Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Economics and Management
Dept. of Industrial Economics and Technology Management

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Long-Term Extrapolation of Electricity Forward Curves - A Novel Approach Utilizing Forecasts and Risk Premia

Master's thesis in Industrial Economics and Technology Management
Supervisor: Stein-Erik Fleten
Co-supervisor: Sjur Westgaard
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Preface

We have received a great deal of help and guidance throughout the analysis. Professor Stein-Erik Fleten, our supervisor, deserves special recognition. We have a more robust understanding of power markets as a result of our discussions.

We would also like to thank Sjur Westgaard for giving technical direction and contacting the appropriate commercial actors. In addition, we would like to express our gratitude to the companies and analysts who supplied us with the assistance and confidential data required to perform the study. Hydro ASA's Lasse Torgersen assisted in defining the problem statement and gave invaluable counsel throughout the duration of the project. We are grateful for Montel AS for providing us with information regarding the futures prices of the Nordic and German markets. We want to thank Morten Hegna for his assistance and explanations of the data whenever they were required. We would also like to thank Volue ASA for providing fundamental market estimates for the Nordic and German electricity markets. Finally, we would like to thank Marina Dietze for supplying us with the code and explanations required to compute elementary forward prices.

The authors are responsible for any potential errors in this thesis.

Abstract

We extrapolate the forward price curve based on long-term spot price forecasts and an assumption of a converging forward risk premium in the maturity dimension. The hypothesis of a converging forward risk premium is examined using paired t-tests on the forward risk premia of two- and three-year contracts. Extrapolations are produced using three distinct forward risk premium methods, measuring the maturities between one and two years ahead. The three forward premium methods are referred to as Level, Log-Return, and Rate premium. To calculate the Level premium, we take the difference between the average forward and forecast over the period. For the Log-Return premium, we calculate the log change between the average forward and forecast. Lastly, to calculate the Rate premium, we take the log-return between the forward and forecast price of every maturity in the period, discounting each by their maturity, and then taking the average of these values. The resulting extrapolated forward curves extend to 2050. We measure the out-of-sample accuracy between the extrapolated forward curves and the elementary forward prices. The accuracy of the extrapolated curves measured in MAPE is 8.364%, 8.256%, and 11.439% for the Level, Log-Return, and Rate premium, respectively. Based on the results, we can conclude that the Level and Log-Return methods provide significantly higher accuracy than the Rate premium approach for all investigated accuracy measures. Market participants on both sides of the market can benefit from the long-term forward prices, for production planning and risk management purposes.

Sammendrag

Vi ekstrapolerer forward kurven basert på langsiktige spotprisprognoser og en antakelse om at risikopremien konvergerer i modningsdimensjonen. Hypotesen om en konvergerende risikopremie blir vurdert gjennom en paret t-test for to- og treårskontrakter. Ekstrapoleringene gjennomføres for tre ulike metoder: Level, Log-Return, og Rate premie. For å beregne Level premie, benyttes differansen mellom gjennomsnittlig forward og prognose over perioden. Log-Return premie benytter log-endring mellom gjennomsnittlig forward og prognose. Tredje metode, Rate premie beregnes ved gjennomsnitt av log-endring mellom forward og prognose for hvert modningstidspunkt over perioden diskontert for modningstiden. Vi benytter beregnede premier og langsiktige prognoser til å ekstrapolere forwardkurver fram til 2050. Vi tester nøyaktigheten mellom metodene og forward kurven ved å benytte out-of-sample tester. Resultatet målt i MAPE er 8.364%, 8.256%, and 11.439% for Level, Log-Return, og Rate premie. Basert på resultatene kan vi konkludere at Level og Log-Return metodene er signifikant mer nøyaktighet enn Rate premie. Markedsaktører på både tilbud- og etterspørselssiden av kraftmarkedet kan benytte våre ekstrapolerte forward kurver i forbindelse med risikohåndtering og produksjonsplanlegging.

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1 Introduction

This thesis explores the long-term forward curve of electricity in the Nordic market. We apply an extensive smoothing method to traded electricity futures to construct an elementary forward curve. By analyzing the long-term ex-ante forward risk premium, we find evidence that supports the assumption of a stabilizing premium in the long-term maturity dimension. We extrapolate the forward curves for maturities up to 30 years in the future by combining the risk premium with long-term forecasts.

The extrapolation of forward curves is of interest for both the buy-side and sell-side of the power market. They can use the long-term futures prices for investment analysis and risk management purposes. Participants in the power market are typically strongly susceptible to market risk, more specifically price risk (Weron, 2007). Investors and power producers would want to value their projects and expected future cash flows accurately. Using the prices of long-term futures, one would be able to quantify the expected future income with higher accuracy and thus make better investment and production decisions. Electricity consumers would want to minimize the risk associated with the variable cost of electricity and be able to perform long-term production planning (Benth, Cartea, et al., 2008). They can achieve this by hedging their market positions with forwards, thereby achieving stable prices. The maximum duration for contracts offered on the financial market is five years. Therefore, it will be difficult for players to utilize futures to hedge their long-term positions. Power purchase agreements (PPAs) are becoming an increasingly popular way for both consumers and producers to enter into long-term contracts, and variable renewable power producers sell the majority of their electricity through these agreements (Akinci & Ciszuk, 2021). Long-term futures prices can be used as a substitute for these agreements, and increasing the knowledge of the long-term futures price, will thus be of great interest to all the actors involved.

When hedging their positions, consumers and producers may be incentivized differently and generally have different hedging horizons. Due to demand inelasticity and sudden unexpected price peaks, the price can be a critical risk factor for consumers in the short run. On the other hand, producers of electricity have an incentive to reduce the variability of their profits by obtaining a stable income in the long run. As a result, we anticipate that consumers will hedge more in the short run, and producers will hedge more in the long run. In other words, there will generally be a higher demand for futures in the short run, pushing the prices up, and a higher supply of futures in the long run pushing the prices down (Benth, Cartea, et al., 2008).

Electricity possesses some remarkable properties that distinguish it from other commodities. First, electricity prices are known to be mean-reverting, which indicates that they tend to revert to their long-term average. Second, spot prices for electricity experience spikes and jumps (Schwartz & Smith, 2000). Short-term outliers and spikes, are typically the results of an imbalance between supply and demand. These variations are often observed in the short run, whereas prices converge to a level in the long run. Additionally, the nature of electricity prices and stock markets is quite different. While stock market prices can fluctuate "freely", electricity prices will gravitate toward the cost of production (Cartea & Figueroa, 2005). As a result, electricity prices have been extensively modeled using mean-reverting processes and jumps to account for price spikes.

Instant generation and consumption, seasonality, non-storability, and grid-bound transportation are all essential characteristics of electricity as a commodity (Benth, Benth, et al., 2008; Botterud et al., 2010). Instant generation and consumption imply that the production and consumption of electricity happen simultaneously. The inability to store electricity is due to the absence of economically viable methods for storing significant quantities. As a result, the price is susceptible to changes in demand or supply. In addition, this implies that the relationship of no-arbitrage observed in other commodity markets will not apply to the electricity market.

The delicate balance between production and consumption leads to significant price volatility. Negative spot prices may result from periods of low demand and high supply, whereas extreme positive outliers may result from periods of high demand and limited supply (Bessembinder & Lemmon, 2002; Valitov, 2019). These negative prices and positive outliers increase the risk for the power producers and consumers, respectively.

Another distinguishing characteristic of electricity is that it is a "flow commodity". In electricity markets, forward and futures contracts have continuous delivery periods, such as a month, quarter, or year. In contrast, other commodities have a predefined delivery date in the future. Thus, electricity contracts are essentially swap contracts. The electricity forward curve comprises several of these contracts with delivery periods of different lengths, resulting in an overlapping structure.

The most common method for obtaining continuous electricity forward prices is to use smoothing techniques. This strategy was first applied in fixed-income markets and later to commodity markets with predefined delivery periods. Fleten and Lemming (2003) do this using a bi-objective quadratic optimization procedure to estimate the prices by reducing the squared error between the estimated curve and the prices of bottom-up forecasts. They restrict the ideal solution using bid and ask prices observed in the market. This approach recreates the swap contracts using a smooth forward price curve. Dietze et al. (2022) provide a new structural model for this in electricity markets. They compute a continuous daily forward curve as a deterministic seasonality plus a residual term. The residual term is estimated using the maximum smoothness criterion to find residuals that minimize the arbitrage opportunities between this forward curve and the observed contracts while being as smooth as possible. This approach is along the lines of the theory presented by Benth, Benth, et al. (2008), where the fundamental forward prices are described as a combination of a seasonality function and a residual correction term.

There is no consensus in the literature regarding the thresholds for short-, medium- and long-term electricity prices. Short-term forwards and forecasts usually include contracts with maturity up to a few days ahead. This is the category that has the highest priority in day-to-day market operations (Weron, 2014). The medium-term perspective covers from a few days and up to some months ahead. The contracts with this horizon are important for risk management. Historically, the long-term time horizon has been from a couple of months to several years and is crucial for investment and operational decisions. Most of the focus in the literature has been on short- and medium-term forecasting. There are some studies on the long-term horizon for up to one year, e.g., Nowotarski et al. (2013).

However, there is little existing literature for longer horizons, with time to maturity of more than a year and extrapolations beyond the maturity of tradable contracts.

In this thesis, we obtain an electricity forward curve up to 2050 for the Nordic market. We exploit some of the key findings from our project thesis (Falch & Rolstad, 2021). The forward risk premium appears to be decreasing with time to maturity up to a certain point before it stabilizes for the Y+2 and Y+3 contracts. Conducting linear regression of the differences and testing the significant difference between the premia supports the assumption of convergence in the maturity dimension. In addition, we perform an explanatory analysis of futures and forecast data through principal component analysis. Finally, we use our findings to justify extrapolating the forward curve by adjusting it relative to long-term forecasts.

The remaining sections of this thesis are structured as follows. Section 2 provides a review of work relevant to extrapolation of forward curves, and background and theory of the Nordic power markets. Section 3 presents the input data together with an exploratory analysis conducted using PCA. This section also includes an examination of the assumption of a steady premium. Next, Section 4 explains how we estimated the elementary future prices and applied the forward risk premium to extrapolate the curve relative to long-term forecasts. Section 5 presents the main findings of the thesis. Finally, Section 6 concludes the report and elaborates on possible future work.

2 Related Work

This section presents a review of work related to the purpose of this thesis and our research of the Nordic long-term forward market. First, we analyze the existing state of knowledge on the extrapolation of forward curves. In addition, we will discuss the modeling of seasonality in the power market and the smoothing of swap contracts to establish elementary forward prices. We will also present the forward risk premium work and discuss how this could be applied to our methodology. Finally, we will describe briefly how principal component analysis could be utilized to explain and further analyze our data.

