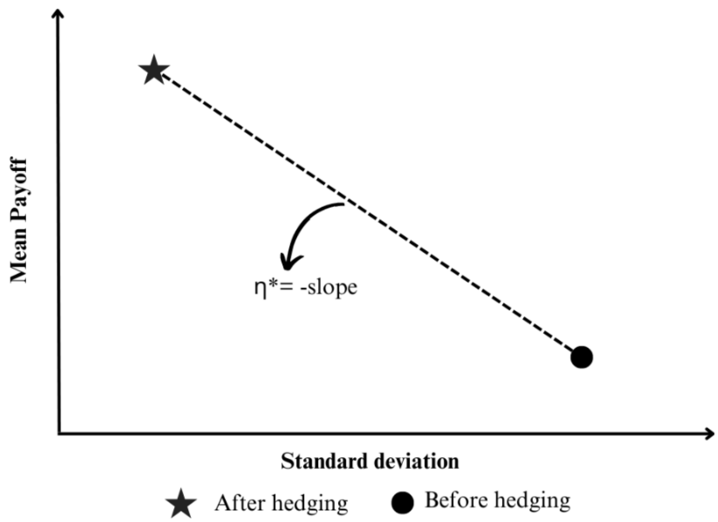


Fig. 1. Illustration of risk-adjusted payoff calculation

4. Results

In this section, we evaluate our models with real data from the German electricity market. Several reasons make the study of the German market relevant. Firstly, the German market is large, with a low HHI index and a prominent level of liquidity. Also, the German electricity market is the largest and the primary daily reference market for wholesale power in Europe. Consequently, the German electricity market plays a key role in the energy transition due to its ability to absorb large volumes of electricity from renewable sources.

In Table 1, we present the data sources, frequency, and units for each variable. The study period is from 1st January of 2015 to 31st March of 2023.

Table 1.
Data sources and units

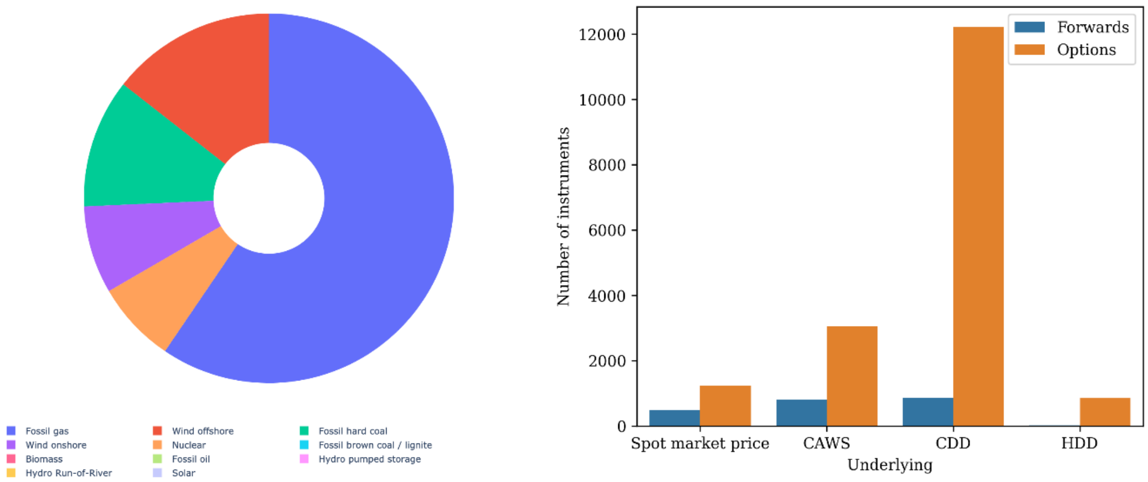
Data	Notation	Units	Frequency	Source
Market prices	p	Euro/MWh	Monthly	https://www.energy-charts.de/}{https://www.energy-charts.de
Quantity demand	q	MWh	Daily	https://www.smard.de/}{https://www.smard.de
Temperature	h_1	Â°C	Hourly	https://www.energy-charts.de/}{https://www.energy-charts.de
Wind Speed	h_2	m/s	Hourly	https://www.energy-charts.de/}{https://www.energy-charts.de
Installed capacity	c	MWh	-	https://www.energy-charts.de/}{https://www.energy-charts.de

We use the Gurobi optimizer for numerical experiments to find the optimal hedging portfolios and quantities. We use a retail rate of r = 100 Euro/MWh and a risk aversion parameter of $a = 1$.

