Executive Summary of the Thesis

Cannibalization Effect and Volumetric Risk in Power Purchase Agreements

Laurea Magistrale in Mathematical Engineering - Ingegneria matematica

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1. Introduction

Renewable energy technologies have become increasingly central to global energy strategies. Driven by environmental and climate commitments, falling costs, and favorable policy and regulatory support, their relevance has grown significantly. In this context, companies are progressively shifting towards renewable electricity procurement, with the **Power Purchase Agreement** (PPA) emerging as the primary contractual vehicle for such exchanges.

A PPA is a long-term contract between two parties: a seller (typically a renewable energy producer) and a buyer (often a corporation or utility), in which the buyer agrees to purchase electricity at pre-agreed terms. In its simplest form, the buyer commits to buying either a fixed quantity of electricity or a share of the seller's production at a fixed price.

While PPAs offer stability, they also introduce new risks. Price risk is common to most financial contracts, whereas **volumetric risk**, which is uncertainty around the actual energy produced, is specific to renewable PPAs. Since output depends on environmental conditions, if generation falls short of expectations, sellers or buyers may need to cover the gap by purchasing electricity on the market.

This uncertainty is amplified by the **cannibalization effect**. As renewable generation increases, it erodes its own market value by driving down the prices it can earn, which means that covering low production will be more expensive than selling surpluses. These dynamics increase the severity of tail events, making risk management and accurate pricing essential in PPA structuring.

2. Brief discussion of this work

This study builds on Prol et al. (2020), who quantify the ex-post impact of wind and solar penetration on each other's revenues using historical data, focusing on individual technologies rather than aggregate Variable Renewable Energies (VRE) penetration. Our analysis aims to better capture the real market implications for wind-based PPA valuations.

We replicate and extend the framework of Tranberg et al. (2020), applying it to updated DK1 (Western Denmark) data and to the Spanish market. We implement a joint modeling approach using Generalized Autoregressive Score models, ARMA-GARCH processes, and a time-varying GAS copula to capture the dynamic dependence between prices and wind generation. This allows us to assess volumetric risk un-

der different market structures and generation mixes.
While prior studies use daily data, we highlight the relevance of hourly settlements Dominy and Zubair (2021). Even for wind generation, which is less temporally concentrated than solar, incorporating hourly granularity improves the estimation of risk and contract valuation.

3. Cannibalization effect

3.1. Methodologies of the cannibalization effect analysis

The starting dataset comprises of hourly day-ahead electricity prices, as well as hourly solar and wind generation data. From these raw quantities, we derive the daily key metrics of our analysis, as defined in Equation 1: penetration (sh_t^j), units of revenue (UR_t^j), and value factors (VF_t^j) for each technology j.

$$\begin{aligned} sh_t^j &= \frac{\sum_{h=1}^{24} q_{h,t}^j}{\text{consumption}_t} \quad \% \\ UR_t^j &= \frac{\sum_{h=1}^{24} p_{h,t} \cdot q_{h,t}^j}{\sum_{h=1}^{24} q_{h,t}^j} \quad \text{EUR/MWh} \\ VF_t^j &= \frac{UR_t^j}{\frac{1}{24}\sum_{h=1}^{24} p_{h,t}} \quad \% \end{aligned} \tag{1}$$

In the above, $q_{h,t}^j$ denotes the generation from technology j, and $p_{h,t}$ is the electricity price at hour h on day t. Penetration measures the share of daily electricity consumption met by technology j. The units of revenue represent the generation-weighted average price received by the technology over the day. UR_t is used to capture the **absolute cannibalization effect**: the decline in revenue per MWh as a technology's market share increases. Finally, the value factor expresses the relative value of the technology's output compared to the average daily electricity price. It is used to assess the **relative cannibalization effect**, which reflects how the technology's value evolves relative to the average market price as its share grows.
For each country under consideration, we estimate a linear regression model via OLS (Ordinary Least Squares) for both the unit of revenue and the value factor, separately for solar- and wind-generated electricity. The covariates included in the model are the penetration levels of the most relevant energy sources in the region (including solar and wind), the daily electricity consumption, and natural gas prices. To adjust for seasonality and structural calendar effects, we include dummy variables encoded in the matrix D_t, which contains indicators for the day of the week, month of the year, and year. The linear model is expressed in Equation 2.