2.1 Extrapolating Forward Curves

Commodity-pricing models are often evaluated based on how well they fit the futures prices. The prices of such models can be obtained using either risk-neutral or risk-adjusted probability distributions. Under a risk-neutral probability distribution, futures prices match the expected spot price. However, for risk-adjusted probabilities, futures are traded at a premium. Commodity-pricing models are primarily used for pricing derivatives. However, as pointed out by Cortazar et al. (2015), they are also commonly used for risk management or net present value calculations.

Electricity derivatives are typically priced using two methods: spot and forward modeling. Spot models attempt to capture the dynamics of spot prices and obtain a closed-form solution for forward prices using no-arbitrage constraints. One of the most well-known methodologies in this category is the Schwart-Smith method. The model was modified to combine two stochastic factors to deal with price spikes. This includes a long-term equilibrium level, often a Brownian motion process, and an Ornstein-Uhlenbeck process for the short-term deviations. One then uses the relationship between forward prices and the conditional expectation of spot prices throughout the delivery dates when constructing predictable elements such as seasonality with a jump-diffusion method Dietze et al. (2022).

Forward-based methods, often attributed to the Heath-Jarrow-Morton (HJM) category, attempt to define a solution for stochastic forward curves directly. The HJM framework is derived from fixed income markets and assumes instantaneous forward prices. For electricity, the forward contracts with swap structure need to be converted into elementary forward curves while considering the no-arbitrage assumptions. The usual way of formulating models within the HJM framework is with a number of K factors, each representing an independent Brownian motion. The number of factors, including the volatility term structure, is often determined by applying Principal Component Analysis (PCA). This process is introduced later in Section 2.6.

Our objective is to create estimations of long-term electricity futures prices. Current practice is to calibrate price models using tradable futures contracts with maturities of up to a few years. There is limited research on the performance of these models across longer maturities. The majority of studies focus on calibrating models that forecast the short-term forward prices, e.g., Nowotarski et al. (2013).

The problem to be solved is how to derive reliable estimates of the long-term forward curve in the absence of futures contracts with sufficiently long maturities. For example, Cortazar et al. (2008) demonstrate that extrapolating models calibrated exclusively on short- and medium-term contract prices to obtain long-term futures prices is unreliable for the oil market. Consequently, the models must be calibrated based on something with a longer horizon. One alternative source of information could be power purchase agreements, which are bilateral over-the-counter arrangements in which the parties commit to long-term power delivery. The contract periods may exceed twenty years and typically provide consumers with a discount relative to the futures market. Consequently, the market for power purchase agreements is comparable to the long-term forward market. Unfortunately, the information regarding these contracts is considered sensitive, and hence, the prices and delivery capacity are not publicly available.

Another possible source of information is analytical forecasts from independent providers. It is not standard among researchers to use analytical forecasts as input in a no-arbitrage term structure model. It is challenging to quantify the exact amount of new information offered by predictions that are not already reflected in market pricing. However, if the forecasts are accurate, they reflect the market's anticipation of the spot price. It has been demonstrated through forecasts that macroeconomic indicators, such as yields, inflation, and GDP, can be accurately predicted (Altavilla et al., 2017; Stark et al., 2010). It is not common to consider spot price estimates when predicting commodity futures. However, this has been accomplished with success in oil markets by Cortazar et al. (2019). Their paper incorporates a consensus curve of long-term forecasts of the oil price and uses this to calibrate their N-factor Gaussian model of the future oil price. This thesis finds inspiration from their methodology for extrapolating the forward curve by combining forecasts and risk premium.

2.2 Seasonality

Seasonality on an annual, weekly, and daily basis must be considered when discussing price levels. Significant fluctuations in demand and supply account for the seasonality and are especially evident in regions where seasonal temperature fluctuations are extreme. For example, in the case of Nord Pool, particularly low-temperature winter months increase the demand for heating. Temperatures also influence the inflow of water into reservoirs, which significantly impacts the supply in a hydro-dominated power market. These are annual cycles that affect the prices. In addition, the weekly demand shifts from being high during the week to being lower on weekends. Lastly, the general working hours influence intraday fluctuations, resulting in off-peak demand at night.

Nowotarski et al. (2013) explain that the most common representation of the spot price, P_t, is to combine one stochastic component, X_t, and a trend-seasonal component, f_t. The seasonal component comprises a short-term seasonal component (STSC) and a long-term seasonal component (LTSC). The STSC is weekly periodic and of less importance for the valuation of power derivatives with long-term delivery periods (monthly, quarterly, yearly). Minor weekly fluctuations will have a diminishing impact when looking at a 30-year horizon. As the objective of our study is to evaluate the long-term forward curve, we believe the short-term weekly seasonalities to be of less value and do not account for them in our research.

The long-term seasonal component is of more significant importance as it represents changes in the fuel price levels, seasonal variations in weather, and consumption. Thus, the LTSC is crucial for the model's accuracy, and potential misspecification can lead to bad out-of-sample tests. In the worst case, small mistakes could develop and result in undesirable future curves where seasonality is inaccurate over 30 years of predictions. The paper of Nowotarski et al. (2013) goes into depth about seasonal decomposition as they find that the subject has been neglected in many academic papers.

Studies regarding the modeling of LTSC can be divided into three categories; The first one is to apply piecewise constant functions, dummies, and linear trends (Fleten et al., 2011; Haugom & Ullrich, 2012; Lucia & Schwartz, 2002). This includes fitting a piecewise constant function or dummies typically for each month. Fitting these is a trivial task and results in the seasonality being relatively well represented, only limited by the number and frequency of the dummies. However, a consequence of this approach is a non-smooth trend-seasonal component with clear jumps between months. This may lead to spurious seasonality as explained by Abeysinghe (1994).

The second approach is wavelet decomposition or similar nonparametric techniques for smoothing, e.g., Hodrick-Prescott filter, Fredman's supersmoother, and spline functions (Conejo et al., 2005; Garcia et al., 2005; Janczura & Weron, 2010; Janczura & Weron, 2012; Stevenson et al., 2001; Weron & Zator, 2014). This technique is less periodic and more robust against outliers than other approaches. The wavelets come in pairs of so-called father and mother wavelets, with new sequences being projected onto either one. The order of the wavelet is decided as a trade-off between smoothness and frequency. The procedure is a form of lowpass filtering, which yields a linear smoother.

The third and final approach, which will be applied in this study, is to model the seasonality as a sum of sinusoidal functions of different frequencies (Benth et al., 2012; Cartea & Figueroa, 2005; Weron, 2008). The spot and forward prices exhibit rather complex annual patterns. This makes it infeasible only to consider one simplistic sine function. The solution to this problem could be to apply other sine and cosine functions of higher frequency. However, whether the periods should be the harmonics of annual frequency is an open question. Pilipovic (2007) and Weron (2007) shows that Fourier decomposition of a signal exhibits a natural appearance of harmonics. The choice of the number of terms in the Fourier series can vary between different papers and is, to some degree, decided ad hoc (Benth & Koekebakker, 2008). The LTSC of a Fourier series does not perform as well as the wavelet decomposition for in-sample fitting. However, using a Fourier series for out-of-sample estimations is straightforward and solely based on the extrapolation of the Fourier series with known amplitudes and frequencies.

Nowotarski et al. (2013) find that wavelet-based models are significantly better than both sine-based and simplistic dummy-variable models at forecasting spot prices for the short-term maturities within a year. This is not the case for the longest forecasting horizons they tested, 275 – 365 days ahead. A reason for this could be that while the periodic functions of sinusoidal and dummies are easily extrapolated into the future, the wavelets

LTSC have a hard time being predicted further than the following weeks. The good short-term fit of wavelets could also make the model perform well in the upcoming months and quarters. However, the predictive power will decrease with time to maturity, and thus we expect the sinusoidal-based models to outperform the wavelet decomposition for long-term extrapolations. Further, the simplistic dummy variable approach also outperforms the sinusoidal approach in the short term. However, due to the limitations of the dummy variables as explained above, we choose to model the seasonality using the sinusoidal-based Fourier series.

2.3 Smoothing

Electricity is a so-called “flow commodity”. This means that the forward and futures contracts have a defined delivery period where the price is set constant for a period (e.g., week, month, quarter, or year), as opposed to other commodities where the delivery is set to a fixed date the future. The contracts are settled in cash against the system price continuously over the delivery period. Thus, futures contracts are written on the average hourly spot price for the contract duration. Consequently, electricity contracts are, in reality, swap contracts with overlapping structures as they introduce a fixed, average futures price for the floating spot price (Benth & Koekebakker, 2008).

To be able to model the forward price dynamics, it is necessary to represent the forward prices by continuous term structure curves (Benth & Koekebakker, 2008). Consequently, it is necessary to calculate so-called elementary forward prices. The concept of elementary forward prices aims to find forward prices that can reconstruct the swap prices while being the smoothest function over the analyzed maturities. The curves are derived from the market’s observable prices for products with a delivery period. This task has been studied for many years in the fixed income market, with the seminal paper of McCulloch (1971). Benth and Koekebakker (2008) present a mixture of two main approaches of Anderson et al. (1996).

Most of the work done on this topic originates from the maximum smoothness criterion, introduced by the study of Adams and Van Deventer (1994). Regarding electricity markets, Fleten and Lemming (2003) used a bottom-up model to integrate the forward market prices with forecasts. They then calculate the elementary forward prices through a quadratic bi-objective optimization problem. In this optimization problem, the first goal was to minimize the difference between the forward prices and the bottom-up model results. The second goal was the maximum smoothness criterion, weighted by a factor λ.

We base our smoothing approach on the semiparametric structural model introduced by Dietze et al. (2022). They developed a method based on the no-arbitrage relationships between overlapping contracts. The work points out that trading a quarterly swap contract is essentially the equivalent of a portfolio of three monthly swaps with consecutive delivery periods in an efficient market. If this relationship does not hold, we have a source of arbitrage that market participants should take advantage of without incurring any risk. The arbitrage net present value is defined as:

$$\Delta_{t,i} = \sum_{j=h_{t,i}}^{h_{t,i}+\Delta T_{t,i}} \frac{F_{t,i} - f_{t,j}}{(1+r)^j}, \qquad \forall t \in \mathcal{T}, \forall i \in \mathcal{N}_t \tag{2.1}$$

Where $F_{t,i}$ is the observed swap price for maturity i on the date t with delivery over the time period $(h_{t,i}, h_{t,i} + \Delta T_{t,i})$. $f_{t,i}$ is the elementary forward price which is not observed in the market, and r is the risk-free interest rate. With the assumption that there is an arbitrage-free market, we have that $\Delta_{t,i}$ should be zero. This is unrealistic for most real market cases. A solution would be only to consider contracts without overlaps. However, elementary forwards are state variables calculated from established swap prices, and thus the intersection between delivery periods incorporates important information. Dietze et al. create arbitrage-free prices by adjusting the observed swap contracts to minimize the arbitrage element. From this, the elementary forward prices can be created (Dietze et al., 2022).

