NTNU
Handelshøyskolen

Håkon Undli
Magnus Schatvet

Using Weather Derivatives to Hedge Precipitation Exposure for a Norwegian Hydropower Producer

Hvordan bruke værderivater for å hedge nedbør eksponeringen for en norsk vannkraftprodusent

MASTEROPPGAVE - Økonomi og administrasjon/siviløkonom
Trondheim, dato: 22.05.2018

Hovedprofil: Finansiering og investering

Veileder: Denis Becker

Preface

This resarch paper represents the completion of our Master`s degree in Business Administration & Management at NTNU business school, Trondheim. In the process of deciding topic for our thesis, we read about the use of weather derivatives in different industries and countries. This led us to the use of weather derivatives in Norway and more specifically in our own region. By contacting firms in the electricity industry we got the impression that the focus lies on hedging the spot price and not the volumetric risk. We therfore wanted to see if weather derivatives could potentially be used to hedge a hydropower producers operating income in Norway.

We would like to express our gratitude to our thesis advisor Denis Becker. We would also like to thank Fosenkraft As for supplying the financial data used in this article and for their collaboration. Any error or omissions are the authors own.

Abstract

Purpose - This article aims to examine the effect on a Norwegian hydropower producer`s operating income by hedging volumetric risk with the use of weather derivatives, and evaluate the effectiveness of weather derivatives as an alternative management tool.

Design/methodology/approach - The paper adopts a case study approach to meet the above-mentioned objectives, focusing on a hydropower producer in Norway, which provides a perfect example for a business with operating income dependent on precipitation.

Results - We find that the production of hydropower in Norway is directly affected by the long-term aggregate precipitation. We show that for periods characterized by lower precipitation and high standard deviation can effectively be hedged by using monthly options on precipitation.

Value - This article will be of value to those who have a stake in hydropower production.

Abstrakt

Formål - Denne artikelen ønsker å utforske muligheten for å sikre risiko tilknyttet produksjonsvolumet til en Norsk vannkraftsprodusent ved hjelp av værderivater, og vurdere værderivater som et alternativt styringsverktøy.

Design/metode/tilnærming - Artikelen bruker en casestudie tilnærming for å møte de nevnte målene, med fokus på en norsk vannkraftprodusent, som er et perfekt eksempel på en bedrift med inntekter avhengig av nedbør.

Resultat - Funnene våre viser at produksjon av vannkraft i Norge er direkte påvirket av langsiktig aggregert nedbør. Vi viser at perioder karakterisert med mindre nedbør og høyt standardavvik kan effektivt sikres ved hjelp av månedtlige opsjoner med nedbør som underliggende.

Verdi - Denne artikkelen vil være av verdi for de som er innvolvert i vannkraft produksjon.

Table of Contents

List of Figures

List of Tables

1. Introduction

The purpose of this study is to examine the effect on a Norwegian hydropower producer`s operating income by hedging volumetric risk with the use of weather derivatives. Weather is the most significant uncontrollable risk factor (Sharma og Vashishtha, 2007) and according to Alexandridis og Zapranis (2013) almost 70% of US companies are affected by weather in some way. The list of businesses subject to weather risk is long and includes energy producers and consumers, supermarket chains, the leisure industry and agricultural industries (Alaton, Djehiche, & Stillberger, 2002). For instance, earnings of the power industry depend on the retail prices and the sales quantities of electricity, which in turn are affected by weather conditions (Cao & Wei, 2004). Weather risks are a result of the uncertainty in cash flows and earnings caused by non-catastrophic weather events such as temperature, humidity, rainfall, snowfall and wind (Brockett, Wang, & Yang, 2005). The weather does not have to be extreme for it to have negative impact on cashflow, sometimes it is merely enough for it to be uncommon, unseasonal or unexpected (Berlage, 2013).

Until the mid-90`s, earnings stabilization for utility firms was primarily achieved through price hedging mechanisms, while volumetric risks were left unhedged. The deregulation of energy and power industries increased competition and made it necessary for companies to hedge volumetric risk caused by unexpected weather conditions. This necessity is what created weather derivatives (Cao & Wei, 2004). The intention of the deregulation was to create more efficient power markets. This led to the establishment of the power exchange Nord Pool ASA in 1996. Currently, the Nord Pool participants include the Scandinavian countries and the Baltic States. Nord Pool is one of the world's largest, multinational, deregulated and advanced power market, with a yearly average electricity production of 420 TWh (Huisman, Michels, & Westgaard, 2014). In Norway, 2016 was an all-time high production year, yielding 149 TWh of which 96% of the produced power came from hydropower generation. Norway has a hydro reservoir storage capacity for 70% of the yearly energy demand of the country, this allows for a higher level of flexibility in production, which can easily be adjusted to demands at a very low cost ("Electricity Production," 09.10.2017). Hydropower producers have the option to either generate power or wait, their decision is based on whether the gain of producing outweighs the expected loss from not being able to generate power in the future, when prices might be higher (Huisman, Michels, Westgaard, 2014). When reservoir levels are high producers will produce at full capacity to avoid unnecessary spill overs which yield no income.

In September 1999, the first exchange-traded weather derivative futures contract was launched on the Chicago Mercantile Exchange (Leggio & Lien, 2002). Hamisultane (2008) points out that, despite the interest aroused by weather derivatives, their development has not been as rapid and significant as hoped. He explains that the departure of main actors such as Enron, Aquila and El paso lowered the number of transactions, thus reducing the liquidity in the market. Weather derivatives also abbreviated as WDs are contingent claims with payoffs determined by future weather events as temperature, snowfall, and rainfall (Härdle & Osipenko, 2017). In other words, weather derivatives are designed to hedge weather dependent risk, which may be termed as financial gain or loss due to variability in daily climatic conditions (Sharma & Vashishtha 2007, s124). Contrary to a stereotypical weather insurance, the pay-out of WD`s are based on parametric weather indexes. An index could for example be mm of rainfall or a cumulative frequency distribution of temperatures across locations (Kekre & Girish, 2017). The market for weather derivatives is a typical example of an incomplete market because the underlying variable is not tradeable (Alaton et al., 2002). Since the underlying could be wind or sunshine it cannot be assigned a monetary value, and therefore it cannot be bought or sold (Kekre & Girish, 2017).