$$\begin{aligned} y_t = \; & c + \beta_1 \text{solar\_sh}_t + \beta_2 \text{wind\_sh}_t + \; \ldots \\ & + \beta_5 \text{cons}_t + \beta_6 \text{gas\_price}_t + \gamma D_t + \epsilon_t \end{aligned} \tag{2}$$

where y_t denotes either the unit of revenue or the value factor for solar or wind on day t, and ϵ_t is an error term assumed to follow a zero-mean i.i.d. normal distribution. By analyzing the estimated coefficients associated with the solar and wind penetration variables, we can assess both the magnitude and the sign of the relationship.

3.2. Analysis of the Spanish and Danish market

This section presents the results of our analysis of the Spanish market from January 2015 to December 2025. Considering the Spanish case, the regression model includes additional penetration variables from hydro and nuclear sources. In Table 1, we report the estimated coefficients of the linear model for solar and wind penetration, using UR_t and VF_t as target variables.

y_t	$solar\_sh_t$	$wind\_sh_t$
UR_t^s	−1.930	−0.883
UR_t^w	−0.871	−0.880
VF_t^s	−1.506	−0.287
VF_t^w	0.291	−0.020

Table 1: Estimated coefficients for solar and wind penetration in the linear regression model in Spain.

We report that all p-values related to the coefficients are approximately zero, highlighting their significance (except for wind penetration on wind value factors coefficient, whose p-value is around 0.08), and all models explain at least 80% of the variance in the target variable.
For solar, a one-percentage-point increase in its market share results in a statistically significant decrease of −0.83 EUR/MWh in its unit revenue. We note that for both units of revenue,

an increase in penetration leads to a decrease in the technology value.

When considering value factors, most renewable energy penetrations have a negative impact, except for solar energy, which has a positive impact on wind value factors. The positive association arises from the complementary generation profiles of the two technologies: wind generation often occurs during hours when solar output is low, coinciding with higher prices. This explains the growth of the wind value factor over the specified period.

Moreover, we partition the dataset based on different levels of consumption and solar penetration. We then refit the linear model for value factors on each subset to capture potential variations in the magnitude of the effects. The results provide evidence that the cannibalization phenomenon becomes more pronounced during periods of lower consumption or higher solar penetration. These findings are consistent with underlying supply and demand dynamics.

We report the results for the Danish market over the same period, in the DK1 zone (Western Denmark). Unfortunately, the regressions on solar and wind value factors yield low R^2 values, making it difficult to draw meaningful conclusions about the coefficients. In Table 2, we report the coefficients for the estimation of the units of revenue regressions.

y_t	$solar\_sh_t$	$wind\_sh_t$
UR_t^s	-1.134	-0.219
UR_t^w	-0.002	-0.176

Table 2: Estimated coefficients for solar and wind penetration in the linear regression model in DK1.

We show strong evidence of cannibalization for solar, with statistically significant negative coefficients for both solar and wind penetration. A 1.0% increase in solar (wind) penetration reduces solar unit revenues by approximately -1.13 (-0.219) EUR/MWh. For wind, cannibalization appears weaker: a 1.0% increase in wind penetration corresponds to a -0.18 EUR/MWh drop in wind revenues, and the coefficient for solar penetration is not statistically significant. It is essential to note that wind penetration is, on average, significantly higher in Denmark than in Spain, indicating that even if the coefficients are lower in the Danish case, their overall effect is greater.

4. Volumetric risk in PPA contracts

4.1. Methodologies

In this section of the analysis, we present the GAS framework, as introduced by Tranberg et al. (2020). We consider daily average prices and wind load factors, which are defined as the ratio of generation to total installed capacity. Load factors are transformed using a logit transformation. Then, both variables are demeaned and deseasonalized using daily and monthly dummy variables. The time series obtained are modeled using a two-component Generalized Autoregressive Score (GAS) model, with a Student's t-distribution as the conditional distribution, and an ARMA-GARCH model with a skew-normal conditional distribution, respectively. A Gaussian GAS copula model is used to model the correlation between the two quantities. The reason we use score-driven models, particularly the multiple-component variants, is that they can handle both long-memory dynamics and frequent extreme events more effectively (Harvey and Sucarrat, 2014).

