A Structured Financial Product applied to Renewable Energies

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Abstract

Faced with the globally spread increase in electricity consumption, renewable energies are rushing to set themselves as leaders on the already ongoing "next energy transition". As a consequence, it becomes evident the need for investigating a new strategy that allows retail investors, producers and financial institutions to benefit from this transition, without jeopardizing consumers, through the creation of a socially responsible structured financial product applied to electricity generation from renewable sources. To cope with this investigation we first decided to go back in history and learn from the mistakes that have left their mark on financial engineering. We then continued by establishing the legal framework that currently drives this industry as a whole in Portugal, as well as the incentives that were created to foster this transition, proving this way the potential interest of introducing the product we propose. Lastly we have defined a strategy that enables one to create such financial product with special emphasis on the variable component, which was made possible by using the models mostly recommended by the scientific community. Finally we were able to conclude that there is in fact a market from which everyone could benefit, but its success is subject to transparency and openness.

Keywords: Derivatives, Jump-Diffusion, Electricity, Structured Product, Renewable Energy.

1. Introduction

One of the core tasks of investment banking is the constant search for opportunities to create new financial instruments. Typically, this task is fulfilled by innovatively combining already existing components to form new financial instruments. According to the definition provided in Célérier & Vallée (2015) this process is called ''financial engineering'', as investment bankers act similarly to engineers or natural scientists when planning and creating complex financial innovations.

We propose the creation of a structured product adapted to the renewable energy sector, a task that only became a possibility with the restructuring of the electricity market when it moved away from the traditional regulated principles to those of the free market that obey the rules of supply and demand. In fact, according to Castro (2012) the initiation of the market liberalization process dates back to 1995, however it is only in 2007 that the market takes the shape as it is known today and, under this new regime, all agents involved trade electricity with a monetary value defined by the point where supply meets demand, traded at a power exchange.

The initial idea for our structured financial product would be to provide one that was able to derive its value (for the variable component) directly from the renewable energy being injected in the grid. Failing to do so, due to the fact that there is still no legal framework that contemplates the ability of separating energy sources as seen in EEX (2017), we have decided to address this component by looking at the electricity spot market as a whole. We assumed this to be a reasonable assumption based on the fact that all technologies operate in the same market and that renewable sources are dispatched with priority. As a consequence, the price is always defined by the marginal cost of production, which makes the spot price (as it is) a reasonable indicator of "how much" is being injected from renewable sources.

Note that these investment products can be seen as the combination of two or more financial instruments being one of them, at the very least, a derivative – as it *derives* its value from an underlying asset or a combination of assets. Such derivatives written on this commodity can already be seen trading in foreign markets as (e.g.) the Nord Pool. Hence, integrating this concept with the knowledge that structured products tend to increase demand when traditional products are offered with low interest rates can prove to be interesting for what we are trying to accomplish; see Pinto (2013).

Ambiguous opinions arose since the creation of structured products, due to their complexity, especially if one bears in mind that financial engineering was on the basis of recent financial crisis spread worldwide (e.g. Buffett, 2003). Hence the importance for us to maintain this as a socially responsible investigation, particularly if one considers electricity to be a financial asset that cannot be addressed as traditional instruments, in the sense that any financial irresponsibility could pose a threat to a whole sector and its consumers. On that premise we do find it important that in the wake of deregulation of power markets "a proper representation of the dynamics of spot prices becomes a necessary tool for trading purposes…" (Geman & Roncoroni, 2006).

The aim of this article is to provide an innovative framework for the Portuguese context of renewable energy investment. Its organization can be divided in two main components. First we will address the concept of creating a structured financial product while pinpointing their main features and providing with the framework to create one. Secondly we will focus on detailing our derivative component focusing on the underlying asset, since we know from the literature that a proper representation is essential to produce adequate results. To achieve it we will define the framework to properly model electricity spot prices in the Portuguese context (although we had initially planned to focus solely on renewable sources).