2. Weather Derivatives

There are several reasons for companies to use weather derivatives, some of which include smoothing of revenues, covering excess cost, reimbursing lost opportunity costs, stimulating sales and for diversification purposes (Leggio, 2007). Hedging with weather derivatives is desirable for businesses looking to hedge non-catastrophic weather events, because it significantly reduces the year-to-year volatility of their profits. Some of the benefits of lower profit-volatility includes the possibility of reduced interest rates, which often translates into lower volatility in share prices, and reduced risk of bankruptcy (Jewson & Brix, 2005). The relatively low correlation between weather derivatives and conventional financial assets suggests that weather derivatives can be excellent for diversification purposes. Leggio (2007) shows that the use of derivatives on precipitation exposure can have a positive cash flow effect on industries with direct weather exposure. Although the industries studied in his article are not in energy production, they are perfect examples of businesses that have seasonal cash flows dependent on weather conditions. Furthermore, Moschini and Lapan (1995) show that presence of both production and price risk implies that options become a useful hedging tool. They go on to show the usefulness of options under production uncertainty related to the covariance between price and production, which affects the curvature of profit in future prices, although they show that there is a distinct role for options even when production and price risk is independently distributed (Moschini & Lapan, 1995). This is also supported by the research by Broll et.al (2001) who concludes that when the underlying uncertainty is non-linear in nature, the asymmetric payoff profile of options (as opposed to linear future contracts) are more suitable for hedging purposes.

Sharma & Vashishtha (2007) performed an empirical study on the use of WDs, in the energy sector in India, they point out that there are some obvious limitations to these contracts, such as spatial risk and the non-availability of weather data to the parties concerned. They believe that these limitations are not insurmountable and that WDs are undoubtedly a low-cost, flexible and sustainable option. Because the pay-off of a WD depends on a weather index, not on the actual amount of money lost due to the weather, it is unlikely that the pay-off will compensate exactly for the money lost. The potential for such a difference is known as basis risk. In general, the basis risk is smallest when the financial loss is highly correlated with the weather, and when contracts of optimal size and structure, based on the optimum location, are used for hedging. For a company deciding on how to hedge its risk there is often a trade-off between basis risk and the price of the derivative (Jewson & Brix, 2005). Manfredo and Richards separate basis risk into spatial- and technological basis risk. Hedgers may face spatial basis risk because the reference weather index, to which the derivative contract is written, may differ from the actual weather experienced at the location of interest. Second, hedgers are likely to face a form of technological basis risk arising from the relationship between weather, or more specifically temperature, and the hedged volume (Manfredo & Richards, 2009). Similar to any other derivative security, WDs serve the ultimate purpose of risk transfer. Individual power and utility companies are interested in smoothing their earnings by engaging in price and volumetric hedges (Cao, Li, & Wei, 2003).

3. Data

The weather data we have collected is downloaded from the Norwegian Meteorological institute. A firm producing hydropower, Fosenkraft As, has supplied the financial data that will be used in this paper. We obtained weekly production volume and realized spot price from this producer. Our focus is to examine if and in what scale accumulated monthly precipitation effects profits. In this segment we will provide descriptive statistics of the data used.

3.1 Precipitation Data

We have collected daily precipitation reports from the period 2008-2017 for the weather station Ørland 3, station nr: 71550 ("Eklima," 2018) the station is located approximately 9 meters above sea level and approximately 20 km from the power plant. This station was chosen because it is closest to the production facility, and the one Fosenkraft feels is most representative. Choosing a station with a low geographical distance will aid in minimizing the spatial basis risk.

One of the main issues regarding meterological data is quality and availability. Even recent meteorological data has significant problems with reliability and homogeneity, and earlier data is usually significantly worse (Jewson & Brix, 2005). In our dataset there are several missing data points. Missing values can be a result of malfunctioning equipment, lack of reporting, loss of data or scheduled maintenance on that particular day or period. The Norwegian meteorological institute substitutes all the missing data points with a zero value when accumulating the monthly precipitation. One way of solving this issue may be a multistation index model, which may remove some of the spatial basis risk in pricing the derivatives. When pricing WDs on an index such as temperature, this may be the best suited option as the regional differences on temperature are negligible. Given the stochastic distribution of precipitation this might give a false representation of the actual events at the specific location. Alexandridis & Zapranis (2013) suggests that the missing data will be replaced with the average measurement of the 7 days before and after the missing value. Missing values are filled using:

$$Precipitation_{t,avg} = \frac{\sum_{j=1}^{7} Precipitation_{t-j} + \sum_{j=1}^{7} Precipitation_{t+j}}{14}$$

Table 1: Descriptive Statistics for Monthly Cumulative Precipitation 2014-2017 in mm

Variable	**Mean**	**Std.Dev**	**Min**	**Max**	**Skewness**	**Kurtosis**	**N**
Cumulative precipitation	115,9094	51,14327	17,34837	248,1619	0,696287	0,5966	48

Table 2: Descriptive Statistics for Quarterly Cumulative Precipitation 2014-2017 in mm

Variable	**Mean**	**Std.Dev %**
Q1	246,7147	34,71%
Q2	265,3214	6,98%
Q3	402,4299	19,06%
Q4	476,4467	22,66%

Table 1 summarizes the descriptive statistics. We observe large differences from month to month. With a minimum value of 17,34 mm in February 2015 and a maximum value of 248,16 mm in december 2016. There is some right skewness and kurtosis, the values are 0,6962 and 0,5966 respectively. The corresponding standard deviation is 51,14 mm. Table 2 shows a large difference in quarterly precipitation with a average precipitation in Q1 of 246,71 mm and in Q4 476,45 mm. From the table we observe a clear pattern of more precipitation during the second half of the year. Q1 has the lowest expected precipitation and largest standard deviation. Which indicates that this is the most risky production period during the year for the producer.

The Shapiro Wilk normality test is rejected at a 5% level with a test statistic of 0,916 and a p-value of 0,003. Thus, we can not say that the cumulative monthly precipitation in the period 2014-2017 fits a normal distribution curve. We also conducted the Shapiro Wilk test for the period 2008-2017, it yields the same results.

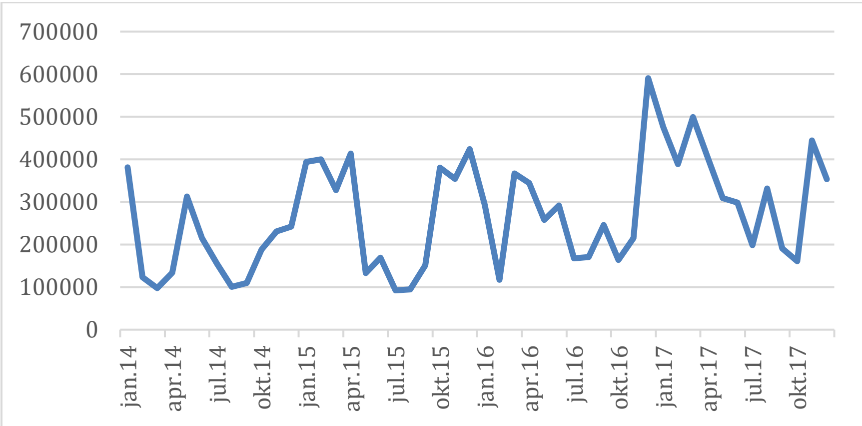
3.2 Financial Data

Table 3: Descriptive Statistics for Operative Income 2014-2017 in NOK.