Structural models are time series frameworks that incorporate dynamic evolution through time where unobservable state variables work as time-varying coefficients. The measurement equation gives the relation between elementary forward prices (state variables) and the times series swaps and is given as:

$$F_{t,i} = \sum_{j=h_{t,i}}^{h_{t,i}+\Delta T_{t,i}} f_{t,j} \frac{(1+r)^{-j}}{J_{t,i}} + \zeta_{t,i}, \qquad \forall t \in \mathcal{T}, \forall i \in \mathcal{N}_t \tag{2.2}$$

The measurement equation incorporates a $J_{t,i}$ term defined as: $J_{t,i} = \sum_{j=h_{t,i}}^{h_{t,i}+\Delta T_{t,i}} (1+r)^{-j}$. It also includes an error term $\zeta_{t,i} = \frac{\Delta_{t,i}}{J_{t,i}}$. It is unrealistic to have zero arbitrage, especially due to low liquidity particularly in the long-term. The state equation where the transition of state variables is given:

$$f_{t,i} = \mathbf{x}_{t,j}^T \beta + \epsilon(t, j), \qquad \forall t \in \mathcal{T}, \forall j \in \mathcal{J} \tag{2.3}$$

The residual ϵ is dependent on time and maturity and assumed to be a function of the set of smooth functions. The state equation explains the elementary forward price dynamics. Seasonality effects through sinusoidal functions are inserted in the vector $x_{t,j}$. T represents the transpose of the vector. The vector β contains the coefficients of the seasonality function. The functions have a natural periodicity, and compared to dummy variables, they are continuous, meaning there are no sudden jumps between periods. Such a series of sinusoidal functions or a truncated Fourier series with a number of n harmonics is defined:

$$S_{t,T} = a_0 + \sum_{i=1}^{n} \left[a_i \cdot sin\left(\frac{i \cdot b_i \cdot \pi \cdot (t+T)}{365} \right) + c_i \cdot cos\left(\frac{i \cdot d_i \cdot \pi \cdot (t+T)}{365} \right) \right] \tag{2.4}$$

As introduced earlier, the choice of terms for the seasonality can be decided ad hoc. We can apply any seasonal periodicity through this approach, from yearly to weekly or even intra-daily resolution. Based on the arguments provided by Benth, Benth, et al. (2008) we choose to implement a four-term Fourier series with yearly periodicity.

2.4 Forward Risk Premium

When using frameworks to price derivatives on a commodity, it is essential to adjust them to account for the commodity's specific characteristics. Since there is a lack of ways to store electricity in significant quantities, the no-arbitrage assumption of the storage theory is invalid. A risk-free position cannot be obtained by simultaneously selling the future and holding the underlying commodity. This is the reasoning behind Näsäkkälä (2005) assertion that energy is not a financial asset.

Further, one approach is to set the equilibrium considerations based on a premium between the forward price and the commodity price. Weron and Zator (2014) points out that the terminology "risk premium" is used inconsistently in the literature. The terms risk premium and forward premium have been used indiscriminately when defining different premia. Bessembinder and Lemmon (2002), Haugom et al. (2020), and Longstaff and Wang (2004) among others, uses the terminology forward premium, which we will stick with throughout this study.

The forward risk premium is defined as the difference between the forward and expected spot prices and is regarded as compensation for holding the risk of the commodity. The risk arises from the possibility of demand and price fluctuations. Theoretically, the forward price is an unbiased estimate of the spot price in a market with equal short and long hedging demands. However, suppose that the hedging demand is net short or long. In that case, the futures price will differ from the expected spot price and consequently appear biased from a statistical standpoint (Smith-Meyer & Gjolberg, 2016).

Producers seeking to manage their risks generate a short position in forwards. In addition, the idea of normal backwardation argues that market players' risk preferences influence the forward premium. A market in backwardation is characterized by futures prices that are lower than the spot price due to excessive producer hedging pressure. As a result, producers must pay a premium to hedge future prices. Assuming a complete market, the premium encourages speculators to purchase futures. However, we observe the reverse effect when the market is in contango. In this scenario, the forward premium is positive, and buyers who lock in future prices pay a premium to sellers.

Koolen et al. (2021) analyze how the introduction of various renewable energy technologies affects the short-term hedging pressure and, consequently, the forward premium. They find that introducing large-scale renewable energy production (e.g., solar and wind farms) increases producers' hedging pressure. Therefore, recent developments of large-scale wind farms in the Nordic region could have negatively affected the forward risk premium.

When looking at forward risk premium, one often distinguishes between ex-ante and ex-post and measures it in either level ($€/MWh$) or log-return (%) values. In contrast to other financial markets, commodities markets are typically described by log values representing relative price changes rather than a return. We use the notation log-return in this analysis when referring to the continuous price change in %. The ex-ante forward premium $FP^{ea}(t,T)$ is the difference between the futures contract traded at time t with maturity at time T, $F(t,T)$, and the expected spot price at time T predicted at time t, $E_t[S(T)]$. The $lnFP^{ea}(t,T)$ is the ex-ante premium measured in log-return values.

$$FP^{ea}(t,T) = F(t,T) - E_t\left[S(T)\right] \tag{2.5}$$

$$lnFP^{ea}(t,T) = ln(F(t,T)) - ln\left(E_t\left[S(T)\right]\right) \tag{2.6}$$

The ex-post risk premium is defined as the difference between the futures price and the realized spot price at maturity, i.e., $FP^{ep}(t,T) = F(t,T) - S(T)$. Stated in log-values we have $ln(FP^{ep}(t,T)) = ln(F(t,T)) - ln(S(T))$. Ex-post is more practiced in the literature since it utilizes the captured spot price instead of the more difficult-to-collect expected spot price. However, one issue with this is the limitation in data for extrapolation purposes. As ex-post requires realized spot prices, it is not too meaningful to use it for extrapolation many years into the future.

On the other hand, the ex-ante approach uses expected spot prices from professional forecast providers. Thus, it can be used to connect futures curves to long-term forecasts, yielding information about the futures curves' long-term price level. Nevertheless, this solution becomes dependent on a subjective choice of spot price expectation if no consensus forecast exists. Cortazar et al. (2019) analyze the ex-ante risk premium in the oil forward market. They combine analysts' forecasts from several sources to create a consensus curve. They defend their methodology by claiming that market participants utilize forecasts to estimate market expectations and as a foundation for their resource planning models. In addition, analysts' compensation is often related to the accuracy of their forecasts, which reduces their motivation to withhold information for personal gain. Hence, Cortazar et al. (2019) claims that the ex-ante risk premium approach is suitable for the energy futures market.

The literature focuses on different durations when examining the forward risk premium. Short-term contracts have received great focus in the literature. The reason for this might be that the trading volumes and liquidity of contracts increase when approaching maturity and for shorter delivery periods (Fleten et al., 2015). Examples of work done on short maturities are Botterud et al. (2002), Longstaff and Wang (2004), Weron and Zator (2014) and Lucia and Torró (2011). Most research on shorter contracts finds evidence of a positive forward risk premium in the Nordic market.

Medium-term contracts are defined as contracts with up to some months. This contract length has been examined by Bessembinder and Lemmon (2002), Pietz (2009), Redl and Bunn (2013), Redl et al. (2009), Valitov (2019), and Viehmann (2011), among others. Some of these studies have found a positive forward risk premium, whereas others have identified a negative premium. Bessembinder and Lemmon (2002) present an equilibrium model that implies the future price to be a downward biased predictor of the spot price if predicted power demand is low, and demand risk is modest. This is equivalent to a negative forward premium. The study also suggests that the forward risk premium decreases with the expected variance of the spot price and increases with estimated spot price skewness. Smith-Meyer and Gjolberg (2016) demonstrated that the ex-post risk premium of Nasdaq had decreased after 2008, making future contracts unbiased and more precise forecasts of the spot. They argue that the Nordic power futures market may have fully matured and is currently at least weak-form efficient.

Our literature review did not uncover any analysis of forward risk premia of longer maturity than one-year contracts in the Nordic electricity market. One possible explanation for this might be that most work is done using the ex-post approach. Thus, many changes have happened in the market between the trading date of the futures contract and the actual trading date of the realized spot price. Another reason might be that the short-term contracts make up a substantial part of the transactions at Nasdaq (as well as in other commodity futures markets) (Gjolberg & Brattested, 2011). Therefore, we contribute to the literature by computing the ex-ante forward risk premium for long-duration contracts and use these premia when extrapolating the forward curves. Table 2.1 summarizes the main contribution to the field of forward risk premium in the Nordic market.

Table 2.1: *The highlights of the literature review are presented in matrix form. The research is mapped based on different categories presented in different columns. These include the ex-post or ex-ante approach, duration of the contracts, power market, time range considered, and the sign of the forward risk premium. We define the contracts with a maturity of up to one month as short. Medium duration is between one month and one year, while long duration is for contracts above one year. We emphasize where our work fits in, marked with bold font.*

Paper	Ex-post vs. Ex-ante	Duration	Market	Time Range	Sign of Premium
Bessembinder and Lemmon (2002)	Ex-post	Medium	PJM and CALPX	1997 – 2000 and 1998 – 2000	Negative
Botterud et al. (2002)	Ex-ante	Short	Nordic	1995 – 2001	Positive
Longstaff and Wang (2004)	Ex-post	Short	PJM	2000 –2002	Positive
Redl et al. (2009)	Ex-post	Medium	Nordic and German	2003 – 2008	Positive
Botterud et al. (2010)	Ex-post	Short	Nordic	1996 – 2006	Positive
Gjolberg and Brattested (2011)	Ex-post	Short	Nordic	1995 – 2008	Positive
Lucia and Torró (2011)	Ex-post	Short	Nordic	1998 – 2007	Positive
Weron and Zator (2014)	Ex-post	Short	Nordic	1998 – 2010	Positive and Negative
Fleten et al. (2015)	Ex-post	Short	Nordic and German	2003 – 2012	Positive
Cortazar et al. (2019)	Ex-ante	Medium/Long	Oil Market	2011 – 2015	Positive
Our Contribution	**Ex-ante**	**Medium/Long**	**Nordic**	**2012 – 2021**	**Negative**

We further base our argument for doing this on our risk premium calculations obtained in our work with a project thesis conducted in autumn 2021 (Falch & Rolstad, 2021). The data that laid the foundation for calculations of forward risk premium in that project is applied further in this thesis. The forward risk premium measured for the Nordic market in our project thesis is presented below. We present the premia based on electricity futures price observations from Nord Pool and analysts' forecasts for the same maturity range for maturities ranging from one month to three years. This forward risk premium is calculated based on fewer contracts than for the analysis of this thesis. However, it shows how the premium changes for different maturity lengths.