We will discuss five cases: all available sources, only renewable sources, only non-renewable sources, a mix between non-renewable and solar, and a mix between non-renewable and wind. For the last two cases we did not present the analysis in detail since the solutions were the same as for another case. Specifically, the solution for the renewable solar case is the same as that of non-renewable. And the renewable + wind solution was the same as the base case.

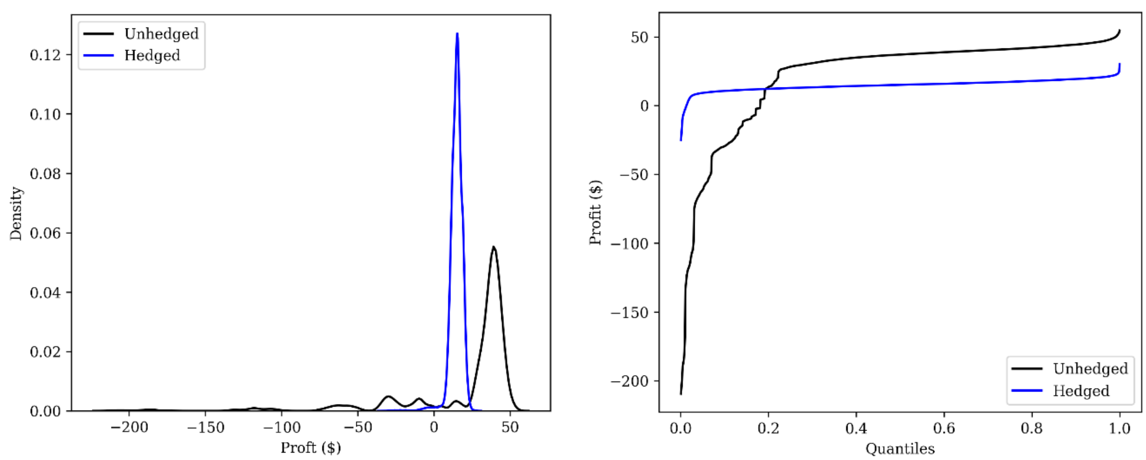
4.1. Base Case

In the base case, all sources of generation are available (subject to the installed capacity limit indicated by the vector c). The optimal solution for this case can be seen in Fig 2. Two components make up this solution: the first is the optimal distribution of generation sources from which the retailer should purchase its energy. Second, there is the number of instruments required for the price and weather hedging portfolios. As can be seen in part A of Fig 2, the optimal distribution of sources is characterized by low weights assigned to renewable sources. There are approximately 22% of renewable energy sources allocated (only wind onshore and offshore). Additionally, no weight is assigned to hydro, solar, or biomass energy sources. Accordingly, a substantial proportion of sources are attributed to fossil fuels, which can be explained in part by their lower price compared to other sources. The optimal number of instruments in each portfolio is shown in part b of Fig 2. The number of options and forwards associated with each underlying index is presented; however, it is important to keep in mind that the model assumes that short and long positions can be taken in these instruments. The strategy recommends maintaining a significant position in both the price and weather portfolios, although the weather portfolio is more significant.



(a) (b)

Fig. 2. Optimal solution for the base case



(a) (b)

Fig. 3. Profit distributions for hedged and unhedged payoffs (thousands of Euros) for the base case.

Next, we will examine how this hedging affects the retailer's profits as shown in Fig 3. The blue line indicates the distribution of profits after hedging and the black line indicates profits before hedging. As can be seen from the graph, hedging portfolios have a positive impact on the retailer's profits. Using a hedging strategy, it is possible to significantly reduce the risk without adversely affecting profits. We observe that the distribution of unhedged profits is skewed heavily to the left, indicating that the retailer may suffer significant losses. These losses are obviously mitigated by hedging. Fig

3b also demonstrates this, where the quantiles are shown, indicating the wide difference between quantiles 0 and 0.5 between the two distributions.