Variable	Mean	Std	Min	Max	Skewness	Kurtosis	N
Monthly Operating income	268 809	125 474	92 389	590 572	0,390856	-0,67445	48

Descriptive statistics for monthly operating income are reported in table 3. There is a large spread between the lowest operating income and the highest, with a minimum value of 92.389 NOK in July 2015 and a maximum value of 590.572 NOK in December 2016. The corresponding standard deviation is 125.474 NOK. As shown in figure 1 there are seasonal fluctuation.

Figure 1: Operating Income for the Period 2014-2017 in NOK



3.3 Regression and Descriptive Statistics

There have been some suggestions in previous literature on the use of WDs to hedge production quantity risk for hydropower producers. This may seem reasonable as producers relie on the flow of water to produce its power. Norwegian hydropower producers are in a special position as they are able to store up to 70% of yearly energy demand of the country. Since we do not have any data about the storage capacity of our producer we must assume that this storage capacity is representative for our producer. The water reservoirs are affected by several factors, the production site has streams running in from two adjacent lakes. These lakes and the main production reservoir are accumulated by the amount of precipitation in the period and the amount of inflow from melting of snow in the nearby area, which again is a result of the precipitation in the prior periods. The use of WDs only makes sense if the operating income is somehow dependent of weather conditions, we therefore analyzed the effects of precipitation on production in NOK.

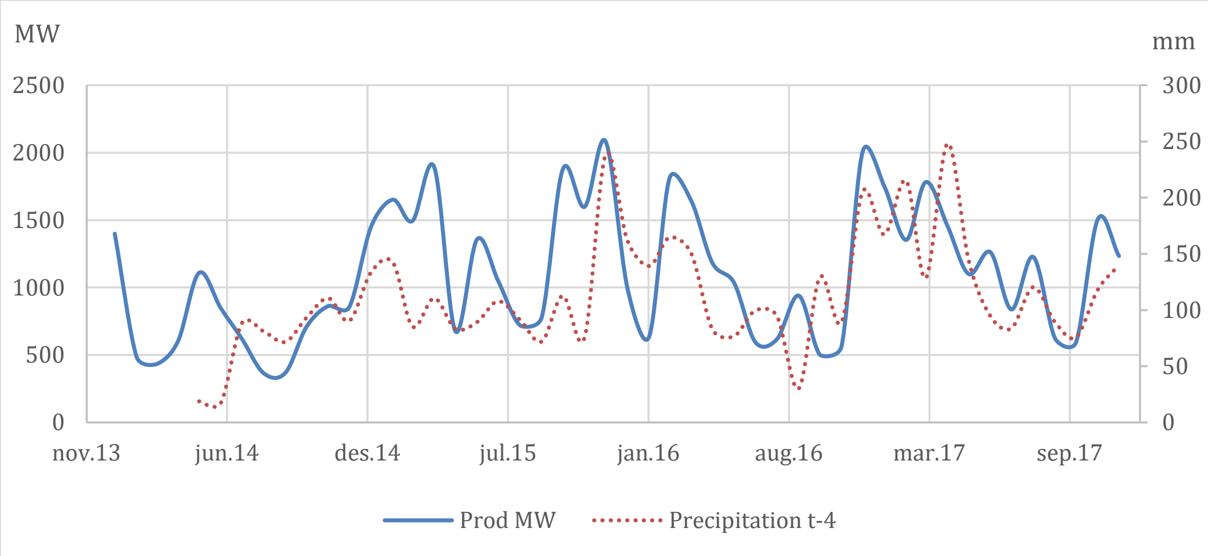
Precipitation is not a continuous variable and rainfall is a binary event, i.e. every day there may or may not be observed precipitation. Precipitation evolves much more irregularly and unevenly then temperature changes, furthermore it does not have the same geographical correlation structure found for temperature (Stowasser, 2011). Precipitation data are non-negative, highly skewed and typically with many zero values. Due to the many zero values in precipitation data a logarithmic transformation is not the right approach (Benth & Benth, 2012), we therefore conducted both quadratic and linear regression on the historical precipitation data. The quadratic-models showed no signs of any non-linear trends.

Table 4: Regression Models for Operating Income with Lagged Monthly Precipitation

Model	**R Square**	**Adjusted R Square**	**Sig**
(1) $OI_t = 118332{,}45 + 1402{,}77 * Precipitation_{t-4}$	,324	,308	,000
(2) $OI_t = 66848{,}34 + 691{,}34 * Precipitation_{t-3} + 1159{,}47 * Precipitation_{t-4}$	,387	,357	,000

We found that in the short-term (daily lagged variables) none of the variables were significant. This is understandable since the short-term production has already been planned in accordance with the given level of reservoirs. Knowing this information, we tested a linear-regression model with multiple lags of the monthly aggregated precipitation. The results suggest that the production is explained by the total precipitation in previous months. With the monthly modelling approach, using lagged variables, we found that on a 5 % significance level the only predictive variables are monthly accumulated precipitation, 3 and 4 months prior to production at time t. By incorporating more variables in model (2), R-squared increased by 0,063 in comparison to model (1), meaning 6,3% increase in the variance explained by model (2). Both models are significant on a 1% level and 32.4% of the variance in production at time t is explained by the precipitation 4 months in advance. Precipitation $_{t-4}$ is the variable with the most predictive power.

Figure 2: Production Volume in MW (left axis) and Precipitation in the Month t-4(right axis)



Assuming that income is a function of previous periods of aggregated precipitation, we made a quarterly lagged model.

Table 5: Regression Model for Operating Income with Lagged Quarterly Precipitation

Model	**R Square**	**Adjusted R Square**	**Sig**
(3) $OI_q = 240992{,}36 + 1722{,}86 * Precipitation_{q-1}$	,488	,448	,004

This model has the highest R-squared of the three, with 48,8% of the variance in operating income explained. As a quarterly variable encompasses the monthly accumulated precipitation for 3 months it is natural that this variable has a higher R-squared. This model is significant on a 1% level and has the highest explanatory power. Since the quarterly variable in this equation is an aggregate of the monthly variables, this confirms our notion that production volume is a result of precipitation over a longer aggregated periode. When choosing a function, it is important to choose one that fits the pricing methods. The models used in this paper assume a linear relationship and we will therefore use a linear function in our pricing. We chose to use model (1) as we wanted to illustrate the use of monthly WDs.