2. Structured Financial Product

Typically a structured product consists of two main components that can be distinguished as a part that establishes a capital guarantee or minimum profitability and the other that works with the variable payment. The first component can be seen as "insurance" on the money being invested, depending on the client's risk profile, or as a means to minimize eventual losses with the variable part. It can guarantee the investor's full or partially recover of the initial capital being invested. This can be achieved by applying a part of the initial capital in a fixed rent asset (as treasury bonds) that at maturity will recover the pre established amount. The second component usually relies on the use of an option portfolio whose return is indexed to the performance of any financial market (see our financial market in OMIP, 2017). According to Pinto (2013), these structured products combine the lower risk feature of the bond markets with the variable return component that is enhanced in periods of high volatility of the underlying financial asset. The variable component is responsible for the requirement of a proper valuation model in order to adequately valuate the whole structured product, which is why we dedicate our efforts to this task. However we first argue the main features to include when creating a structured product, presenting a simple version that comes from combining a working contract (from a very well known Portuguese bank, Banco BPI) with an example provided in Nunes (2015). The reasoning is that for hedging purposes the product is decomposed in:

$$GC = \mathrm{C} \cdot \frac{\left[1 - \left[\frac{1}{(1+r)^T}\right]\right]}{r} + \frac{\mathrm{F\,V}}{(1+\mathrm{r})^{\mathrm{T}}} \qquad (1)$$

where

- CG: Guaranteed Capital
- C: Coupon payment
- r: interest rate
- T: time to maturity
- FV: face value

and

$$VR_T = \max\left(0\%\,; \frac{S_T - S_0}{S_0}\right) \times X\% = \frac{X\%}{S_0} \max\left(0\,; S_T - S_0\right) \qquad (2)$$

where the variable return VR_T to be paid at maturity is given by the percentage $X\%$ of the growth of an index, if any, i.e. $\max\left(0\%\,; \frac{S_T - S_0}{S_0}\right)$. To note that $\max\left(0\,; S_T - S_0\right)$ is the terminal payoff of a call option with maturity at time T, which means that for an investor to consider this, $X\%$ has to be such that the guaranteed capital added to the variable return's present value is equal to at least 100% of the issue price.

However it is important to note that the structure being issued depends on the perception regarding the future of any given underlying asset. For that there are innumerous strategies for the replicating portfolio to be used, namely the use of barrier options which we have considered to be of particular interest to further develop its application to our market in future studies. Despite that we have addressed this issue under the simplest scenario where the financial instrument is a European Call that depends on the performance of a hypothetical index that tracks the percentage of renewable energy being injected on the grid. Since we wish to promote new investment in new installed capacity and consequently an increase in injected power from these sources, we believe that our choice is adequate.

We illustrate this with the following structured product: bonds with guaranteed capital recovery and coupon rate of 1% with variable return annually distributed and indexed to the performance of an hypothetical index that accurately tracks the amount of electricity being injected on the grid from renewable sources, i.e. the variable return to be paid at maturity (T=3years) is given by a percentage of the growth rate (if any) of the index. With a face value of 1.000€ and the interest rate equal to the latest known treasury bonds issued by the government, i.e. 1,939%.

Under this scenario we investigate what would $X\%$ be equal to, such that the fair value of the product would be 100% of the issue price, yielding:

$GC_0 = 97{,}289\%$

$VR_0 = 2{,}711\%$

$X\% = 11{,}856\%$

given that: $\max(0\,; S_3 - S_0) = c_0(S_0; k = S_0; T = 3)$ is the present value of an ATM call option with maturity in three years the replicating portfolio is given by:

1. A deposit today worth 972,89€
2. 3,95 European ATM Call options, given by:

$$\#Calls = \frac{FV \times VR_0}{c_0(S_0; k = S_0; T = 3)} \tag{3}$$

We then proceed with an evaluation of the performance of such product under different scenarios. Under this assessment we realized the need to create a strategy to reduce potential losses in premiums in the option market. This strategy is presented in a structured product by means of introducing a cap on growth, such that the replicating option strategy is:

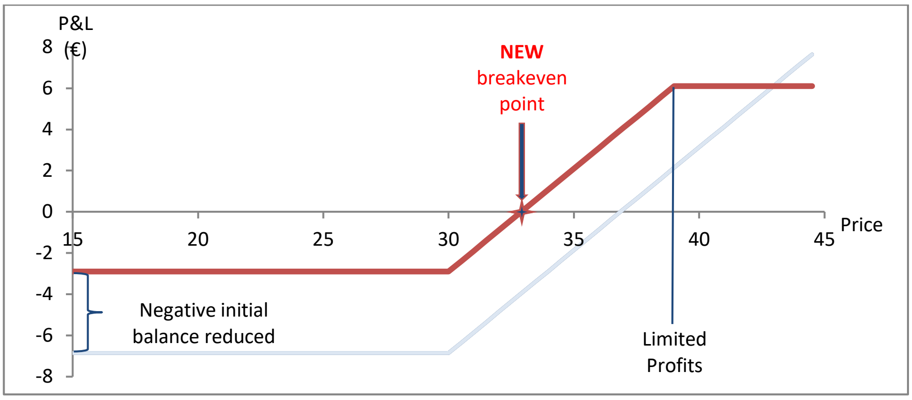

Figure 1 – Hedging strategy with cap on growth

Such strategy is known as a Bull Vertical Spread and the losses are diminished (from the negative initial balance) by selling an OTM contract and consequently collecting on that credit. Although the net position initially is still negative, the breakeven point is much smaller at the cost of reducing potential gains.

The example we provide, although very simple, is from our understanding an adequate starting point to provide with a framework to design the financial structured product we initially proposed, once policy makers enable us to separate the electricity market by sources. Being unable to do so at the present day forced us to address the task of pricing the derivative component of the contract while addressing the market as a whole. However, if we think in terms of electricity prices and injection of renewable power one can understand that they follow the same path in an inversely proportional manner. Hence we believe that a correct model for electricity spot price can be a good first step towards modeling the renewable injection market.

3. Pricing Derivatives

To address this issue we have decided to cross examine two widely used models for pricing derivatives: the Black-Scholes-Merton formula and the Monte Carlo process (for 10.000 simulations). Despite the fact that the first one relies on unrealistic assumptions, it has proved to be the chosen method to price options due to the fact that the users do not need to develop much elaborate mathematical models in order to produce accurate results as it only depends on the adequate choice of the inputs to use. Yet another reason for us to decide to investigate this model resides in the fact that under the framework provided in Geman (2005) the Merton extension could be used to price options on commodity spot prices as long as we consider its behavior as that of a stock paying continuous dividend equal to the convenience yield. However, since this concept is directly related with the ability to maintain a storage level we should question its applicability in electricity markets as (apart from hydroelectricity) no efficient form of electricity is known to be storable. We also question its use due to the fact that the main underlying assumption of the model is that the underlying asset price follows a *geometric Brownian motion:*

$$\frac{dS_t}{S_t} = (r - g)dt + \sigma W_t^{\mathbb{Q}} \qquad (4)$$

that does not account for the occurrence of jump events which, as we prove with the Monte Carlo model, are very important to address when pricing electricity derivatives. In fact it is argued that this later framework can accommodate more realistic stochastic processes, as is the case of the one we present. However we have decided to preserve both the models as our main purpose is to rather present all the tools for a potential investor to understand the market.

As Nunes (2015) states, it is clear that the Monte Carlo provides an estimate for the value of some function by simulating a sufficiently large number of times the path of its underlying independent variable. Given the time step and the number of simulations, by running the objective function it will provide with n paths that will have its own value.

4. Electricity Modeling

As we are aware, correctly representing the dynamics of spot prices in electricity markets presents as a key element for trading purposes. Among innumerous authors that have been working on this issue, some stand out and on whom we rely to carry on. Such authors can be named as Geman & Roncoroni (2006), Escribano *et al.* (2002) or Benth *et al.* (2007). As they suggest, to correctly model the market implies to properly capture the main features that characterize this utility and path, as seen in Figure 2.

Regarding those features we can first point out the mean reverting trend that most markets exhibit. This means that there exists a mean (probably deterministic) level to which prices fall after an extreme event, and this level can be described by the average marginal cost of production as Burger *et al.* (2006) and Geman & Roncoroni (2006) propose.