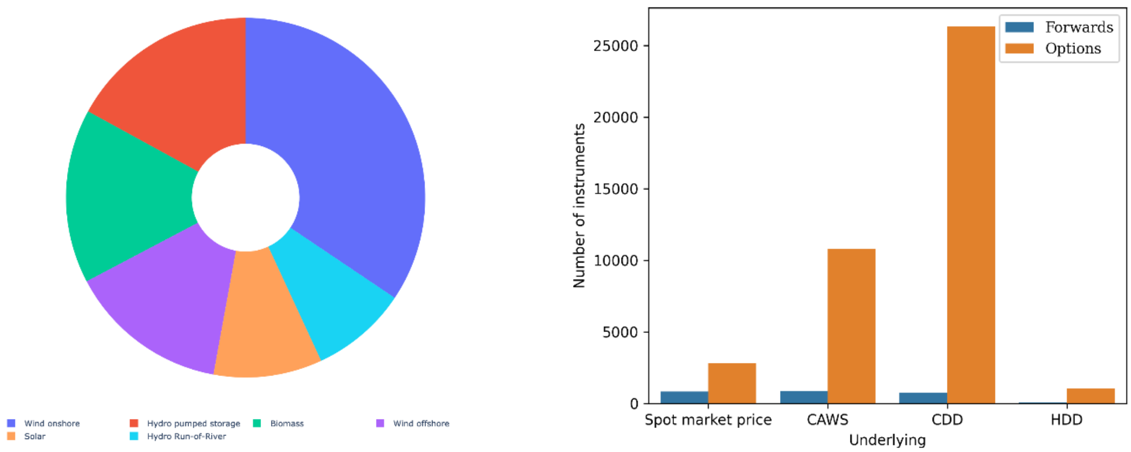
Table 2.
Descriptive statistics of unhedged and hedged payoffs (thousands of Euros) for the base case

	Mean	Std	Min	25%	50%	75%	Max
Unhedged	21.53	39.73	-216.1	28.22	37.07	41.08	54.55
Hedged (Price \& Weather)	37.14	4.46	-13.37	35.17	37.49	39.67	52.52
Hedged (Only Price)	38.03	4.05	-8.45	36.54	38.12	40.38	50.26
Hedged (Only Weather)	20.65	39.78	-221.02	26.81	35.99	40.44	56.82

Table 2 presents the descriptive statistics of the retailer's profits before and after hedging. Furthermore, statistics are presented for situations in which only price hedging or only weather hedging have been undertaken. On the one hand, the results support what was shown in the previous graphs: hedging reduces the risk (standard deviation) while increasing the expected value. On the other hand, maximum losses are much lower when hedging. A combination of price hedging and weather hedging is, therefore, better than using one or the other alone. When analyzing the individual solutions of price and weather, we could affirm that the price portfolio contributes the most to the reduction of risk, whereas the weather portfolio favors an increase in profits (this is not always the case, as we will see in the following cases).