4. Methodology

4.1 Obstacles When Pricing Wheather Derivatives

For traditional financial derivatives the underlying assets can be traded, and prices reflect the price of the asset. Pricing methods for financial derivatives like the Black-Scholes method relies upon the existence of an underlying physical asset (Leggio & Lien, 2002). Since the assumptions necessary for traditional methods does not hold, conventional risk-neutral valuation by no-arbitrage does not apply. A wide selection of different pricing models exist and WDs are often looked at as risky products where sellers tend to charge a high premium because of the difficulties in evaluating such contracts (Hamisultane, 2008). WDs are publicly traded, but they are limited to a few geographical locations outside of Norway and only offered on the Chicago Mercantile Exchange. The WDs are only traded over the counter (OTC) in Norway, and since there is no standard pricing model, there will always be a certain level of uncertainty in the fairness of the price. We will examine how to price such derivatives and how they can be used to reduce risk for a producer in the hydro energy sector.

4.2 Traditional Pricing Methods

Actuarial pricing methods use conditional expectation of the WDs future payoffs to calculate the price (Hamisultane, 2008), which is fundamentally the same method used by insurance companies. Different probabilities and statistical analysis are required for different events to be insured. Based on the historical probabilities an insurance premium is calculated accordingly. These methods however, are less applicable for WDs as the underlying variable such as temperature, rainfall, snowfall, wind etc. tend to follow a recurrent, predictable pattern (Cao, Li & Wei, 2003). Despite this, the model does have some applicational value, if the contract was to insure for extreme conditions such as extreme heat or coldness, then the actuarial method is useful. Cao, Li and Wei (2003) argue that this is the only appropriate method for extreme weather conditions.

Historical burn analysis is considered the benchmark approach for pricing temperature derivatives (Alexandridis & Zapranis, 2013). This is perhaps the simplest in terms of implementation, and as a result the most probable to cause pricing errors. Historical burn analysis evaluates the contract against historical data and takes the average of realized payoffs as the fair value estimate. The main assumption of this model is that all future events have already happened in the past, i.e the method´s assumes that the past payoffs accurately depicts the futures payoff´s distribution. This assumption is far-reaching in most cases (Cao, Li & Wei,2003). Benth and Benth (2012) address the issue of using historical burn analysis on derivatives with aggregated values as the underlying variable. With a long time-series, the number of data points are reduced drastically when using cumulative values. Furthermore, they state that this again may lead to an uncertain option value because of the few non-zero payoff values among the data points. Our time series with 4 years of daily precipitation level observation will be reduced to only 48 data points when calculating monthly cumulative precipitation level, where non-of the values equal zero. However, as the derivative security's payoff depends on the future behavior of the weather rather than the historical data, it may not be a good idea to use burn analysis in pricing of weather derivatives. Both the models described above do not take the risk element into account (Beyazit & Koc, 2012).

Monte Carlo simulation method involves simulating several different precipitation scenarios over a prespecified period to determine the derivatives possible payoff. In the case of precipitation, Alexandridis and Zapranis (2013) suggest using a two-state, first order markov chain model on historical data. This method is repeated n times and the rainfall index is found by averaging each scenario. From the rainfall index, the payoff and hence, the price of the derivative can be obtained. Hamisultane (2008) points out that the obstacle with this strategy is that already quoted contracts are not yet sufficiently liquid. Thus, Monte-Carlo pricing method will give unreliable prices.

4.3 Indifference Pricing Method

The indifference pricing approach is a utility based approach which has been presented by both Brockett et al. (2006) and Xu et al (2007). This method is different from other pricing methods because it is based on the basic principle of equivalent utility and makes use of investors risk preferences and a corresponding utility function (Alexandridis & Zapranis, 2013). The method uses the expected utility to produce the indifference prices. A utility function is defined and as Brockett et al. (2006) and Xu et al (2007), we use an exponential utility function:

$$(1) U(X) = -e^{(-\lambda X)}$$

The proposed pricing method uses two market participants, a seller (bank or insurance company) and a buyer, for simplification purposes a two date economy is assumed. At $t = 0$ both actors optimize their investment portfolios in order to maximize wealth at time T and between these dates no trading of the derivative is allowed. First, we consider the portfolio of the buyer. The risky production part depends on weather conditions and will have the return r_b. r_f denotes the return of a risk-free asset. Value of portfolio at time T is given by:

$$(2) X_b^{wo} = (X_b - a_b)q_f + a_b q_b$$

Where $q_f = 1 + r_f$ and $q_b = 1 + r_b$. a is the amount of initial wealth invested in the risky asset, where X is the initial wealth. Furtheron, we include the opportunity of investing in k units of the weather contract. The terminal value of the portfolio at time T is:

$$(3)\ X_b^w = (X_b - a_b - kF_b)q_f + a_b q_b + kW_T$$

W_T is the payoff at time T related to a predetermined weather index and F is the price of the option.

The Weather derivate has the payoff:

$$(4)\ W_T = \theta \max(K - H_i, 0)$$

Where θ is the ticker. We do the same for the seller, the value of the portfolio at time T is:

$$(5)\ X_s^{wo} = (X_s - a_s)q_f + a_s q_s$$

The value of the portfolio when including an option of selling k shares of a weather derivative:

$$(6)\ X_s^w = (X_s - a_s + kF_s)q_f + a_s q_s - kW_T$$

Next, we derive the buyer`s indifference price. The optimal portfolio is found where the buyer is indifferent between including a WD in the portfolio or not. Thus, the solution is found when the two strategies, (2) and (3), have the same expected utility:

$$(7)\ sup_{a_b} E[u(X_b^{wo}] = sup_{a_b} E[u(X_b^w]$$

In order to find the closed form solution of the indifference price we need to find the certainty equivalent of the utility function. By assuming normal distribution, we can compute the CE by using second order Taylor expansion of U(x). Using the first and second derivative of the exponential utility function we find the CE:

$$(8) CE = E(X) - \frac{1}{2}\lambda\sigma_{\tilde{X}}^2$$

$\mathrm{E(X)}$ represents expected wealth and σ_x^2 is the variance at time T. Next we replace the expected utility in (7) with the certainty equivalent of wealth. Furthermore, we obtain the expressions for the certainty equivalent with and without derivatives. The two expressions for certainty equivalents, are now set equal. Solving for F_b yields the indifference price for the buyer:

$$(9)\ F_b = \frac{1}{q_f}\left(E(W) + \frac{1}{2}\lambda_b k \sigma_w^2 (corr^2(q_b, W) - 1) - \frac{\sigma_W}{\sigma_{qb}}\left(E(q_b) - q_f\right) corr(q_b, W)\right)$$

$$(10) = \frac{1}{q_f}(E(W) + \pi_b)$$

with

$$(11)\ \pi_b = \frac{1}{2}\lambda_b k \sigma_w^2 (corr^2(q_b, W) - 1) - \frac{\sigma_W}{\sigma_{qb}}\left(E(q_b) - q_f\right) corr(q_b, W))$$

The price F_b consists of the discounted value of expected payoff $E(W)$ and a risk premium π_b. Assuming that $\lambda_b > 0$ and $corr^2(q_b, W) < 0$, the first term will always be negative. If one also reasonably assumes $E\left(q_b - q_f\right) > 0$, then the second will be positive. Hence the sign of the risk premium depends on the specific parameter values (Xu et al. 2007).