The second property (and from our understanding dependent on the first) that needs to be well captured is the occurrence of small random movements of the price process around the trend which come as a consequence of temporary supply/demand imbalances, as Geman & Roncoroni (2006) propose.

Lastly (but not less important) there is a feature that is, in our opinion, intimately related to the (lack of) capacity of generating inventories when referring to electricity production and also to the inelastic nature of demand for this commodity, i.e. the so called price spikes (up and downward directed).

To correctly accomplish the task of spot price modeling, we will use the logarithmic scale of the price in order to guarantee the strict *positiveness* of those prices, enhancing the robustness of the calibration procedure as originally suggested by Cartea & Figueroa (2005).

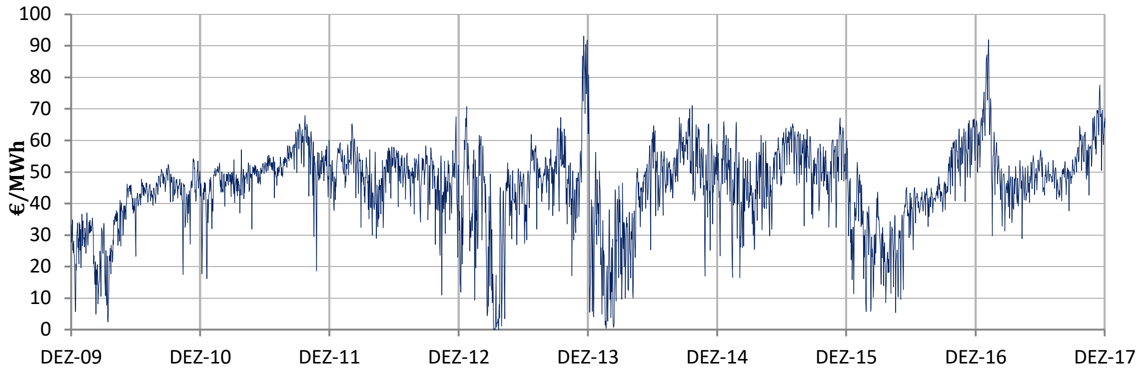

Figure 2 – Electricity spot price in the Portuguese market | source (OMIP, 2017)

Under that reasoning combined with the initial proposal by Lucia & Schwartz (2000), the model we employed is described as follows:

$$\ln(S_t) = \mu(t) + X(t) \tag{5}$$

where (S_t) represents the spot price and $\mu(t)$ the trend it follows and to which the process mean reverts. The last term $X(t)$ is the stochastic process responsible for modeling the random fluctuations. To capture such pattern we adapted the method used in Geman & Roncoroni (2006) without any prejudice to the model itself. The equation reads as:

$$\mu(t) = \theta_1 + \theta_2 t + \theta_3 \cos(\theta_4 + 2\pi t) + \theta_5 \cos(\theta_6 + 4\pi t) \tag{6}$$

The first variable on the function can be seen as the fixed cost associated to power production while the second term is responsible for the growth rate of the total production cost. The remaining components will attribute the required periodicity to the function translating into two maxima per year that can be interpreted as extreme seasons, i.e. both summer and winter. These parameters can be determined by fitting the trend line to empirical observations as in (e.g) a least squares method.

For the stochastic process we opted to employ:

$$dX_t = (\alpha - \kappa X_t)dt + \sigma dW_t + J(\mu_j, \sigma_j)d\prod(\lambda) \tag{7}$$

where $(\alpha - \kappa)$ is responsible for bringing prices back to normal, with (α) accounting for the risk-neutral assumption as in Lucia & Schwartz (2000). The jump size, as in Cartea & Figueroa (2005) and Villaplana (2003) is modeled through a normal distribution with mean μ_j and standard deviation σ_j. Finally $\prod(\lambda)$ accounts for the arrival of the extreme events, that is, it is a Poisson process with a time-dependent constant rate of arrival (λ), i.e. jump intensity. However, we felt that we could introduce a minor change here in a similar way as in Geman & Roncoroni (2006) and transform it into an inhomogenous Poisson process. The rationale being that we have reasons to believe that the arrival of these events can be deterministic and modeled as:

$$s(t) = \left[\left(\frac{2}{1 + \left|\cos\left[\frac{\pi(t-\tau)}{k}\right]\right|}\right) - 1\right]^d \tag{8}$$