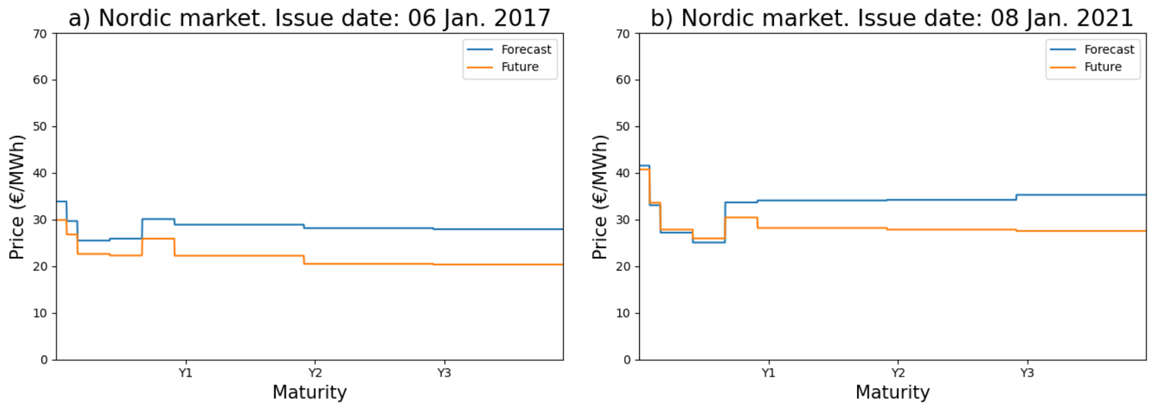
Table 2.2: *The Nordic electricity market's forward risk premium. The premium is calculated using weekly data between February 2012 and June 2021. We present the results as logarithmic values in percentages and level values as €/MWh. HAC standard errors (Newey and West (1987)) are reported in parentheses. Stars(*) denote significance levels of 10%, 5%, and 1%.*

Maturity	Nordic premium Feb. 2012 – Jun. 2021			
	Log (%)		Level (€/MWh)	
M+1	-6.16	***	-1.03	**
	(2.00)		(0.43)	
Q+1	-4.04	***	-0.81	**
	(1.50)		(0.34)	
Y+1	-8.66	***	-2.48	***
	(1.40)		(0.41)	
Y+2	-12.29	***	-3.54	***
	(1.60)		(0.46)	
Y+3	-12.30	***	-3.54	***
	(1.80)		(0.53)	

The average premium for the one-month contracts is −6.16%. The premium decreases and appears to stabilize at approximately −12.30% for the two- and three-year contracts. Furthermore, the premium is significantly different from zero for all maturities, at a 1% significance level using Newey-West (HAC) standard errors.

Figure 2.1 presents the future and forecast curves at two selected dates. In addition to the contracts presented in Table 2.2, we add a few more inside the first year to generate curves for the whole maturity range. M indicates a monthly contract, Q a quarterly contract, and Y an annual one. Each contract represents the arithmetic mean of daily prices during the delivery period. Consequently, seasonal factors impact the portion of the graphs depicting short delivery periods. Spot and futures prices for contracts with short maturities appear to be higher than the rest of the forward curve. This is due to the winter effect dominating the contracts having a short time to maturity and delivery period.

Figure 2.1: *Electricity futures and analysts' forecasts plotted for a) 6 January 2017 and b) 8 January 2021. The graphs show curves for maturities up to and including three years.*



Further, Figure 2.1 indicates the estimated risk premium as the difference between the futures and expected spot prices in both plots. It can be seen that the forward risk premium is negative for the longer maturities for both issue dates presented. It is also a sign that the forward risk premium is relatively stable and seems to be converging in the maturity dimension for the longer contracts. One interesting observation can be seen in Figure A.1 in Appendix. The Y+1 futures, forecasts, and forward risk premium are plotted against issue dates. It demonstrates that there appears to be a change in the premium across the time dimension. Consequently, we cannot assume any convergence in this dimension and must account for these changes in our models.

The descriptive statistics of the forward risk premium are shown in Table B.1 in Appendix. It is expected that the forward risk premia with a shorter time to maturity and shorter delivery periods are more volatile than those with longer maturities and longer delivery periods. This is consistent with the Samuelson effect, which states that the volatility has an inverse relationship with their time to maturity (Samuelson, 1965). Also, contracts with longer delivery periods are not affected by seasonal variations to the same degree as contracts with shorter delivery periods. They are the average value over a larger maturity range.

Additionally, it is reasonable to expect the volatility to stabilize at a low level for longer contracts, as it cannot decrease indefinitely. This, combined with Bessembinder and Lemmon's results, supports the hypothesis that the forward risk premia converge in the long run of the maturity dimension. We will examine this assumption further in Section 3.4.

2.5 The Nordic Power Market

Hydropower is the dominant source of renewable energy in the Nordic power market. In 2019, hydropower contributed around 51.7% of total renewable energy, while variable renewable energy (VRE) sources such as solar and wind energy accounted for approximately 12.9% (Gogia et al., 2019). Hydropower can be stored to some extent, whereas VRE cannot. Both hydropower and VRE are significantly affected by weather, although hydropower is less affected in the short run due to its storability.

The Nordic electricity market is divided into two sections based on whether transactions are settled physically or financially. Nord Pool is the physical delivery power exchange. It serves 16 European countries, making it Europe's leading transaction marketplace for electricity contracts (Nord Pool, 2020). The spot price is the price agreed upon by the participants and serves as the reference price for financial futures contracts.

The Nordic financial electricity market is known as Nasdaq Commodities Europe. With 250 companies trading from 20 different countries, it is one of the largest international electricity markets (Nasdaq, 2022a; Nikkinen & Rothovius, 2019). The forward market was founded in 1993 as Statnett Marked AS and now trades various power derivatives such as forwards, options, base and peak load futures, and Electricity Price Area Differentials (EPADs), which were previously known as CfDs. The maximum duration of derivatives available is five years. Since the contracts are only considered financial, there is no physical exchange of power (Nasdaq, 2022b).

In recent years, bilateral agreements, commonly known as power purchase agreements, have experienced growth across the Nordic region and the rest of Europe. PPAs are a popular strategy for producers and consumers to manage long-term risks. Bilateral power agreements are not a particularly new creation. Producers and customers have utilized traditional agreements to trade power for decades. However, in recent years, the market for these contracts has seen the arrival of new categories of buyers and sellers. Wind farms have dominated the sell-side of new PPA contracts. Due to substantial up-front investments, lenders want developers to demonstrate a reliable income stream. According to Akinci and Ciszuk (2021), investors and financial institutions require producers to sell roughly 70% of their electricity generation through long-term power purchase agreements.

Over the past decade, the Nordic corporate PPA market has expanded while volumes in the Nordic futures markets have fallen. In Europe, the volumes of PPAs have increased from 127 MW in 2013 to 2 330 MW in 2018. Norway and Sweden have been responsible for the vast majority of the agreements signed over the five years (Copenhagen Economics, 2020). On the buying side, most new players are data centers and multinational corporations with an ESG initiative. PPAs are an alternative to futures that is gaining popularity among market participants. Despite the relationship, the majority of the rise in the corporate PPA market is attributable to production capacity that was not previously on the market.

There are two essential distinctions between power purchase agreements and future contracts that influence the decision of market players. First, PPAs can be tailored to the special conditions of the parties involved. In addition to increasing the complexity and expense of hedging, this possibility also increases the cost of negotiations. Second, counterparty risk may represent a considerable hidden cost in PPAs and must be taken into account. However, the regulation of the financial markets considerably minimizes counterparty risk.

In Norway, both the forward market and the power purchase agreements offer market players alternatives for hedging. Due to the importance of the energy-intensive industry, Norway's PPA market is considerably larger than that of other nations. The financial futures market is typically utilized for up to five-year hedges, while the PPA market is utilized for longer hedging. This is seen when comparing the open interest (or total size of active contracts) of the financial market and power agreements. The open interest decreases with time for futures contracts, while it increases with time for power purchase agreements. As a result, we view the new power purchase agreements as meeting new market demands and increasing hedging alternatives (Copenhagen Economics, 2020).

A fair price of futures contracts is strongly related to market liquidity. Further, liquid future markets are needed to ensure sufficient hedging opportunities. Futures market efficiency will be negatively affected by decreased liquidity. Uncertainty over pricing signals might enlarge the bid-ask spread, increasing market participants' costs. Since the 2008 financial crisis, the total traded and cleared futures volume on Nasdaq OMX has decreased, from approximately 2 500 TWh in 2008 to approximately 1 000 TWh in 2019 (Copenhagen Economics, 2020; Houmøller, 2017). Thus, there are indications that the financial Nordic power market is becoming less efficient. A report commissioned by Statnett highlights growing concerns around a lack of liquidity for the financial derivatives utilized for power price hedging (Statnett, 2021).

Changes in collateral requirements may be a contributing factor to poor liquidity. The European Market Infrastructure Regulation (EMIR) and Markets in Financial Instruments Directive (MiFID) have effectively prohibited bank guarantees as an alternative to posting the necessary collateral for clearing financial contracts. These guarantees were a far less expensive way for non-financial enterprises to meet their collateral commitments than borrowing or keeping liquid assets. Before this modification of the law, around sixty percent of market participants relied on bank guarantees for liquidity (Statnett, 2021). Thema Consulting conducted interviews with several market participants, including retailers, consumers, and generators. They indicated that the direct financial expenses of the collateral, management fees, and cash-flow risk associated with an open position are especially high when placing long-term positions on the exchange. Local asymmetries in the supply and demand for contracts may also contribute to poor liquidity. For example, to deliver a similar product to a 10-year PPA starting in 2022, it is necessary to acquire ten annual futures: from 2023 to 2032. With decreasing liquidity, increasing costs, and risk related to the absence of futures contracts with maturities longer than five years, power purchase agreements can be a suitable option for hedging. They are likewise illiquid, but they may be preferable if the hedger wants to construct a long-term hedge or cover area price risk.