Similarly the indifference price for the seller can be derived using:

$$(12)\ F_s = \frac{1}{q_f}\left(E(W) + \frac{1}{2}\lambda_s k \sigma_w^2 (corr^2(q_s, W) - 1) - \frac{\sigma_W}{\sigma_{qs}}\left(E(q_s) - q_f\right) corr(q_s, W)\right)$$

$$(13) = \frac{1}{q_f}(E(W) + \pi_s)$$

with

$$(14)\ \pi_s = \frac{1}{2}\lambda_s k \sigma_w^2 (corr^2(q_s, W) - 1) - \frac{\sigma_W}{\sigma_{qs}}\left(E(q_s) - q_f\right) corr(q_s, W))$$

Trading between buyer and seller can only take place if the price the buyer is willing to pay is higher than the price the seller is willing to sell.

$$(15) - \frac{\left(E(q_b) - q_f\right) corr(q_b, W)}{\sigma_{qb}} > - \frac{\left(E(q_s) - q_f\right) corr(q_s, W)}{\sigma_{qs}}$$

The indifference pricing method circumvents the determination of the markets price of risk. Along with this comes the cost of specifying a utility function, but this is unavoidable whenever no-arbitrage arguments are insufficient to determine a unique price. Second, the model seems to be more adequate for an application to the OTC market. It takes into account individual-basis risk and calculates its impact on the willingness to pay for a weather contract. Compared to other approaches, the indifference approach is less ambitious since it does not attempt to predict a transacted market price. Instead, it calculates price boundaries for seller`s and buyer`s, and simply states if transactions are likely to occur or not (Xu, Odening, & Musshoff, 2008). We find it more convenient to work with distributions of the relevant random variable, rather than to specify stochastic processes in a continuous framework.

4.4 McIntyre Pricing Method

In 1999 McIntyre presented a simple analytical model for pricing WDs, which assumes that data follows a normal distribution. He argues that the statistically more accurate methods, such as a monte carlo simulation, can be complex and computationally intensive. Although the prerequisite assumptions for the model does not fit our dataset we want to use this pricing method, as it is fairly easy to compute and has an intuitive interpretation. McIntyre`s model for pricing weather options is:

$$(16)\ wc = \varphi(m-k)N\left(\frac{\varphi(m-k)}{\sigma}\right) + \sigma^2 P(k)$$

Where m is the mean precipitation, k is the strike price, N is the cumulative standard normal distribution, σ is the standard deviation, $\varphi = \pm 1$ with -1 for put and P is the probability density function for a standard normal random variable. However, the volatility in the equation seen from a price-maker´s perspective is an implied volatility and is such a subjective input. The higher the volatility, the more movement and greater the risk, and hence a higher price for the option. The implied mean of WDs underlying, indicates the price-maker´s expectation of future observations and should take into account recent trends, forecasts and positions. The implied volatility and implied mean together therefore represent the risk and hence the purchase price of the option (Mcintyre, 1999).

5. Empirical Application

To our knowledge, there has been no empirical study conducted on the use of WDs for hedging purposes of electricity production, although there are some suggestions regarding the use of such derivatives in previous litterature. Hydropower producer`s operating income is subject to two main sources of risk, spot price and sales volume. There are several financial instruments that can effectively hedge the risk in spot prices, we propose that the use of WDs on precipitation may be a suitable instrument for hedging volumetric risk. Hydropower producers located in Norway are in a particularly special situation as they are able to store 70% of yearly demand at any given point. This means that, in a short-term perspective, precipitation does not affect production, but in the long term it is clear that reservoirs are a result of precipitation and inflow accumulated over a longer time period. Using autoregressive models, we are able to show that precipitation in previous periods affect production in the current periods. For example, the 32,4% of the variance in operating income at time T can be explained by the accumulated precipitation in $t-4$. Since operating income at time T is highly dependent on precipitation at $t-4$, we purpose using a WD giving a payout at time $t-4$, dependent on precipitation to compensate for lower production volume at time T.

We use the indifference method and calculate both a seller and buyer`s willingness to pay for the derivative and illustrate how the WD can reduce volatility and have a positive effect on operating income. We conduct the McIntyre pricing method for comparison reasons and quality ensurance of the indifference prices. As in Leggio (2007) we choose to set the ticker for the monthly option as the Beta estimated from the regression (model 1). Our regression shows that for each additional mm of precipitation operating income increases by 1402,77 NOK. Therefore, we used this amount as the payout per mm of precipitation below the strike level. This method can be applied by any actor producing hydropower, the only changes needed are tick size, financial data and weather data.

In our analysis we used a strike level of 115,9 mm for our monthly put option, this is the monthly average precipitation at the weather station we have chosen as our index. Such a level will ensure a secure payoff for all months with less than average precipitation. The purpose is not to hedge against extreme weather, but to suggest a way to safely smooth income and reduce volatility in operating income. What strike level you choose is dependent on the level of risk you are willing to take, i.e a risk averse actor would set a higher strike and pay a higher premium for the hedge. The payoff from the put option is received on expiration day T and is dependent on tick size, strike level K and cumulative precipitation in the defined time period $T-t$.

5.1 Indifference Pricing

In the following segment we will apply the indifference pricing method to the hydropower producer, as proposed in Brockett et al. (2006) & Xu et al. (2007). For explanatory purposes all formulas are illustrated with a strike of 115,9 mm. The producers utility is defined as a negative exponential utility function, where X is defined as the producers operating income:

$$U(X) = -e(-\lambda X)$$

The expected payoff of the WD, $E(W)$ and the payoffs standard deviation will change for each strike. This is necessary for the price of the derivative to be representative of the periode it is designed for.