This model takes into account that peaking levels are spread by k multiple years beginning at time τ. The exponent d is responsible for the events spread in time. We have decided to set the paremeters to capture the spike clustering moments with one annual peak ($k = 1$) in March-April ($\tau = 0{,}722$) The process can be seen as:

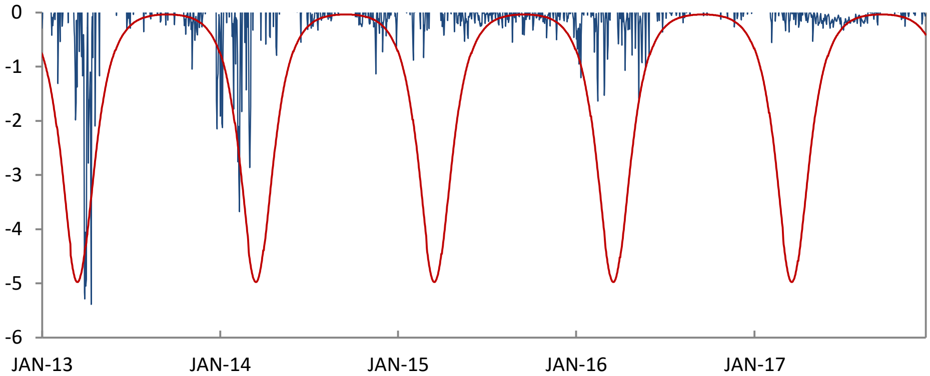

Figure 3 – Overlapping of the intensity shape function with the deseasonalized data series.

Once the model is built, we start by computing the seasonality function which is then removed from the process in order to compute the stochastic component. Here we employ a discretization process as in Villaplana (2003) in order to facilitate the task of discovering the parameters. This is accomplished by minimizing the negative likelihood function applied to the density function that drives X_t conditional to X_{t-1} in order to withdraw the parameter vector that we will want to calibrate:

$$v = \{\alpha, \emptyset, \mu_j, \sigma^2, \sigma_j^2, \theta\}$$

from

$$f(X_t|X_{t-1}) = (\theta s_t \Delta t) N_1(X_t|X_{t-1}) + (1 - (\theta s_t \Delta t)) N_2(X_t|X_{t-1}) \quad (9)$$

$$N_1(X_t|X_{t-1}) = \left(2\pi\left(\sigma^2 + \sigma_j^2\right)\right)^{-\frac{1}{2}} \exp\left[\frac{-\left(X_t - \alpha\Delta t - \emptyset X_{t-1} - \mu_j\right)^2}{2\left(\sigma^2 + \sigma_j^2\right)}\right] \quad (10)$$

$$N_2(X_t|X_{t-1}) = \left(2\pi(\sigma^2)\right)^{-\frac{1}{2}} exp\left[\frac{-(X_t - \alpha\Delta t - \emptyset X_{t-1})^2}{2\sigma^2}\right] \quad (11)$$

5. Results and Discussion

Following the implementation of the processes described to the Portuguese electricity market (from 01/01/2013 to 17/12/2017) we argue on the quality of such representation.

Table 1 – Structural Parameters

$R^2 = 0{,}23$ $p - value \ll 0{,}05$		
Parameter	**Interpretation**	**Estimate**
$\boldsymbol{\theta_1}$	Average (log) fixed cost/price level	3,5165
$\boldsymbol{\theta_2}$	Average (log) cost slope	0,0798
$\boldsymbol{\theta_3}$	Yearly trend	0,3177
$\boldsymbol{\theta_4}$	Trend displacement	1,6581
$\boldsymbol{\theta_5}$	6-month trend	0,1855
$\boldsymbol{\theta_6}$	Trend displacement	0,3700

The low figure obtained for R^2 might induce us into thinking that a seasonality with such a low correlation with empirical data cannot be used to explain the process. However, the model obtains a p-value way below the rejection point which means that there is a high degree of confidence in adding this model to our simulation as from the predictor's perspective its changes are related to changes in actual data. This means that the stochastic component will carry great weight to statistical significance around this trend.