2.6 Principal Component Analysis

Principal Component Analysis (PCA) is a technique for dimensionality reduction. It is used to explain most of the variance in a data set using fewer components. For empirical studies of forward prices, the PCA components' threshold of cumulative explained variance is frequently set to 95%. Cortazar and Schwartz (1994) studies the term structure of copper futures prices. They find that three factors can explain 99% of the term structure. Similar results are found in analyses of oil futures and interest rate markets. The PCA of electricity markets is, on the contrary, yielding mixed results. Koekebakker and Ollmar (2005) find in their analysis that ten factors are needed to explain 95% of the total price variation and that the first two factors explain 75%. They argue that the low total price variation explained by two factors is, as far as they know, a unique feature of the electricity market. They create fixed delivery by smoothing and analyzing price differences and price returns. Benth et al. (2007) take the analysis one step further and go into depth on the characteristics. They need three risk factors to account for around 70% of the total variance, with ten factors required to explain 95%. The authors do not find it appropriate to include that many factors, as the amount of the additional volatility explained by each new factor after the third only account for a small part of the term structure.

Benth, Benth, et al. (2008) extend previous work on PCA for updated data on swaps from the Nordic market. Three factors explain around 70% of the variance of log returns, while ten factors are needed to reach the threshold of 95%. The factor loadings structure of the three major components followed the typical level, steepness, and curvature profiles observed in the interest rate and other commodity markets. By evaluating the correlation matrix of normalized electricity futures returns, they find that contracts of different delivery periods are less correlated than contracts closer together. This finding is more prominent in electricity compared to other commodity markets (Koekebakker & Ollmar, 2005). The consequence is that the factors chosen can have variable explanatory power for different contract lengths.

Yu and Foggo (2017) conduct a PCA analysis on the California electricity peak and off-peak future contracts. The data in their analysis is from 2009 to 2012. They find that the top 3 factors explain more than 90% of the variability of electricity futures price curves. This is very different from that of the Nordic market found by Koekebakker and Ollmar (2005). Another study is presented by Dietze et al. (2022). After removing the deterministic seasonality component from the forwards time series, they analyze the Nordic and Brazilian markets by creating smooth elementary forward contracts and then applying PCA to the residuals. They discover that only three variables are required to account for 97.4% of the variance in the Nordic market from 2013 to 2018. Further, they emphasize that the percentage of explained variance is larger than in other studies. They follow up by pointing out that this could result from taking PCA on the residuals rather than elementary forward prices.

The computation of principal components should yield a large amount of information concerning the process of electricity price movements. We want to apply this to both electricity futures and forecast data. Thus, we assume that the processes can be characterized by a set of independent factors that continuously influence the curves to a specific extent. The results of PCA will be estimates of the most influential factors, and thus there is no guarantee of reaching the optimal eigenvectors. There are chances that we converge at vectors that incorporate estimation errors in the levels of derived components.

Finally, we will use the results from PCA to evaluate both futures and forecasts from an empirical point of view. This is done to explore the assumption of a converging forward risk premium in the long run of the maturity dimension. These analyses are interesting as there is little existing literature on performing PCA of forecast data. The analyses will thus be included in our thesis, regardless of their ability to make inferences about our hypothesis.

3 Data

In this section, we present the data used for our research. A brief overview of our data can be seen in Table 3.1. The futures and forecast data sets consist of two dimensions; the time dimension covering trading/issue dates, and the maturity dimension covering time to maturity and delivery period. Finally, we conduct an exploratory analysis focusing on principal component analysis after describing how we clean the data.

Table 3.1: *Overview of data. We present both raw input data from external providers, including futures prices and forecasts, and the resulting data from our analysis is the long-term extrapolation. Issue Frequency is the frequency of issuance of new data, e.g., daily settled futures prices. The Time Period of data limits the data analysis.*

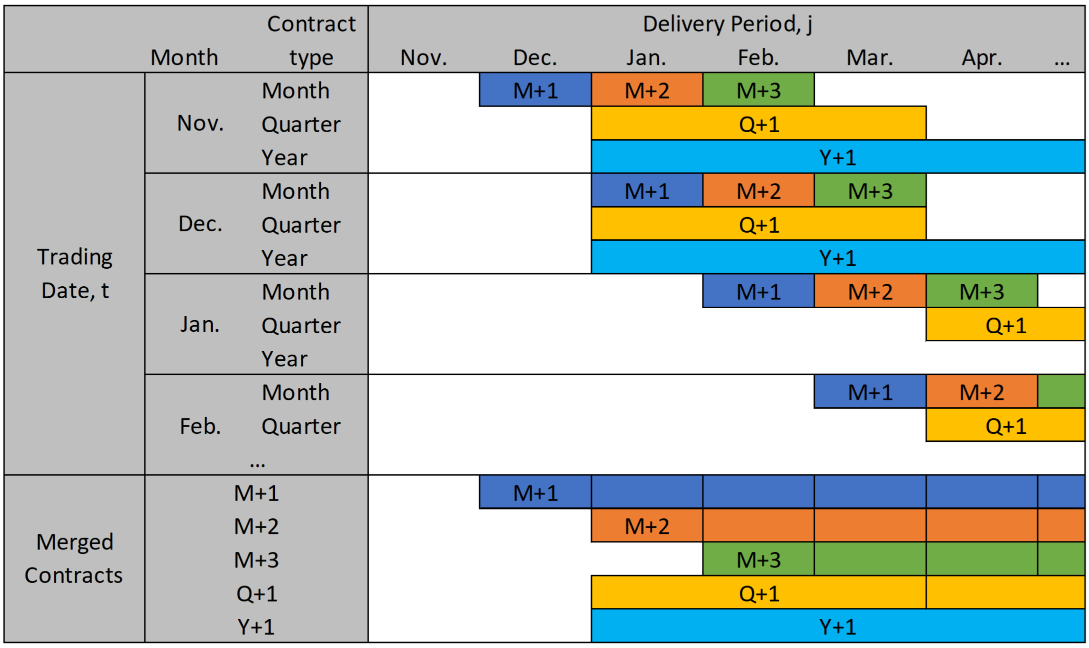
Data Type	Source	Issue Frequency	Time Period
Raw Input			
Futures Prices	Montel	Daily	Jan. 2004 – Nov. 2021
Short-Term Forecast	Volue	Weekly	Feb. 2012 – Nov. 2021
Long-Term Forecast	Confidential	Yearly	May 2011 – Sept. 2021
Our Analysis			
Long-Term Extrapolation		Daily	Feb. 2012 – June 2021

3.1 Future Prices

Our analysis uses M+1, ... , M+6, Q+1, ... , Q+8, Y+1, Y+2, and Y+3 closing forward prices from 2012 to 2021. The volume of traded futures contracts for Y+4 and Y+5 is deemed insufficient for inclusion in our analysis. We use this large number of contracts to capture as much of the forward curve's dynamics as possible. This is crucial when constructing the smoothed curve in an attempt to avoid arbitrage opportunities.

Contracts in the Nordic power market have delivery periods corresponding to the calendar year. This implies that monthly contracts correspond to distinct calendar months, whereas quarterly and annual contracts correspond to distinct calendar quarters and years. When discussing contracts in our analysis, we refer to rolling futures contracts. We produce the data series by concatenating consecutive calendar contracts to create data series for each contract type. This is demonstrated in Figure 3.1. Here the M+1 contract traded in November has a delivery in the following month, December. When December begins, the M+1 contract traded will have delivery in January, and so on. The same holds for the remaining monthly contracts, as well as the quarterly and annual contracts. These contracts can be merged into data series, as explained in the lower section of the figure. These are the data series we use in this thesis.

Figure 3.1: *Visualization of how consecutive calendar contracts are merged into data series. Contracts presented are M+1, M+2, M+3, Q+1, and Y+1.*



As shown in Table 3.1, futures prices are updated daily, and the accessible data set covers February 2004 to November 2021. There are also internal variations in data accessibility. Some contracts have been traded on the market since 2004, while others were added later. Because we need all accessible contracts to compute the elementary forward prices, we have excluded the data for all contracts before February 2012.

Financial markets must have sufficient liquidity to ensure the correct pricing of the futures contracts. Various methods for measuring liquidity include trading volumes, bid/ask spread, order book depth, and trade frequency. We selected the futures with sufficiently high trading volumes using a comparison of daily volume averages. In addition, we have communicated with the commercial provider of futures prices, Montel, who confirmed that the settled prices and corresponding volumes are substantial enough to be trusted.

Table 3.2 present the futures contracts evaluated in our analysis. Volume is stated in MWh and represents the sum of all contracts traded between February 2012 and June 2021. The total trading volume is largest for contracts with the shortest time to maturity. The Q+1, M+1, and Q+2 contracts are the most liquid, followed by the M+2 and Y+1 contracts. The missing trade days denote days for which future prices are unavailable. An explanation for this is that there may be no resolved contracts for those dates. Overall, just a small percentage of pricing days are unavailable. For M+6 contracts, 5.3% of days are absent, while for Q+8 contracts, the volume is only 8 651MWh. We choose to include these futures because they contribute to adjusting the elementary forward prices to avoid arbitrage. There is no structural overlap for the contracts four and five years into the future, Y+4 and Y+5. In addition, their volumes are considered low. As a result, we decided to exclude these contracts from our analysis. They are still displayed to illustrate the decline in trading volumes.

Table 3.2: *Information on trading volumes for different futures contracts. Missing Futures are expressed as a percentage and represent days without a settled price.*

Maturity	**Volume (MWh)**	**Missing Futures (%)**
M+1	445 588	0
M+2	153 820	0
M+3	64 453	0
M+4	35 139	0
M+5	21 735	0
M+6	13 171	5.3
Q+1	870 484	0
Q+2	219 462	0
Q+3	72 512	0
Q+4	42 529	0
Q+5	21 935	0
Q+6	14 891	0
Q+7	10 778	0
Q+8	8 651	0
Y+1	141 958	0.1
Y+2	49 329	0
Y+3	24 866	0
Y+4	7 514	0.9
Y+5	2 386	0.1

When a futures contract has no trading volume during a trading date, Nasdaq OMX can decide on the theoretical closing price for that contract on that date. The price may be determined on trading days with no transactions through a so-called Chief Trader Procedure. A Chief Trader Procedure is a procedure where the price is determined based on prices that exchange members provide. Exchange members must be approved by the exchange at its sole discretion to be eligible for this task. The exchange determines the closing price by calculating the average of all the prices received. The exchange may also choose to remove prices provided through the procedure at its sole discretion. (Nasdaq OMX Commodities, 2022)

The descriptive statistics of future prices are presented in Table 3.3. The bottom section of the table shows the descriptive statistic of each contract length. The table shows that, on average, the length of the delivery period appears to have an inverse relationship with the average price of the contracts. The average prices for contracts with delivery monthly, quarterly, and yearly delivery periods are 31.06, 30.03, and 29.27 $€/MWh$ respectively. In addition, we observe that the standard deviation decreases with time to maturity and contract duration. The average standard deviation for the M+1 contract is 10.62 €/MWh, nearly double that of the Y+3 contract at 5.65 €/MWh. The decreasing standard deviation with increasing maturity is as previously mentioned a sign of the Samuelson effect (Samuelson, 1965). Contracts with shorter duration are composed of fewer delivery dates than longer ones. Thus, the average price is more sensitive to short-term factors on both the supply and demand sides. The same holds for contracts that are closer to their delivery period. These contracts are more susceptible to seasonal effects, such as higher prices and volatility during the winter season in the Nordic market. Short-term price spikes affect contracts with monthly delivery or a shorter time to maturity than contracts with yearly delivery and a longer time to maturity. As a result, they are more exposed to natural variations and become more volatile.