4.1.1 GAS framework for modelling prices

The general modelling framework is given by:

$$\begin{aligned} y_t &= \mu_t + \sigma_t z \\ z &\sim t(\nu), \end{aligned} \tag{3}$$

where μ_t is the location parameter, σ_t the scale parameter, and t denotes the Student's t-distribution. The dynamics of μ_t, σ_t, and ν_t are governed by a multi-dimensional latent process f_t through the link function $\Lambda()$, defined as:

$$\Lambda(f_t) = \begin{cases} \mu_t &= f_{t,1} \\ \sigma_t^2 &= e^{f_{t,2}} \end{cases} \tag{4}$$

Considering the one-component model f_t is updated as follows:

$$\begin{aligned} f_{t+1} &= \kappa + As_t + Bf_t \\ &= \begin{bmatrix} \kappa_1 \\ \kappa_2 \end{bmatrix} + \begin{bmatrix} a_1 & 0 \\ 0 & a_2 \end{bmatrix} s_t + \begin{bmatrix} b_1 & 0 \\ 0 & b_2 \end{bmatrix} f_t \end{aligned} \tag{5}$$

where A and B are diagonal matrices with proper dimensions and s_t (score) is defined as in Equation 6.

$$s_t = \frac{\partial \log p(y_t; f_t)}{\partial f_t} \tag{6}$$

As reported in the work of Ardia et al. (2019), s_t is a martingale difference with respect to the distribution of y_t given $y_{1:t-1}$. Therefore, the process f_t in Equation 5, is mean–reverting around its long–term mean value $(I - B)^{-1}\kappa$ when the spectral radius of B is less than 1.Vector κ and matrix B control the process's level and persistence.
The matrix A controls the influence of the scaled score s_t on the parameter update from f_t to f_{t+1}. Since s_t represents the direction of steepest ascent for improving the model's fit, A acts as a step size. Therefore, A should be chosen to preserve the informational content of s_t without distorting it, meaning $a_i > 0$.
Under the two-component variant, the process f_t is modeled using two auxiliary processes $\tilde{f}^1_{t+1}$ and $\tilde{f}^2_{t+1}$, which model, respectively, long-term behaviours and short-term variations.

$$\begin{aligned} f_{t+1} &= \kappa + \tilde{f}^1_{t+1} + \tilde{f}^2_{t+1} \\ \tilde{f}^1_{t+1} &= A_1 s_t + B_1 \tilde{f}^1_t \\ \tilde{f}^2_{t+1} &= A_2 s_t + B_2 \tilde{f}^2_t. \end{aligned} \tag{7}$$

To distinguish between long–term and short–term dynamics in f_t, we impose $a_{2,i} > a_{1,i}$ to make the short–term component more responsive to recent changes, and $b_{2,i} < b_{1,i}$ to ensure faster decay of its past shocks. These constraints enforce a clear distinction between the two components.

4.1.2 GAS framework for the Gaussian copula

The time–varying correlation of the Gaussian copula is governed by the process f^c_t. The transformation from f^c_t to the correlation coefficient ρ_t is specified in Equation 8, while the GAS update mechanism for f^c_t is detailed in Equation 9.

$$\rho_t = \frac{1 - exp(-f^c_t)}{1 + exp(-f^c_t)} \tag{8}$$

$$f^c_{t+1} = \kappa_c + a_c f^c_t + b_c s_t \tag{9}$$

Here, s_t denotes the scaled score of the copula log–likelihood with respect to f^c_t, computed using the Gaussian copula density $c(u_1, u_2; \rho_t)$, calculated in Equation 10.

$$\begin{aligned} s_t &= I_t^{-\frac{1}{2}} \frac{\partial}{\partial \rho} \log c((u_{1,t}, u_{2,t}), \rho_t) \\ I_t &= E_{t-1}\left[\left(\frac{\partial}{\partial \rho} \log c((u_{1,t}, u_{2,t}), \rho_t)\right)^2\right] \end{aligned} \tag{10}$$

Where $u_{it} = P(Y^i_t < y^i_t | y^i_{j=1:t-1})$, whose conditional laws are described by the marginal models. The score is scaled by the inverse of the square root of its covariance matrix or the Fisher information. To ensure stationarity and mean–reversion of the correlation dynamics, we impose $|b_c| < 1$, preventing explosive behavior in f^c_t. Additionally, $a_c > 0$ ensures that the score update maintains the correct direction without distorting the signal.