Table 2 – Model Parameters

Parameters	Interpretation	Estimate
α κ	Mean reverting speed parameters	4,3468 287,3376
σ θ μ_j σ_j	Volatility Number of spikes per unit time[1] Jump size mean Jump size deviation	4,8003 -1 0.6689 0.05

Since this model was created to account for positive jumps only, as Geman & Roncoroni (2006) suggest, it seems only logical that adapting it to capture downward movements is possible but probably at the expenses of some misguiding results. Usually mean reverting effects take place during times of price pressure in the electric system, that naturally tries to bring them back to normal. The problem is that when the same "treatment" is applied to downward jumps it might become an unrealistic assumption, as it does not account for the weather factor that determines the mean reversion force. Despite that, and despite the fact that the reverting forces are very high, the results we obtained are very satisfactory from the statistical perspective. Path wise however we feel somehow reluctant to comment on its significance since we were not able to investigate all 10.000 simulations. However, due to the statistical quality of the data obtained, one might think that among those simulations there can be some that better fit the path followed by empirical data and, consequently, we are able to suggest that perhaps strong reverting forces can also be used to explain how weather variables also tend to mean revert.

Table 3 – Statistical moments' matching

	Empirical	Simulated
Average	0,000331	0.000375
Standard Deviation	0,379371	0,254794
Skewness	-0.34398	-1,98287
Kurtosis	42,8778	42,78973

For obvious reasons we will not go deeper on how important the first two statistical moments are, especially because the other two are the ones we find more relevant financially speaking, i.e. starting with the skewness one can observe that both empirical and simulated data are negatively skewed which means that they both have their "tails" pointing left. The implications of this from the financial perspective are that returns below (to the left of) the average occur less frequently but have higher magnitudes meaning that there can be major negative price returns movements, which can be rather interesting when considering short positions. On the other hand kurtosis is also an important indicator, and one we were able to perfectly match, in the sense that it reveals the degree to which exceptional values occur. In our case a high kurtosis number reveals us that these extreme events can be very frequent and this information not only can be useful in finance, but also in decision making for electricity markets' designing.

[1] We have modeled the number of spikes as a random number (0,1) with equal probability. Hence this parameter from the original formula stands for us as the direction of the event.

At this stage, failing to derive the risk premium from the market due to difficulties in accessing data required for such, we were forced to conduct our option pricing analysis under the real world probability measure.

Under this analysis what stands out the most is the difference between the prices obtained for both models. That is mostly due to the fact that the BSM relies on certain assumptions that are inadequate for our market, particularly the inability to account for the occurrence of jumps. On the other hand, the Monte Carlo pricing method is extremely biased by the absence of the risk neutral measure, since the pricing measure is directly obtained from the real probabilities given by the 10.000 simulations.

Table 4 – Pricing options | Model Comparison

	BSM σ=25,5%						Monte Carlo					
	k=20		k=35,5		k=50		k=20		k=35,5		k=50	
months	Call	Put	Call	Put	Call	Put	Call	Put	Call	Put	Call	Put
T=3	15,59	0,00	1,56	1,42	0,00	14,32	3,55	1,19	0,10	13,20	0,00	27,55
T=6	15,70	0,00	2,64	2,30	0,08	14,11	22,11	0,00	8,14	1,39	1,70	9,32
T=12	15,92	0,02	3,88	3,20	0,50	14,04	26,45	0,00	12,00	0,76	3,57	6,56

Although policy making concerning Renewable Energy has a great influence in Portugal, it cannot be considered the essential driver, or at least not alone. Policy making is required no longer to subsidize but rather to allow and promote new environmentally and socially responsible solutions that target the increase in installed capacity in renewable sources, whilst avoiding harmful economic practices. The liberalization of a regulated energy market came as an opportunity for such.