Table 3.3: *Descriptive statistics of futures contract prices.*

Maturity	No. of obs.	Mean (€/MWh)	Price S.D. (€/MWh)	Min (€/MWh)	Max (€/MWh)	Skewness	Kurtosis
M+1	2 340	30.56	10.62	4.20	60.53	-0.04	0.25
M+2	2 340	30.78	10.07	4.48	57.3	0.02	0.19
M+3	2 340	31.02	9.86	4.70	57.00	0.02	-0.06
M+4	2 340	31.22	9.61	5.95	56.85	-0.02	-0.28
M+5	2 340	31.31	9.36	8.35	57.25	-0.04	-0.39
M+6	2 215	31.46	9.28	9.00	57.00	-0.06	-0.50
Q+1	2 340	30.88	9.55	7.65	56.70	0.05	-0.22
Q+2	2 340	31.09	8.72	9.00	54.70	0.01	-0.44
Q+3	2 340	30.77	7.85	10.43	49.70	0.05	-0.58
Q+4	2 340	30.04	7.18	15.00	49.80	0.19	-0.51
Q+5	2 340	29.53	7.36	14.20	46.20	0.14	-0.78
Q+6	2 339	29.48	7.29	13.30	45.30	0.03	-0.72
Q+7	2 340	29.43	6.96	15.20	45.60	0.14	-0.69
Q+8	2 340	29.06	6.85	16.10	47.20	0.26	-0.60
Y+1	2 338	30.06	6.56	13.18	46.85	-0.09	-1.02
Y+2	2 340	29.04	5.89	16.40	42.40	0.06	-0.88
Y+3	2 340	28.72	5.65	16.40	42.50	0.11	-0.48
Monthly	13 015	31.06	9.81	4.20	60.53	-0.03	-0.06
Quarterly	18 719	30.03	7.80	7.65	56.70	0.14	-0.35
Yearly	7 018	29.27	6.07	13.18	46.85	0.05	-0.82

3.2 Analysts' Forecasts

The primary objective of the analysts is to forecast electricity prices accurately. The analysts have customers on both the buy and sell sides of the market. Consequently, they want to reduce the forecast biases, i.e., the systematic differences between predicted prices and the actual realized spot prices. When examining the ex-ante forward risk premium, Fleten et al. (2015) asserts that the construction of an analysts' consensus curve is advantageous. Cortazar et al. (2019) describe how they accumulate a broad range of analytical forecasts to eliminate any bias and maintain an objective market perspective.

We were only able to collect data on analyst predictions from two commercial forecast providers. One of the forecasters provided short-term forecasts with high-resolution data for the next four years, and the other provided long-term forecasts with yearly resolution through 2050. As a result, we cannot generate a consensus curve and must anticipate that the results will be less reliable than they could have been. As previously mentioned in Section 1, electricity markets are highly volatile, with large price spikes and jumps. Consequently, accurate forecasting of electricity prices is challenging in the long run.

We argue, however, that the forecasts provided by the commercial providers should be adequate. They are both considered among the market leaders when analyzing the power market, and their enduring business models build on providing solid forecasts. Thus, we anticipate that both forecast providers will have relatively accurate predictions.

To test whether the spot price forecasts are better predictors of the future spot price than the futures prices, we analyze the performance accuracy of the forecasts. We compare the average of the realized spot prices of the following calendar year with the average predicted spot price of the delivery period. First, we find accuracy measures for each issue date and then take the average. We then repeat the procedure for the futures prices by comparing Y+1 contracts with the average of the realized spot prices of the following calendar year. We find that the short-term forecast, long-term forecast, and futures prices result in Mean Absolute Errors (MAE) of 6.32, 6.49, and 7.46 €$/MWh$ respectively. We see that both the short-term and long-term forecasts have higher predictive power than the futures data in our data sets. Thus, we conclude that the forecasts can provide additional value when extrapolating.

Calculating the forward risk premium is restricted by the forecast input data regarding the time period of the data and the frequency of issue dates. These constraints are displayed in Table 3.1. The forecasts, beginning in February 2012, restrict the time period for calculating the Nordic forward risk premium. In addition, the frequency of the forecasts is limited to weekly increments. The data for the long-term forecast spans from May 2011 to September 2021, thereby limiting the endpoint. In addition, Europe has endured an energy crisis over the past year. High inflation rates, rising oil, gas and electricity prices, and an uncertain macroeconomic situation, have contributed to abnormally high prices and volatility. This situation impacted the Nordic power market, which has also experienced a dry year with low water reservoir levels. The spot price of Nord Pool from February 2012 through May 2022 is shown in Figure A.2 in the appendix. As a result, the relationship between forecasts and futures from the second half of 2021 is highly variable and unpredictable. Consequently, we have chosen to cut off all data after 30 June to cover exactly half of 2021.

3.2.1 Short-Term Forecasts

The Sintef EMPS model, optimized for hydropower-dominated markets, is utilized to forecast spot prices in the Nordic market. It is the only application supported by The Norwegian Water Resources and Energy Directorate (NVE), and all major hydropower producers in the Nordic region use it. The inputs for the model include climatic scenarios, consumption, generation from thermal, solar, and wind power plants, transmission constraints, nuclear production forecasts, and fuel market prices (Mo, 2021). The forecasts are generated weekly and have a five-year horizon. By extracting the correct prices, we can generate forecasts that correspond to various periods of the year and match the futures. The issue dates used in this thesis are shown in Table 3.1.

Table 3.4 provides descriptive statistics for the short-term forecasts data series. We have selected to extract the forecasts corresponding to the forward contracts M+1, Q+1, Y+1, Y+2, and Y+3. These contracts provide a reasonable perspective and incorporate the longer-term contracts, which are of greater significance to our analysis. In terms of missing data, the forecast for the Nordic one-month contract on March 13, 2013, is absent. Due to the law of large numbers, we assume that this data point has a negligible impact on the overall mean premia (Bolthausen & Wüthrich, 2013). Therefore, this data point is omitted from our analysis. The table demonstrates that the forecasts have a relatively stable mean price. Looking at the standard deviation column, one can see the Samuelson effect as there is a decline in volatility as maturity increases.

Table 3.4: *Descriptive statistics of short-term forecasts, grouped by a set of maturities. The standard deviations in the Price S.D. column are the normal standard deviations.*

Maturity	**No. of obs.**	**Mean (€/MWh)**	**Price S.D. (€/MWh)**	**Min (€/MWh)**	**Max (€/MWh)**	**Skewness**	**Kurtosis**
M+1	266	31.51	9.23	5.35	54.61	-0.05	0.63
Q+1	267	31.45	8.93	8.29	55.92	0.29	0.53
Y+1	267	32.59	6.21	21.42	49.04	0.45	-0.35
Y+2	267	32.68	5.24	21.73	46.64	0.22	-0.65
Y+3	267	32.33	5.12	21.32	42.57	0.01	-0.94

3.2.2 Long-Term Forecasts

The long-term forecast provider is a reputable agent who operates in Europe's major energy markets. The price forecasts result from an advanced simulation model of the power market that considers the primary price drivers, such as technological advancements, fuel prices, and national climate policies. Long-term predictions place greater emphasis on the latter factor than short-term predictions. We will not disclose the name of the forecast provider as they have requested anonymity.

Table 3.5 presents the descriptive statistics for long-term forecasts. First, we observe that the number of observable forecast series varies from Y+1 to Y+32. The number of annual forecasts is modest and decreases for the longest maturities. Only one price is available for the longest available forecast, Y+32. This number increases relatively quickly to 27 prices between Y+1 and Y+25. The average price rises from Y+1 to Y+32. Moreover, we note that the standard deviation decreases with time to maturity up to Y+10. After Y+10, the standard deviation generally increases with time to maturity to the same level as the shortest contracts for the longest maturities. This increase may be due to the shortage of data points. In comparison to the yearly contracts of the short-term forecasts, both the mean and volatility of the prices in the long-term forecasts are somewhat higher. In addition, the number of observations is almost scaled by a factor of ten, which may explain why the volatility is greater for the long-term forecasts. Lastly, it is worth noting that from Y+1 to Y+28, the mean price exhibits a strict upward trend. Since we do not have a comprehensive knowledge of the methodologies used in the forecasting model, it is difficult to determine the reason for this. The anticipated inflation is a possible cause for the increase. Adjusting for a 2% yearly inflation yields a forecast curve with more reasonable prices. For the maturities Y+10, Y+20, and Y+28, we obtain prices of 39.92, 43.96, and 45.31 $€/MWh$, respectively.