4.1.3 PPA contract

In this study, we consider monthly PPA contracts with daily delivery, in which the buyer pays a fixed price R (**PPA price**) for each MWh of wind power exchanged during the contract period. The daily power exchange Q_t is given by the load factor L_t multiplied by the contract's capacity set to 500 MW. The price R is calculated by imposing the average payoff to zero and solving for R, calculated under the risk-neutral measure Q:

$$\begin{aligned} 0 &= E^Q_{t0}\left[\sum_{t=t_1}^{t_2} Q_t(S_t - R)\right] \\ R &= \frac{E^Q_{t_0}\left[\sum_{t=t_1}^{t_2} Q_t S_t\right]}{E^Q_{t_0}\left[\sum_{t=t_1}^{t_2} Q_t\right]} \end{aligned} \tag{11}$$

We let F denote the forward price of the contract, as defined in Equation 12. This is the fair price of the contract, assuming that daily production and spot prices are independent.

$$F = E^Q_{t0}\left[\frac{1}{t_2 - t_1 + 1}\sum_{t=t_1}^{t_2} S_t\right] \tag{12}$$

We define the **correlation price** as the deviation between the contract price R and the forward price F. Let this adjustment be denoted by c, by substituting in Equation 11 and solving for c we obtain the following equation:

$$\begin{aligned} c &= F - R \\ &= F - \frac{E_{t_0}^{Q}\left[\sum_{t=t_1}^{t_2} Q_t S_t\right]}{E_{t_0}^{Q}\left[\sum_{t=t_1}^{t_2} Q_t\right]} \end{aligned} \tag{13}$$

Given the negative correlation between daily wind generation and electricity prices, we expect the forward price F to exceed the contract price R. We interpret c as a premium (or discount) applied to the forward price to compensate for volumetric risk.

4.2. PPA contract evaluations

After training our model on Spanish data from January 2015 to December 2017, we proceed to price the contract and quantify the value of the correlation price c. To this end, we simulate $10'000$ joint paths of electricity prices and load factors. Starting from January 2018, we price a contract for each month, beginning on the first day of the month. We summarize the results of the OOS analysis for the Spanish market in the following Table 3, where we report the average values of R, F, and c along with their corresponding standard deviations.

	GAS copula		Constant copula	
	Avg.	Std Dev	Avg.	Std Dev
R	46.140	6.663	46.388	6.645
c	1.165	0.147	0.929	0.115
F	47.300	6.716	47.318	6.695

Table 3: Summary of PPA characteristics over 24 OOS months under different model specifications for Spain analysis.

On average, the correlation price under the GAS copula model is 1.17 EUR/MWh, corresponding to a 2.5% discount relative to the forward price of approximately 47.3 EUR/MWh. This highlights the relevance of volumetric risk in Spanish PPA valuation. The constant and time-varying copula models yield similar value and risk metrics, with the time-varying model slightly outperforming in goodness-of-fit tests, hence its use. On average, over the out-of-sample (OOS) period in Spain, the VaR at the 95% confidence level, measured using the GAS copula, is 12.9% higher in absolute value compared to the case where volumetric risk is not considered, with the difference peaking at 20%. Ignoring volumetric risk would therefore lead to a significant underestimation of the overall risk.
Next, we report the results of the same analysis for the DK1 zone (Table 4). We observe a higher correlation price, attributable to the significantly greater renewable penetration in the generation mix.

	GAS copula		Constant copula	
	Avg.	Std Dev	Avg.	Std Dev
R	26.500	2.133	26.794	2.087
c	2.236	0.157	1.968	0.150
F	28.736	2.085	28.76	2.097

Table 4: Summary of PPA characteristics over 24 out-of-sample months under different model specifications (2018-2019) in DK1.