The relative risk aversion (RRA/λ) parameter is a measure of how much risk different markets players are willing to take (Copeland, Weston, & Shastri, 1983). Gandelman & Murillo (2015) conducted an in-depth analysis of RRA on country levels and found that in Norway, RRA is estimated to lie in a range from -0.1 to 2.5. We choose to set RRA to an average value of 1.25, and operating income to the historical monthly average of 268.808 NOK. This yields an absolute risk aversion of:

$$ARA(X) = \frac{RRA(X)}{X} = \frac{1{,}25}{268\ 808{,}6} = 4{,}7E - 06$$

We set seller`s absolute risk aversion to 1x 10^-6 (Monoyios, 2004). The OSEAX is used as a proxy for the market portfolio. With closing data for the last 20 years we estimated the average total return to be 9,36%, with a standard deviation of 0.53%. The correlation between the payout from the WD and the market return is calculated to be -0,033, given a strike of 115,9 mm. There is generally a low correlation between market return and WD payoffs (Brockett et. al., 2006). The risk-free rate is set to 1,47% which is the 5-year government bond (Norges Bank, 2018). Both the market return and risk-free rate is adjusted for monthly contracts.

The same parameters were estimated for the buyer. For the payoff r_b, we have chosen to use return on net operating assets (RNOA) as a measurement of production return. As we do not have the production costs at the specific power plant we have to assume that RNOA for the company is representative for the power plant, given that power production is their main income driver.

$$RNOA = \frac{OI * 100}{Avg\ NOA} = 49{,}91\%$$

RNOA is found by deducting operating liabilities from operating assets. The correlation between r_b and the payoff from the WD is calculated to be -0,111 for the previously stated strike.

Table 6: Indifference Pricing Method: Put Option Characteristics

Parameters	
Tick size θ	1 402,8
Strike level K	115,9
Time to maturity T	1
Expected payoff $E(W)$	27 755
Standard deviation σ_w	34 456
Variance	1 187 179 484
Risk-free rate r_f	1,47 %
Contract size k	1

Table 7: Indifference Pricing Method: Put Option Characteristics for Buyer and Seller

Parameters monthly	**Buyer**	**Seller**
Expected return on risky activity,$E(r_b)$ and $E(r_s)$	3,43 %	0,75 %
Standard Deviation, σ_{qb} and σ_{qs}	3,9 %	0,9 %
Correlation, Corr (qb, W) and Corr (qs, W)	-0,111	-0,033
Absolute risk aversion, λ_b and λ_s	4,7E-06	1,00E-06

Operating income from the specific power plant is used as a benchmark, as operating income is directly attributed to production at the facility. Thus, this will be the most representative numbers for testing the effectiveness of our hedge.

Based on the parameters defined above, the put option is found by using equations (12) and (9) which determines the indifference price of the buyer and seller respectively. The buyer`s and seller's indifference prices are estimated to be 28.252 NOK and 27.896 NOK, with an expected pay-off of 27.755 NOK. Figure 2 shows the indifference prices for the buyer and seller. We see that the buyer's indifference price is higher than the seller's for all strike levels lower than 122 mm. Hence equation (15) holds for all strikes lower than 122 mm, and trading can happen between the buyer and seller for strike lower than this.

Table 8: Monthly Indifference Prices for Given Strike in mm

	Monthly						
Strike	80	100	112	115	118	120	122
Buyer	5 926	16 781	25 081	28 259	29 964	31 673	33 391
Seller	5 399	15 389	24 456	27 904	29 760	31 583	33 471

Figure 3: Indifference Price Curves for Buyer and Seller

Given the defined payoff: $W_t = 1402 * max(115{,}9 - H_i, 0)$, we want to examine the effect of three different strategies when hedging with monthly option; 1.Yearly 2. Quarterly 3. Half year.

Table 9: Operating Income Before and After the Hedge, and Change in Relative Risk Ratio

	OI	**OI/STD**	**Hedged OI**	**Hedged OI/std**	**Change in RRR%**
Yearly	12 902 811	103,9	12 895 650	103,1	-0,81%
First half	7 148 161	61,6	7 572 237	67,7	9,85%
Second Half	5 754 650	45,9	5 323 414	44,4	-3,44%
Q1	3 864 716	29,3	4 136 500	33,5	14,40%
Q2	3 283 445	36,1	3 435 737	38,3	6,21%
Q3	2 007 592	30,1	1 860 779	29,4	-2,23%
Q4	3 747 058	29,3	3 462 634	27,5	-6,06%

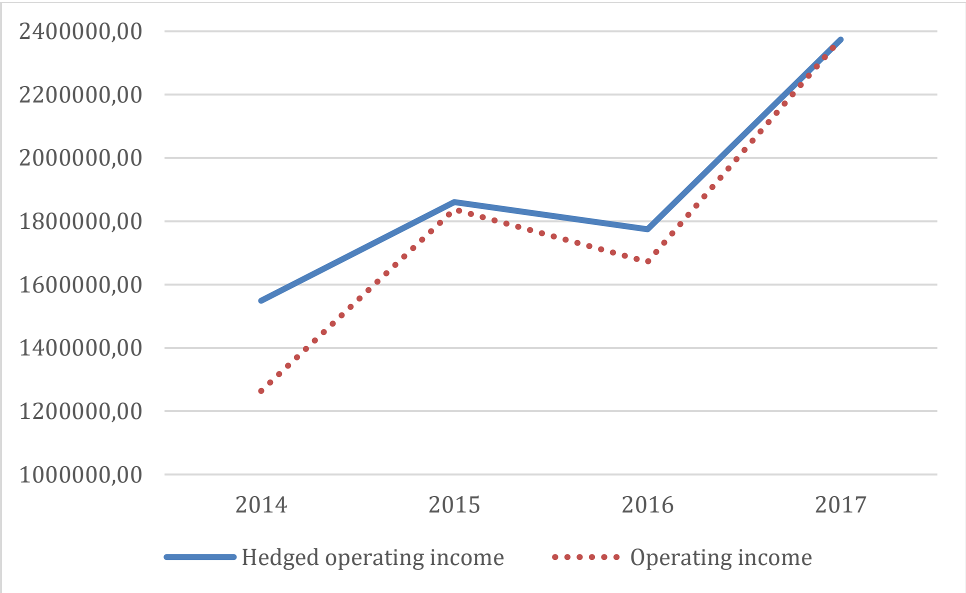
Table 9 illustrates the effect of using monthly WDs to hedge for a whole year, half year or different quarters. The hedged value is found by aggregating historical value of operating income, given that a hedging strategy was applied during the time period 2014-2017. The hedged operating income is defined as:

$$Hedged\ OI = OI\ before\ the\ hedge - Price\ WD + Payoff\ WD$$

We define the change in operating income divided by its standard deviation as a relative risk ratio (RRR) for the period and an increased ratio is a positive sign. For our given strategy an increased RRR is the desirable outcome as this can be seen as income smoothing. Using monthly options, and hedging for lower than average precipitation, is not beneficial on a yearly basis since hedging during the second half of the year, has a negative effect on the RRR. This is typically a higher precipitation period and in aggregate the payoff does not outweigh the cost of the hedge or aid in income smoothing. Precipitation tends to be lower in the earlier months of the year and the first half is the most volatile in terms of precipitation amount. Particularly the first quarter has a low expected value, the highest standard deviation of 30%, and has the highest risk exposure to weather.