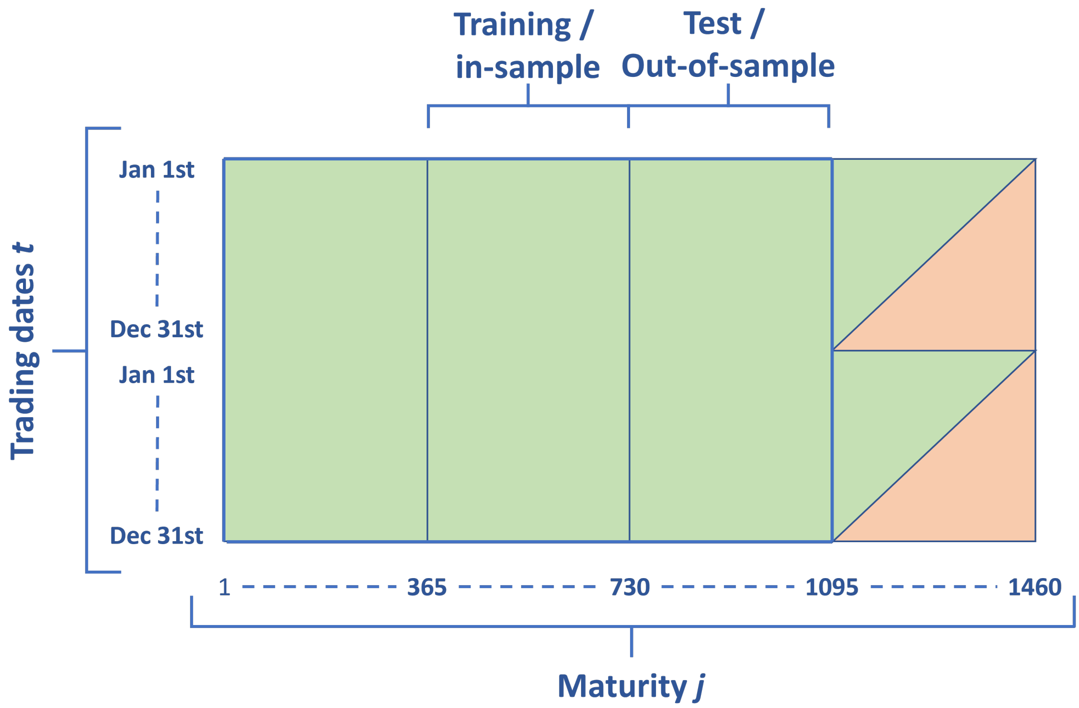
Table 3.5: *Descriptive statistics of long-term forecasts. The forecasts are given with annual delivery and grouped by time to maturity. The standard deviations under the Price S.D. column are the normal standard deviations.*

Maturity	**No. of obs.**	**Mean (€/MWh)**	**Price S.D. (€/MWh)**	**Min (€/MWh)**	**Max (€/MWh)**	**Skewness**	**Kurtosis**
Y+1	28	34.02	8.05	21.93	54.77	0.62	0.00
Y+2	28	34.72	7.60	22.26	49.84	0.24	-1.01
Y+3	28	35.30	7.34	21.97	48.28	-0.03	-1.17
Y+4	28	36.81	7.17	24.14	52.61	0.08	-0.65
Y+5	28	38.44	7.04	27.71	54.32	0.25	-0.76
Y+6	28	40.54	6.70	29.96	54.84	0.23	-0.99
Y+7	28	42.61	6.48	32.74	57.09	0.38	-0.62
Y+8	28	44.92	5.93	35.85	56.83	0.15	-0.85
Y+9	28	47.01	5.56	38.48	57.05	0.06	-0.90
Y+10	28	48.76	5.53	40.23	59.71	0.15	-0.88
Y+11	28	50.16	5.97	39.66	62.44	0.14	-0.80
Y+12	28	51.89	6.26	41.98	65.26	0.22	-0.70
Y+13	28	53.64	6.30	44.89	68.17	0.45	-0.50
Y+14	28	55.49	6.22	46.58	70.96	0.68	-0.09
Y+15	28	57.10	6.33	48.18	73.83	0.83	0.35
Y+16	28	58.73	6.46	49.97	76.79	0.99	0.90
Y+17	28	60.36	6.64	51.67	79.84	1.20	1.59
Y+18	28	62.03	6.84	53.42	82.98	1.40	2.32
Y+19	28	63.77	6.98	55.94	85.78	1.60	2.93
Y+20	28	65.58	7.15	58.30	88.65	1.78	3.49
Y+21	28	67.39	7.39	59.89	91.61	1.93	3.94
Y+22	28	69.20	7.58	61.68	94.64	2.14	4.71
Y+23	28	71.03	7.94	63.53	97.77	2.23	4.93
Y+24	27	71.97	6.49	64.31	92.00	2.08	4.92
Y+25	27	73.94	7.12	61.26	95.16	1.69	4.17
Y+26	25	75.70	8.30	58.07	98.40	1.19	3.20
Y+27	22	78.65	8.36	69.32	101.56	1.77	3.28
Y+28	18	79.33	8.28	69.36	104.98	1.76	4.63
Y+29	13	78.38	6.24	69.36	87.19	0.18	-1.43
Y+30	8	77.22	7.68	69.34	89.60	1.09	-0.38
Y+31	4	84.34	10.24	75.36	93.88	0.02	-5.91
Y+32	1	95.48	NAN	95.48	95.48	NAN	NAN

3.3 Data Cleaning

There is a question regarding which maturity range one should consider when analyzing the forecasts or the elementary forward prices. The maturity range covered by the tradable contracts varies with trading dates throughout the year. The variable maturity range is due to the long-term contracts having delivery periods of whole calendar years, while the trading dates are continuous throughout the year. Figure 3.2 below illustrates this for two years of trading dates. The contracts with the longest time to maturity that are analyzed are the Y+3 contracts, which trade between January 1 and December 31. If the Y+3 contract is traded on January 1, the highest maturity covering the elementary forward curve for this trading date would be approximately $4 \cdot 365 = 1460$ days. The first $3 \cdot 365 = 1095$ days correspond to the time to maturity of the Y+3 contract, while the last 365 days are its delivery period. If, however, the contract is traded on December 31 of the same year, the highest maturity covering the elementary forward curve would decrease to approximately $3 \cdot 365 = 1095$. This decrease is because the time to maturity has now decreased to $2 \cdot 365 = 730$. The first 1095 maturity days constitute the convex set of maturities common for all trading dates. The red triangles in the figure represent the breaks that are not covering the elementary forward curve. In the maturity dimension, these breaks occur for every new calendar year between 1096 and 1460. To achieve consistency in the weighting of each issue date and to get consistent sizes of the training and validation data sets, we have decided to cut all elementary forward curves at maturity 1095.

Figure 3.2: *Visualization of the maximum maturity of the three-year futures contracts (Y+3). The green area is covered by contracts, while the red triangles to the right are not covered. This structure appears as a result of yearly contracts covering full calendar years. The time to maturity decreases for trading dates throughout the year. When reaching a new calendar, a new three-year contract is being traded, and thus the time to maturity increases by a year. This maturity will then decrease throughout the next year until reaching a new calendar year. This decrease in maturity results in the structure shown in the figure.*



3.4 Testing for a Stable Long-Term Forward Risk Premium

Our forward models build on the assumption of a stable risk premium in the long run of the maturity dimension. To test this assumption, we analyze the risk premia for different maturities. Since the length of the tradable forward contracts limits our data sets, we can only achieve empirical tests for this assumption for maturities up until three years. Thus, we compare the risk premia of the two-year and three-year contracts by testing the difference between the two.

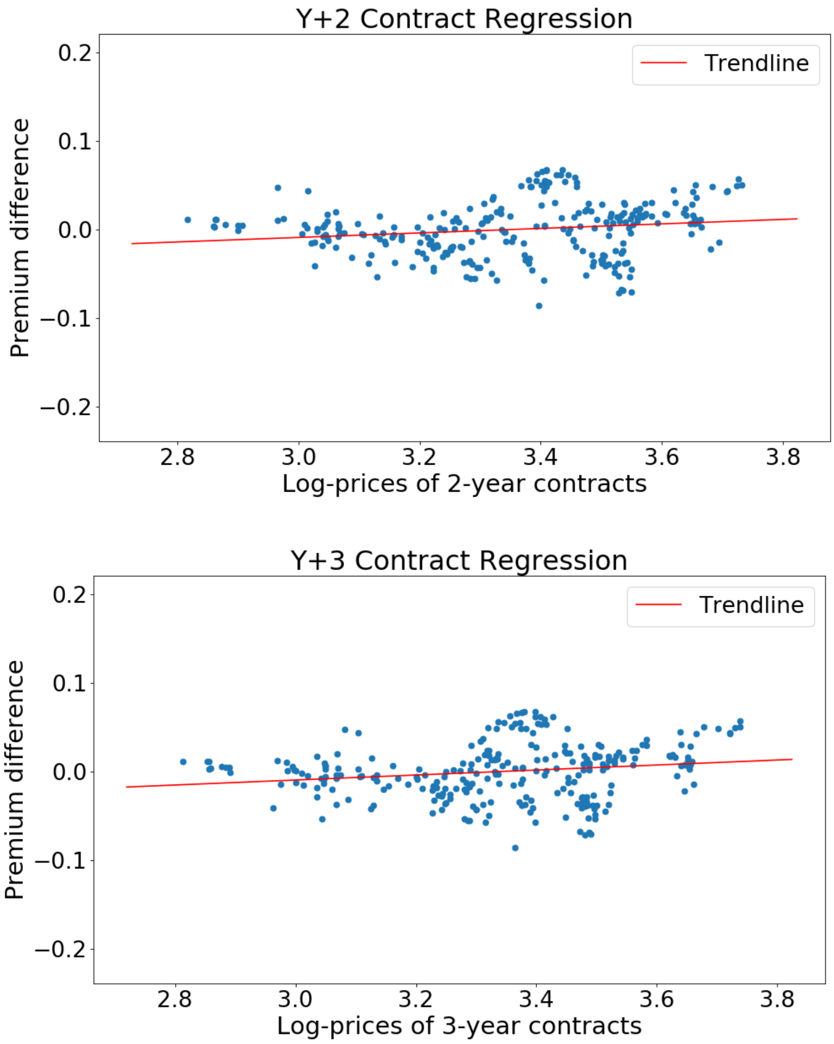
One way to test our assumption is to test the statistical significance of the differences between the two premia. We calculate the premium for each issue date as the log-return between the traded forward price and the average of the forecasted price for the corresponding delivery period. We do this for both two- and three-year contracts. We then calculate the difference between these two premia for each issue date, defined as the premium for the three-year contract minus the premium for the two-year contract. We can test if the difference between the forward premia is statistically significant. The series are stationary and normally distributed for both the log and the level premium difference. Since the spread between the forward risk premia is autocorrelated, we use the Newey-West robust standard error (HAC) to test the statistical significance. In addition to this, the Goldfeld Quandt test in the last column of the table shows that the level difference is heteroscedastic. The complete list of tests performed is presented in Table 3.6. We find that the spread is not significantly different from zero, supporting our assumption that the forward risk premium converges in the maturity dimension for longer maturities.