Neglecting the correlation structure between renewable generation and power prices would lead to an overestimation of the PPA value by approximately 7.8%, along with an underestimation of the risk profile (in terms of VaR).
On average, over the OOS period in DK1, VaR at 95% confidence level, computed using the GAS copula, is 15.7% higher in absolute terms than the independent. The difference peaks at 30%. This highlights that neglecting volumetric risk can lead to a substantial underestimation of the actual risk exposure.

5. Accounting for hourly patterns in PPA pricing

In an hourly exchange, a share of the generated electricity at hour h is exchanged at a fixed price. The contract's cash flow π can be rewritten as follows:

$$\pi = \sum_{t=t1}^{t2} \sum_{h=1}^{24} \tilde{q}_{h,t}(p_{h,t} - R), \tag{14}$$

where $\tilde{q}_{h,t}$ is the share of the contract capacity produced in hour h on day t, and $p_{h,t}$ is the electricity price at hour h on day t. We note that the sum of these shares is precisely the quantity Q_t.Using the definition of the unit of revenues and value factors expressed in Equation 1, we can rewrite the payoff π as follows:

$$\begin{aligned}\pi &= \sum_{t=t_1}^{t_2}\sum_{h=1}^{24} \tilde{q}_{h,t}\, p_{h,t} - Q_t R \\ &= \sum_{t=t_1}^{t_2} Q_t \left(UR_t - R\right)\end{aligned} \tag{15}$$

Using hourly values, we demonstrate a payoff equivalence that depends solely on daily quantities. Since UR_t represents a generation-weighted daily average price, we fit our previous model directly on these daily quantities to capture the underlying hourly patterns, without requiring any specific adjustment.

Proceeding as described in Subsection 4.1, we train our model on Spanish UR_t^w data from January 2015 to December 2017. We simulate 10′000 joint paths of units of revenue and wind load factors. Using this modified framework, we evaluate the same contracts as in Section 4.2, and summarize the results in Table 5.

	Avg price model		**UR model**	
	Avg.	**Std Dev**	**Avg.**	**Std Dev**
R	46.140	6.663	45.704	6.601
c	1.165	0.110	1.095	0.129
F	47.300	6.716	46.799	6.642

Table 5: Summary of PPA characteristics over 24 OOS months under different model specifications for Spain analysis.

We find that the correlation risk estimated using the UR model is, on average, 6.0% lower than that implied by the daily average price model. This reflects the fact that UR_t^w contracts capture higher value than daily average prices, as evidenced by the increasing wind value factor over the period. As shown in Table 1, this trend coincides with rising solar penetration, which enhances the relative value of wind production and contributes to the observed reduction in the correlation price. Moreover, we observe that the estimated correlation price obtained via the UR model is lower in every contract evaluated.

Regarding the VaR evaluation, the UR model yields a 2.6% lower absolute VaR, on average, compared to the prices model. This reduction is driven by the use of hourly wind generation, which mitigates the impact of cannibalization and thereby reduces volumetric risk.

6. Conclusions

We examine the interaction between renewable penetration, the cannibalization effect, and volumetric risk in the context of wind-based PPAs. We can summarize our conclusions in the following points.

- First, we assess the cannibalization effect in the Danish and Spanish electricity markets. We find evidence of absolute cannibalization in Denmark, while both absolute and relative cannibalization are present in Spain. Notably, the increasing solar penetration in Spain positively influences wind value factors due to the complementary generation patterns between the two technologies.
- Second, we apply the framework of Tranberg et al. (2020) to price wind-based PPAs under volumetric risk by explicitly modeling the dependence between electricity prices and wind generation. Neglecting this correlation leads to a significant underestimation of the PPA's risk profile. We find that accounting for volumetric risk results in a discounted PPA price by 7.8% in Denmark and 2.5% in Spain, relative to the average forward price. VaR estimates also increase in absolute value, confirming the relevance of the risk premium.
- Lastly, we extend the pricing framework to contracts with hourly settlement. We show that these contracts benefit from the mitigating effect of solar penetration on wind volatility. The correlation price is, on average, 6% lower compared to daily-settled contracts, and the absolute VaR decreases by 2.6% in absolute value, indicating reduced volumetric risk. These results underscore the importance of hourly modeling and support the design of hedging strategies that exploit the temporal complementarities between wind and solar resources.

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