Our results show that by hedging with monthly options for the period January until June you would have an increase in operating income over the last 4 years of 5,9% (424.276 NOK) and achieved an 9,85% increase in RRR. When the increase in RRR is higher than the increase in operating income, they have also achieved lower volatility in operating income, thus aiding income smoothing. When only using WDs for the most exposed quarter (Q1) you would have increased operating income by 7% (271.884 NOK) and a 14,4% increase in RRR. The strategy also has a positive effect on Q2 with an increase in operating income of 4,6% (152.292 NOK) and an increased RRR of 6,21%. For Q3 and Q4 our defined strategy shows no positive effects.

Figure 4: Hedged Operating Income and Operating income for the Period January-June (2014-2017) in NOK



As shown in figure 4 hedged operating income surpasses the actual experienced operating income for every year in the period 2014-2016. January 2017 has uncommonly high precipitation, leaving the WD with zero payoff this month. This in turn leads the total operating income without hedge to be larger than the one achieved with the hedge for the period Q1-Q2 2017. Despite reducing the operating income in this period, the hedge has a desirable effect in reducing the standard deviation with 8.9% for the period and an increased RRR by 9,67%.

5.2 McIntyre

As for the indifference pricing method the expected payoff of the WD, E(W) and it`s standard deviation will change for each strike. We set the strike equal to the monthly average precipitation as in the indifference pricing method, for comparison reasons. We choose to set implied volatility equal to historic volatility for precipitation, as shown in Leggio (2007).

Table 10: McIntyre Pricing Method: Put Option Characteristics

Parameters	
Tick size θ	1 402,8
Strike level K	115,9
Time to maturity T	1
Standard deviation σw	51
Variance	2 601
Risk-free rate rf	1,47 %
Contract size k	1

Given the parameters in table 10 we get a WD price of 28.525,2 NOK. In comparison, the price found with the indifference pricing method for the same strike was 27.904 NOK. The model assumes that implied volatility and implied mean are fair representation of the risk parameter, however, this does not consider the actors personal risk preference. Correlation between the payout from WD, operating income and risk aversion is not included in the MCintyre method. As shown in table 12 and 13 a decrease in absolute risk aversion will result in an increase in indifference prices and closer to the price found with the MCintyre formula.

Table 11: Operating Income Before and After the Hedge, and Change in Relative Risk Ratio

	OI	OI/STD	Hedged OI	Hedged OI/std	Change in RRR%
Yearly	12 902 811	103,9	12 866 203	102,8	-1,1%
First half	7 148 161	61,6	7 557 605	67,6	5,9%
Second Half	5 754 650	45,9	5 308 598	44,2	-1,7%
Q1	3 864 716	29,3	4 129 191	33,4	4,2%
Q2	3 283 445	36,1	3 428 415	38,2	2,2%
Q3	2 007 592	30,1	1 853 391	29,3	-0,8%
Q4	3 747 058	29,3	3 455 207	27,4	-1,8%

As shown in table 11, a hedging strategy using Mcintyre`s pricing method has the desired effect on the same time periods as a hedge using the Indifference approach. The results are not as strong as with the indifference approach, but this is only a result of the higher WD price achieved with Mcintyre pricing model. This shows that the hedging strategy is also desirable for prices higher than the buyers indifference price.

6. Sensitivity Analysis on The Indifference Pricing Method

The WD`s price is heavily relient on the ARA and correlation for both the seller and buyer of the WD`s. An actor's risk aversion is hard to measure, but Gandelman and Murillo (2015) estimated the relative risk aversion in Norway to be within a range of -0,1 to 2,5. This is a large spread and a subjective input in our model, as stated previously we used the average value of 1,25 in our analysis. We have therefore done a sensitivity analysis on the ARA and correlation between return on risky asset and payoff from the WD for both the seller and buyer. The increments stated for ARA are representative of the whole range for RRA between -0,1 and 2,5. The same increments are applied for the correlation. Correlation is an important parameter because a small negative increase will make the weather contract more attractive thus resulting in a higher price. If we had data for a longer time-period, the correlation may have differed from our estimates. We have therefore included correlation as a parameter in the sensitivity analysis.

Table 12: Sensitivity Analysis for Buyer on ARA and Correlation Between the Payoff From the WD and Operating Income

Buyer		**ARA**						
		1,9E-06	2,8E-06	3,7E-06	**4,7E-06**	5,6E-06	6,5E-06	7,4E-06
	-0,04	27 930	27 378	26 827	26 276	25 725	25 174	24 623
	-0,07	28 584	28 034	27 484	26 935	26 385	25 835	25 285
	-0,09	29 239	28 691	28 143	27 596	27 048	26 500	25 952
Corr	**-0,11**	29 895	29 350	28 805	**28 259**	27 714	27 169	26 623
	-0,13	30 553	30 011	29 468	28 926	28 383	27 841	27 299
	-0,16	31 212	30 673	30 134	29 595	29 056	28 517	27 978
	-0,18	31 871	31 336	30 802	30 267	29 732	29 197	28 663

Table 13: Sensitivity Analysis for Seller on ARA and Correlation Between the Payoff From the WD and Return on Risky Asset

Seller		**ARA**						
		4,0E-07	6,0E-07	8,0E-07	**1,0E-06**	1,2E-06	1,4E-06	1,6E-06
	-0,01	27 799	27 680	27 561	27 442	27 324	27 205	27 086
	-0,02	27 952	27 834	27 715	27 596	27 478	27 359	27 240
	-0,027	28 106	27 987	27 869	27 750	27 631	27 513	27 394
Corr	**-0,033**	28 260	28 141	28 023	**27 904**	27 785	27 667	27 548
	-0,04	28 414	28 295	28 177	28 058	27 939	27 821	27 702
	-0,047	28 567	28 449	28 330	28 212	28 093	27 975	27 856
	-0,053	28 721	28 603	28 484	28 366	28 248	28 129	28 011

Table 12 and 13 shows how the indifference prices change for different levels of ARA and correlation. Based on intuition, an increase in risk aversion for the buyer would mean that they are willing to pay less for the hedge and if the seller`s risk aversion increased they would ask more for taking the risk. The low correlation between market return and return on the WD results in a decrease in price as risk aversion increases. With an increase in risk aversion for both buyer and seller, the derivative is less likely to be traded. This is exemplified by holding correlation constant at -0,11 and -0,033, and changing the buyer`s risk aversion from 4,7E-06 to 5,6E-06 and at the same time increasing the seller`s risk aversion from 1,0E-06 to 1,2E-06. We then get a higher seller indifference price than the buyer is willing to pay, and the derivative would not be traded. Similarly, an increase in buyer`s ARA from 4,7E-06 to 5,6E-06, while holding correlation and seller`s ARA constant, would result in the WD not being traded. The contracts are more likely to be traded when there is less risk aversion, the correlation has the opposite effect, since an increase in correlation will lead to more traded contracts.