By reducing taxes on financial products, such as the one we propose that help address the issue of gathering new renewable energy investment could be the first and most immediate solution towards sustainability, in the sense that it could encourage retail investors to invest a part of their income on renewable energy and consequently increase production. The market could benefit from it, especially if we consider major European players that are struggling to find solutions to replace nuclear power stations (such as Germany that aims to shut down 17 nuclear power stations by 2022) and other conventional technologies.

Financial institutions should also be encouraged to create these products through tax benefits, i.e. profits that are derived from these products (commissions, etc) should be taxed differently. However those products should at all times be kept transparent and open to constant monitoring from public entities. To ease this task, banks could use credits granted to producers to directly issue the financial product, hence enabling keeping track of the process and directly connecting retail investors to the renewable sector.

To draw more conclusions regarding the potential attractiveness of what we propose, we would suggest a survey to be conducted in the future directed to potential clients, in order to understand what the retail market would be expecting from such a product.

We also find it important that once it is possible to separate electricity production by source, a new investigation on the choice of model to represent the spot price should take place. We would suggest for that matter investigating the flaws in our proposal and combining that knowledge with the model proposed in Geman & Roncoroni (2006) as it has proven to produce the best results for this task. Note that this analysis should be conducted with full access to market data, and for that we recommend that such information is solicited in advance, in order to correctly calibrate the risk measure. This way, one would be able to promote market transparency and we do believe that transparency promotes liquidity!

References

[1] Banco BPI. (n.d.). *Particulares*. Retrieved from BPI: http://www.bancobpi.pt/particulares/poupar-investir/produtos-estruturados

[2] Benth, F. E., Kallsen, J., & Brandis, T. M. (2007). A Non-Gaussian Ornstein-Uhlenbeck Process for

[3] Electricity Spot Price Modeling and Derivatives Pricing. *Applied Mathematical Finance 14* , 153-169.

[4] Buffett, W. E. (2003). *Berkshire Hathaway INC. 2002 Annual Report.*

[5] Burger, M., Klar, B., Müller, A., & Schindlmayrt, G. (2006). A spot market model for pricing derivatives in electricity markets. *Journal of Quantitative Finance 4* , 109-122.

[6] Cartea, Á., & Figueroa, M. G. (2005). Pricing in Electricity Markets: A Mean Reverting Jump Diffusion Model with Seasonality. *Applied Mathematical Finance 12* , 313-335.

[7] Castro, R. (2012). *Uma introdução às Energias Renováveis: Eólica, Fotovoltaica e Mini-hidrica.* IST Press.

[8] Célérier, C., & Vallée, B. (2015). "Catering to Investors Through Product Complexity". *ESRB Working Paper Series 14* .

[9] EEX. (2017). *Wind Power Futures*. Retrieved from EEX: https://www.eex.com/en/products/energiewende-products/wind-power-futures

[10] Escribano, A., Peña, J. I., & Villaplana, P. (2002). Modeling Electricity Prices: International Evidence. *Economics Series 8, Working Paper* , 2-27.

[11] Geman, H. (2005). *Commodities and Commodity Derivatives - Modeling and Pricing for Agriculturals, Metals and Energy.* John Wiley & Sons, Ltd.

[12] Geman, H., & Roncoroni, A. (2006). Understanding the Fine Structure of Electricity Prices. *The Journal of Business 79* , 1225-1261.

[13] Lucia, J. J., & Schwartz, E. S. (2000). Electricity prices and power derivatives: Evidence from the Nordic Power Exchange. *UCLA: Finance* , n/a.

[14] Nunes, J. P. (2015, April). Lecture Notes. *Applied Derivatives* . Nova SBE.

[15] OMIP. (2017). *Derivatives Market - Products.* Retrieved from OMIP (The Iberian Energy Derivatives Exchange): http://www.omip.pt/MarketInfo/Produtos/tabid/76/language/en-GB/Default.aspx

[16] Pinto, A. S. (2013). *Master Thesis: "Os produtos Estruturados Colocados no Mercado Português: Evolução das Características e da Complexidade".* Faculdade de Economia da Universidade do Porto.

[17] Villaplana, P. (2003). Pricing power derivatives: A two-factor Jump-Diffusion approach. *Business Economics Series 5, Working Paper* , 3-18.