4.1. Only Renewable Sources

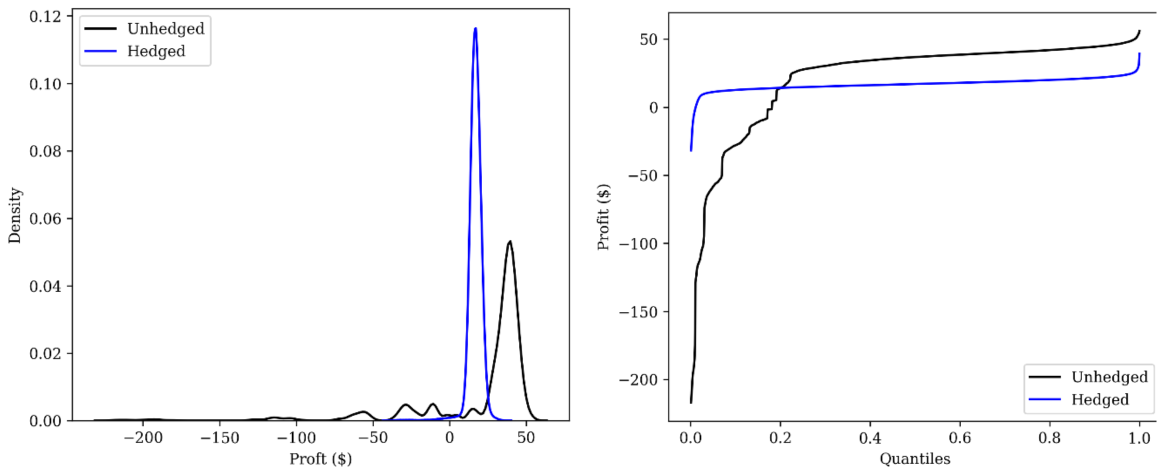
The following case considers a scenario where only renewable energy is available. Fig 4 presents the optimal solution in terms of the weights assigned to each source and the number of instruments in the hedging portfolios. We observe that approximately 48% is allocated to wind sources (onshore and offshore), 26% to hydro sources, 16% to biomass and the remainder to solar. Wind energy's dominance is not only due to its price compared to other sources, but also to the use of weather derivatives based on wind speed in the hedging portfolios. Due to the higher correlation between the prices of these instruments and the price of wind energy, hedging is likely to be more effective when there is a higher proportion of wind energy.



(a) (b)

Fig. 4. Optimal solution for the renewable case

Meanwhile, when taking a closer look at the number of instruments for hedging portfolios, an analogous situation as in the base case can be observed. However, when we carefully review the quantities of each instrument, we can see that the optimal solution for renewable sources requires twice as many financial instruments as the base case. According to this result, more financial derivative instruments are required for scenarios in which renewable energy sources dominate to achieve similar hedging as the base scenario. As a result of the greater volatility of renewable energy sources, it is logical that more instruments are required since there is a greater risk involved. It is further evident from this result that as the transition to renewable generation sources is made, a greater degree of liquidity will be required in the derivatives market to allow retailers to effectively hedge their risks. Moreover, this result gives rise to the question of whether it is necessary not only to maintain and strengthen current weather derivative instruments, but also to develop other derivatives related to renewable energy sources. For example, derivatives based on solar radiation, river flows, among others.



(a) (b)

Fig. 5. Profit distributions for hedged and unhedged payoffs (thousands of Euros) for the renewable case. [4]

As a next step, we evaluate the results of the hedging. Firstly, Fig 5 shows the distribution of the retailer's profits before and after hedging. Similarly to the base case, hedging generates a positive impact on profits. As a result, the variance is reduced, losses are reduced, and at the same time, the expected profits are increased. Table 3 contains the descriptive statistics for the profits, which also confirm this conclusion. Furthermore, the table demonstrates that combining the price hedging portfolio with the weather hedging portfolio is better than doing just one or the other. Moreover, contrary to what occurred in the base case, on this occasion, the weather portfolio contributed significantly to the reduction of risk, whereas the price portfolio contributed to the increase in profits. This makes sense if we consider that there are more instruments based on weather than on electricity price.

Table 3.
Descriptive statistics of unhedged and hedged payoffs (thousands of Euros) for the renewable case

	Mean	Std	Min	25%	50%	75%	Max
Unhedged	21.55	39.60	-223.87	27.64	36.84	41.05	55.92
Hedged (Price & Weather)	37.62	5.00	-21.58	35.59	37.87	40.21	60.21
Hedged (Only Price)	16.17	37.26	-8.42	-2.34	0.00	9.68	206.28
Hedged (Only Weather)	-0.11	1.89	-4.00	-1.59	-0.18	1.27	5.64

[4] Density functions are estimated with a Kernel Density Estimate (KDE) using the function kdeplot from seborn in Python. A KDE plot smooths the observations with a Gaussian kernel, producing a continuous density estimate.