7. Conclusion

Our aim in this study was to price a constructed precipitation level put option and empirically test if a Norwegian hydropower producer could increase revenues by using this as a risk management strategy for volumetric risk. Our findings are in support of Leggio (2007), weather derivatives allow firms to hedge their exposure to revenue-reducing weather conditions. We find in different degree the same effects with the indifference and McIntyre pricing models. The derivatives allow hydropower producers to transfer weather risk to a third party. We show that for periods characterized by low precipitation and high standard deviation can effectively be hedged by using monthly options on precipitation, resulting in increased operating income and reduced volatility. The method applied is applicable for other firms with volumetric risk caused by precipitation. To our knowledge weather derivatives on precipitation are not currently used for these hedging purposes in Norway. The implications of our findings suggest that there are unexploited hedging opportunities with weather derivatives for Norwegian hydropower producers.

To further develop this field of study we believe that alternate pricing models should be applied to a larger dataset, including several powerplants at different geographical locations.

8. Referances

Alaton, P., Djehiche, B., & Stillberger, D. (2002). On modelling and pricing weather derivatives. *Applied mathematical finance, 9*(1), 1-20.

Alexandridis, A., & Zapranis, A. (2013). Wind derivatives: Modeling and pricing. *Computational Economics, 41*(3), 299-326.

Bank, N. (2018). Statsobligasjoner daglige noteringer. Retrieved from https://www.norges-bank.no/Statistikk/Rentestatistikk/Statsobligasjoner-Rente-Daglige-noteringer/

Benth, F. E., & Benth, J. S. (2012). Modeling and pricing in financial markets for weather derivatives *World Scientific, 17*.

Berlage, K. (2013). The Weather Business. Retrieved from https://www.agcs.allianz.com/assets/PDFs/Reports/2484%20Allianz%20Weather%20Risk%20LR.pdf

Beyazit, M. F., & Koc, E. (2012). Using Weather-Related Derivative Products for Tourism and Hospitality Businesses. In *Visions for Global Tourism Industry-Creating and Sustaining Competitive Strategies*: InTech.

Brockett, P. L., Wang, M., & Yang, C. (2005). Weather derivatives and weather risk management. *Risk Management and Insurance Review, 8*(1), 127-140.

Brockett, P. L., Wang, M., Yang, C., & Zou, H. (2006). Portfolio effects and valuation of weather derivatives. *Financial Review, 41*(1), 55-76.

Broll, U., Chow, K. W., & Wong, K. P. (2001). Hedging and nonlinear risk exposure. *Oxford Economic Papers, 53*(2), 281-296.

Bunn, D., Andresen, A., Chen, D., & Westgaard, S. (2015). Analysis and forecasting of electricity price risks with quantile factor models.

Cao, M., Li, A., & Wei, J. Z. (2003). Weather derivatives: A new class of financial instruments.

Cao, M., & Wei, J. (2004). Weather derivatives valuation and market price of weather risk. *Journal of Futures Markets, 24*(11), 1065-1089.

Considine, G. (2000). Introduction to weather derivatives. *Aquila Energy, http://www. cmegroup. com/trading/weather/files/WEA_intro_to_weather_der. pdf*.

Copeland, T. E., Weston, J. F., & Shastri, K. (1983). *Financial theory and corporate policy* (Vol. 3): Addison-Wesley Reading, Mass.

Eklima. (2018). Retrieved from http://eklima.met.no

Electricity Production. (09.10.2017). Retrieved from https://energifaktanorge.no/en/norsk-energiforsyning/kraftproduksjon/

Gandelman, N., & Hernández-Murillo, R. (2015). Risk aversion at the country level.

Hamisultane, H. (2008). Which method for pricing weather derivatives?

Huisman, R., Michels, D., & Westgaard, S. (2014). Hydro reservoir levels and power price dynamics: empirical insight on the nonlinear influence of fuel and emission cost on Nord Pool day-ahead electricity prices. *The Journal of Energy and Development, 40*(1/2), 149-187.

Härdle, W. K., & Osipenko, M. (2017). A Dynamic Programming Approach for Pricing Weather Derivatives under Issuer Default Risk. *International Journal of Financial Studies, 5*(4), 23.

Jewson, S., & Brix, A. (2005). *Weather valuation: The Meteorological, Statistical, Financial and Mathematical Foundations* Cambridge university press.

Kekre, I., & Girish, C. (2017). WEATHER DERIVATIVES–CONCEPT, CHALLENGES, AND FEASIBILITY.

Leggio, K. B. (2007). Using weather derivatives to hedge precipitation exposure. *Managerial Finance, 33*(4), 246-252.
Leggio, K. B., & Lien, D. (2002). Hedging gas bills with weather derivatives. *Journal of Economics and Finance, 26*(1), 88-100.
Manfredo, M. R., & Richards, T. J. (2009). Hedging with weather derivatives: a role for options in reducing basis risk. *Applied Financial Economics, 19*(2), 87-97.
McIntyre, R. (1999). Black-Scholes will do. *Energy Power and Risk Management, 11*.
Monoyios, M. (2004). Performance of utility based strategies for hedging basis risk.
Moschini, G., & Lapan, H. (1995). The hedging role of options and futures under joint price, basis, and production risk. *International economic review*, 1025-1049.
Pérez-González, F., & Yun, H. (2013). Risk management and firm value: Evidence from weather derivatives. *The Journal of Finance, 68*(5), 2143-2176.
Proff. (2018). Fosenkraft Energi AS. Retrieved from https://www.proff.no/selskap/fosenkraft-energi-as/bjugn/energiforsyning/PN4838243I409/
Sharma, A. K., & Vashishtha, A. (2007). Weather derivatives: risk-hedging prospects for agriculture and power sectors in India. *The journal of risk finance, 8*(2), 112-132.
Stowasser, M. (2011). Modelling rain risk: a multi-order Markov chain model approach. *The journal of risk finance, 13*(1), 45-60.
Xu, W., Odening, M., & Mußhoff, O. (2007). *Indifference pricing of weather insurance.* Paper presented at the 101st seminar of the European Association of Agricultural Economists (EAAE)"Management of Climate Risks in Agriculture.
Xu, W., Odening, M., & Musshoff, O. (2008). Indifference pricing of weather derivatives. *American Journal of Agricultural Economics, 90*(4), 979-993.