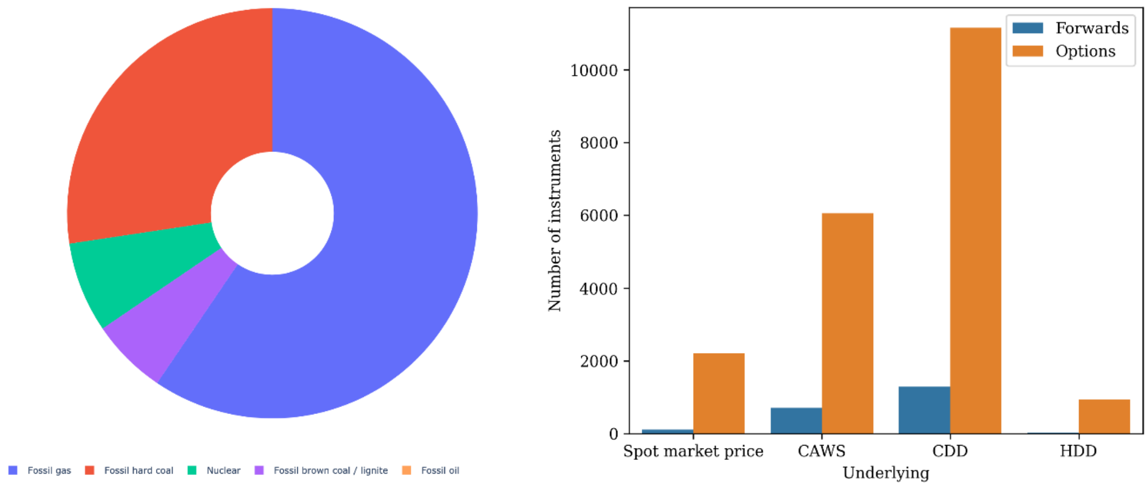
4.2. Only Non-Renewable Sources

Lastly, we present the results for the case in which only non-renewable sources of energy are considered. In Fig 6, we present the optimal distribution of sources and the number of instruments in the hedging portfolios. Many of the sources assigned are fossil resources (93%), like the results obtained in the base case. Likewise, it is observed that the strategy suggests having a significant position in all derivative instruments (including weather-based instruments). However, when comparing the quantities with the two previous cases, we observe that in this case fewer instruments are needed. This result can be explained by the lower volatility of non-renewable energy sources, therefore less weather-based instruments are needed, as they are not linked to weather conditions.

On the other hand, Fig 7 shows the profit distributions before and after hedging. After hedging, the distribution no longer has a heavy left tail, mitigating the retailer's losses. Furthermore, Fig 7 shows that profits are less widespread after hedging, without shifting leftwards compared to the before-hedging distribution. Table 4 presents the descriptive statistics of the results. In this case, hedging solely based on price yields better results than hedging based on both price and weather. Although the differences are small, this result makes sense since the weather portfolios are composed of variables highly correlated with the generation of renewable energy sources. Although it would not be correct to say that it is better to only do price hedging, it is true that it is not essential to do so in this case.

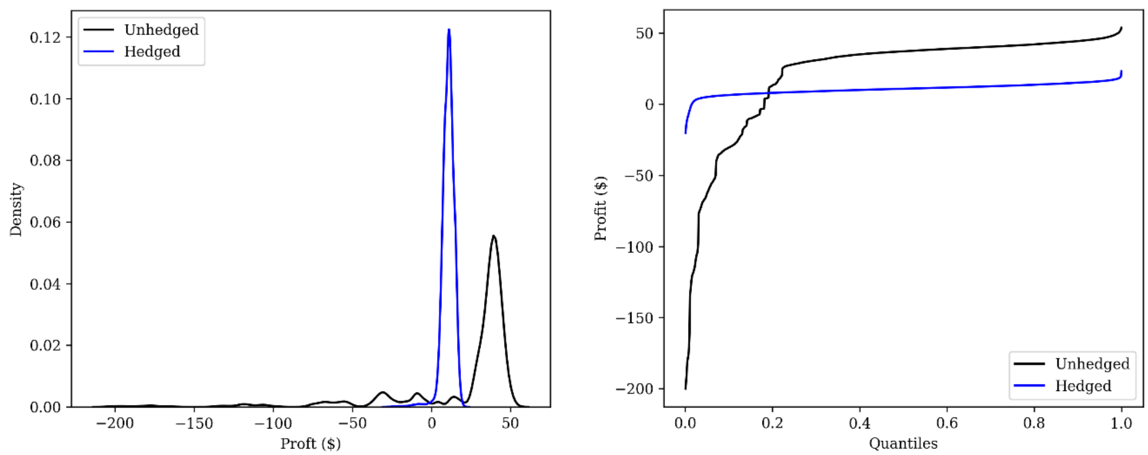
Table 4.
Descriptive statistics of unhedged and hedged payoffs (thousands of Euros) for the nonrenewable case

	Mean	Std	Min	25%	50%	75%	Max
Unhedged	21.48	39.57	-206.30	28.18	37.14	41.15	53.77
Hedged (Price & Weather)	37.28	4.05	-3.36	35.21	37.56	39.77	49.92
Hedged (Only Price)	38.22	3.62	1.13	36.63	38.30	40.60	47.00
Hedged (Only Weather)	20.53	39.62	-210.79	26.84	36.02	40.42	56.69



(a) (b)

Fig. 6. Optimal solution for the non-renewable case



(a) (b)

Fig. 7. Profit distributions for hedged and unhedged payoffs (thousands of Euros) for the non-renewable case.

4.3. Performance

Table 5 displays the performance metrics for each of the previously analyzed scenarios. Starting with the percentage reduction in VaR (Value at Risk), it can be observed that in all cases, the hedging strategy achieves a VaR reduction of more than 100%. Furthermore, when analyzing VaR before and after hedging, in all cases, we found that after hedging, the VaR becomes negative, indicating that at a 99% confidence level, there are no losses but rather gains. Accordingly, hedging, as demonstrated by previous results, has a significant impact on losses mitigation. It is also important to note that the cases with the greatest reduction in VaR are those that primarily rely on nonrenewable energy sources. However, the difference from the other cases is not large enough to imply an advantage in using non-renewable energy sources. The results for the Expected Shortfall (ES) are similar. A reduction of more than 100% was achieved in all cases, with the greatest reduction occurring in cases in which non-renewable sources predominated.

Regarding the hedging efficiency (HE), we note that the values for all scenarios are close to 98%, indicating that hedging strategies entirely reduce the variance of the retailer's profits. Furthermore, all values are quite similar across different scenarios, indicating that, regardless of the available sources of energy generation, the proposed hedging strategy can deliver efficient solutions (variance reduction).

Finally, when analyzing the risk-adjusted payoffs, a particular situation arises. It is observed that a significantly higher value is observed for renewable energy sources in this case. As a result, the hedging strategy for renewable sources can improve the expected value of profits when risk reduction is considered. For the other scenarios, the values are quite similar and hover around 0.44.

Table 5.
Performance metrics for the different scenarios of hedging strategies

	%VaR	%ES	HE	η
All	1.1149	1.0544	0.9874	0.4425
Renewable	1.1085	1.0279	0.9841	0.4644
Non-renewable	1.1370	1.0821	0.9895	0.4449
Non-renewable + solar	1.1370	1.0821	0.9895	0.4449
Non-renewable + wind	1.1149	1.0544	0.9874	0.4425

Two important conclusions can be drawn from these results. The first is related to the impact of hedging. Hedging provides numerous benefits that could be observed repeatedly and exhaustively. The results showed that hedging not only significantly reduces risk but also improves the expected value of profits. On the other hand, the second and most important conclusion is that the hedging efficiency is maintained regardless of the availability of energy generation sources. Furthermore, in the presence of renewable energy sources, hedging is equally effective as when non-renewable sources are used. It corroborates that the hedging strategy is robust enough to handle any scenario. Furthermore, it allows us to conclude that this strategy will continue to remain valid and appropriate as time passes, and more renewable energy sources are used to meet global decarbonization goals.

4.4. Different Risk Aversion Parameters

To complete the analysis of this section, we will conduct a sensitivity analysis on the risk aversion parameter. This parameter, as the name suggests, represents how risk-averse or not the retailer is. In this sense, the small value of this parameter implies that the retailer is not risk-averse and therefore is willing to assume greater risk to obtain (in expected value) a greater return.

We varied the parameter a above and below the base value (a=1) to observe changes in hedging. Table 6 presents the descriptive statistics for the profits for all cases. The same situation is observed in all cases: as the risk aversion parameter is lower, the distribution of the profits seems to move to the right, but at the same time, it has a greater variance. Conversely, when the risk aversion parameter is higher (the retailer is more risk averse), the distribution moves to the left, and the values are mostly concentrated near the mean (there is less variance). That is, when the retailers is more risk-averse, hedging generates a solution with less variance and less profit. When the retailer is less risk-averse, hedging allows for greater profits but also greater risks. In this way, although in all cases good hedging is achieved, the result in terms of variance and expected profits will depend on the retailer's risk aversion. In this sense, it is recommended to calibrate the parameter when using the proposed model.

Table 6.
Descriptive statistics for hedged payoffs when changing the risk aversion parameter.

Case	Metric	$a = 1 \times 10^{-3}$	$a = 1$	$a = 10$	$a = 100$
Base	Mean	49.7418	37.1439	37.1340	37.1330

	Std	5.2898	4.4551	4.4549	4.4549
	Min	-6.0931	-13.3652	-13.3737	-13.3746
	25%	47.1369	35.1724	35.1623	35.1614
	50%	50.1943	37.4945	37.4847	37.4837
	75%	53.0424	39.6683	39.6582	39.6572
	Max	68.4627	52.5192	52.5075	52.5064
Renewable	Mean	48.6009	37.6165	37.6066	37.6056
	Std	6.0407	4.9979	4.9974	4.9974
	Min	-18.8944	-21.5831	-21.5930	-21.5940
	25%	45.8939	35.5933	35.5837	35.5827
	50%	49.0348	37.8682	37.8584	37.8575
	75%	52.0392	40.2115	40.2013	40.2003
	Max	75.1857	60.2114	60.1979	60.1966
Non-Renewable	Mean	48.7011	37.2825	37.2709	37.2697
	Std	4.7012	4.0492	4.0498	4.0498
	Min	3.3962	-3.3616	-3.3781	-3.3798
	25%	46.1956	35.2137	35.2016	35.2004
	50%	49.0546	37.5595	37.5483	37.5472
	75%	51.7382	39.7740	39.7627	39.7616
	Max	61.8798	49.9197	49.9114	49.9106

4. Conclusions

We explored hedging strategies in various scenarios related to energy generation sources. Detailed subsections dissected scenarios such as renewable, non-renewable, and mixed sources. For each case, we presented optimal distributions of generation sources and the corresponding hedging portfolios. The impact of hedging profits was thoroughly examined through visual representations and statistical analyses.

In scenarios involving renewable sources, our findings demonstrated the intricate dynamics of optimal source allocations, emphasizing the dominance of wind energy and the need for a substantial number of financial instruments. The effectiveness of our hedging strategy was corroborated by a notable reduction in risk and an improvement in expected profits. Results consistently showcased the symbiotic relationship between price and weather hedging portfolios, each playing a crucial role in mitigating risk and enhancing profits.

In scenarios dominated by non-renewable sources, our analysis highlighted the efficient use of hedging. The distribution of profits, before and after hedging, showed a significant reduction in risk and the stabilization of profits. Comparative analyses across scenarios revealed the robustness of our hedging strategy, demonstrating its adaptability to diverse energy generation landscapes.

A comprehensive performance evaluation, including metrics such as VaR reduction, Expected Shortfall reduction, hedging efficiency, and risk-adjusted payoffs, underscored the consistent efficacy of our hedging strategy across various scenarios. These results provide valuable insights into the applicability and adaptability of the proposed hedging model in dynamic energy markets.

Our research contributes not only to the academic understanding of weather derivatives and hedging but also offers practical insights for stakeholders navigating the complexities of energy markets. As we confront the imperative of transitioning to renewable energy sources, the applicability and adaptability of our proposed models become increasingly pertinent. This study, by unraveling the intricate interplay of market dynamics, weather derivatives, and hedging strategies, provides a valuable resource for academics, practitioners, and policymakers navigating the evolving landscape of energy markets.

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