Table 3.6: *Examining the significance of the difference in forward risk premium between two- and three-year contracts. We conduct these tests on the time series obtained by subtracting the forward risk premium of the two-year contracts from that of the three-year contracts. Furthermore, we test for stationarity, normal distribution, autocorrelation, and heteroscedasticity. The result of each test is underneath their p-values.*

	Mean	Newey-West Standard Error	Newey-West (p-value)	ADF (p-value)	Jarque Bera (p-value)	Breuch Godfrey (p-value)	Goldfeld Quandt (p-value)
Log Premium Difference	-0.0001	0.004	0.97	0.0186	0.600	1.2E-35	0.18
Conclusion			No Significant Difference	Stationary	Normally Distributed	Autocorrelated	Homoscedastic
Level Premium Difference	-0.0008	0.132	0.995	0.0224	0.801	3.5E-37	0.002
Conclusion			No Significant Difference	Stationary	Normally Distributed	Autocorrelated	Hetroscedastic

We also want to perform linear regressions of the difference in premium with the logarithm of the price points at different maturities as explanatory variables. We are interested in testing if the difference in risk premium can be explained by the logarithm of the prices of either the two-year or three-year contracts. First, we again calculate the difference between the two-year and three-year contract premium. We then extract and take the logarithm of the prices of the two- and three-year contracts for each issue date. We run linear regressions getting estimations of the coefficients for the intercept and the slope of the explanatory variables. The relationships are visualized in the scatter plot in Figure 3.3.

Figure 3.3: *Two scatter plots of the difference between the three- and two-year forward risk premia. The top graph plots the difference against the log-prices of two-year contracts. The graph below plots the difference against the log-prices of three-year contracts.*



The estimated coefficients from the linear regressions can be seen in Table 3.7. We use the Newey-West robust standard error (HAC) to test the significance of these coefficients. Estimates of the analysis with two- and three-year contracts result in p-values of 0.077 and 0.053, respectively. We conclude that the slope coefficients are not significantly different from zero, using a significance level of $\alpha = 0.05$. The logarithm of the prices has no significant explanatory power on the difference between the risk premium observed for two-year and three-year contracts.

Table 3.7: *Significance test of the difference between the three- and two-year forward risk premia. The test examines whether the slope coefficient of the regression is significant. HAC standard errors (Newey and West (1987)) are applied, and stars denote significance levels of 10%, 5%, and 1%.*

	Mean	Newey-West Standard Error	Newey-West (p-value)
Two-year slope coeff	0.0026	0.014	0.077 * No Significant Difference
Three-year slope coeff	0.028	0.014	0.053 * No Significant Difference

3.5 Exploratory Analysis: Principal Component Analysis

We performed PCA on the elementary forwards and the short-term forecasts as an exploratory analysis to better understand our data. We wanted to test if PCA could be used to support our hypothesis of a converging forward risk premium in the maturity dimension. Our analyses result in us being able to explain a large part of the variance of the forwards with only a few components. The variance of the forecasts, on the other hand, is more difficult to explain. Consequently, these analyses cannot make any inferences about the stability of the forward risk premium in the maturity dimension. Nevertheless, due to the limited existing work on PCA of forecasts, our analyses might contribute to this area of the literature. Thus, we have decided to include the results of the PCA in this part of our thesis.

The time series should be stationary to perform PCA, which can be explained by having a constant mean, variance, and autocorrelation structure over time. Time series with a trend or seasonality are non-stationary; the value of the time series will depend on the point in time. Not considering this could lead to spurious regressions (Granger et al., 2001). Electricity is a commodity well known for seasonality, and both elementary forwards and forecasts exhibit seasonal patterns. One can conduct the Augmented Dickey-Fuller (ADF) test to check for the hypothesis of stationarity in the data (Hyndman & Athanasopoulos, 2018).

There are different ways to handle the issue of non-stationarity. One solution is to take the difference in the data until one gets all stationary data. However, this approach makes it difficult to interpret the original data, and one can only make inferences about the new data sets created. Another solution is to apply seasonal differencing, the difference between an observation and the previous observation from the same season, $y_t' = y_t - y_{t-m}'$, where m is the number of seasons. This method subtracts the observation after a lag of m periods and is also known as "lag-m difference". One focuses on the last observation from the relevant season when forecasting from this system. This is equivalent to having naive seasonal forecasts.

Our analysis already has a fitted function for the seasonality found in the elementary forward curve. By removing the four-term truncated Fourier series from the series, we expect to obtain non-seasonal data series.

3.5.1 Futures

Firstly, we obtain the price correction term by subtracting the seasonality-adjusted Fourier series from the elementary forward curve. Then, analyzing the correction term with the Augmented Dickey-Fuller test reveals that, assuming the presence of unit root, we cannot reject the null hypothesis. Consequently, we choose to compute the differences in the data series before applying PCA.

Table 3.8 shows the output of the analysis. We find the first three components to account for 86.61% of the total variance in the data. We need ten components to explain more than 95%. This result is interesting as the explainable variance is less than the findings of Dietze et al. (2022), even though we apply much of the same methodology. The difference is that we take the differences in the price correction term to obtain stationary data. Our findings are closer to the results of Benth, Benth, et al. (2008) and Koekebakker and Ollmar (2005).

Table 3.8: *PCA outcomes of elementary forward prices, with variance from the largest components explained. To capture more than 95% of the variance, we require ten components.*

Number of factors	% Variance explained	% Cumulative variance
1	67.82	67.82
2	13.37	81.19
3	5.43	86.62
4	2.16	88.78
5	1.63	90.41
6	1.26	91.67
7	1.17	92.84
8	1.04	93.88
9	0.85	94.73
10	0.73	95.46

Only the first three principal components and corresponding factor loadings are chosen after considering their importance and cumulative size. The factor loadings are modeled in-sample using regressions with equations of linear and exponential forms:

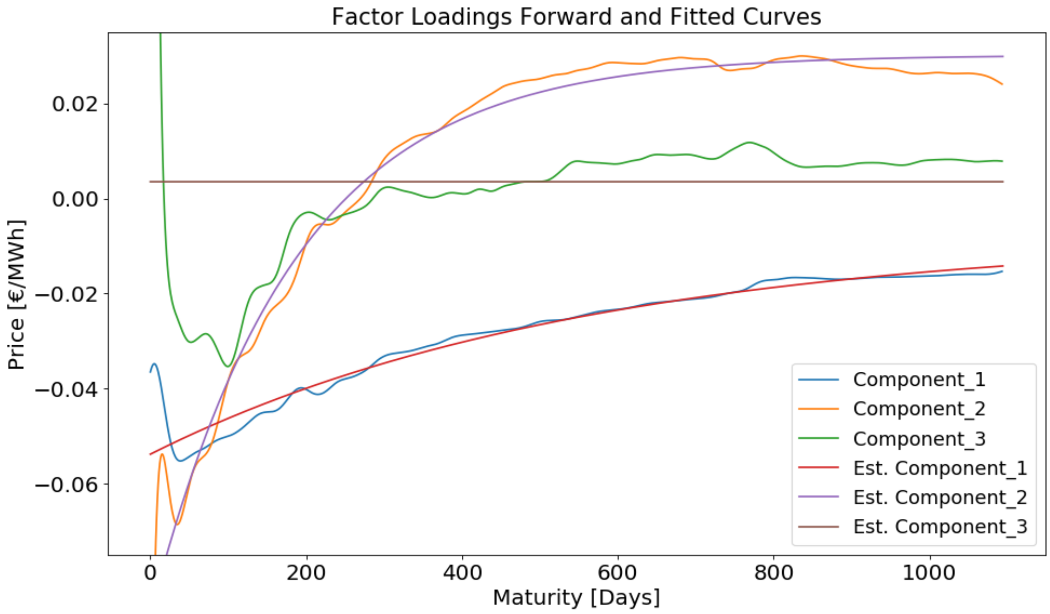
$$\omega(j) = -a_1 e^{-b_1 \cdot j} + c_1 \tag{3.1}$$

$$\omega(j) = -a_2 e^{-b_2 \cdot j} + c_2 \tag{3.2}$$

$$\omega(j) = c_3 \tag{3.3}$$

The original factor loadings are presented in Figure 3.4 together with the estimated equations. We see that all three components seem to stabilize at a value for increasing maturities. This is analogous to the futures curve of every issue date having a constant slope when maturity increases. Further, if the PCA of the forecasts yields similar results, this could be used to make inferences about our assumption of the forward premium stabilizing in the long run of the maturity dimension.

Figure 3.4: *The three largest factor loadings of the forwards data are plotted together with their estimated curves.*



3.5.2 Short-Term Forecasts

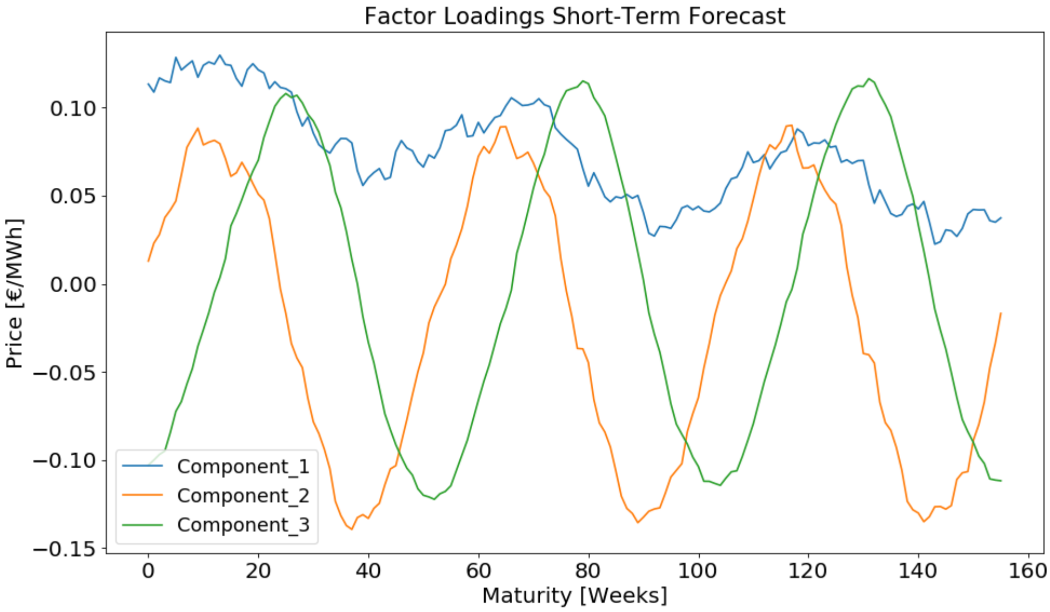
Applying PCA to the short-term forecast follows the same routine as in the case with futures data. First, we remove the seasonality of the forecasts by subtracting the same Fourier function as the elementary forward curve. This was done for simplicity and as it proved to match the natural seasonality of the forecast relatively well. Further, we calculated the differences of remaining residuals to obtain stationary time series.

The results from the PCA show that we need 40 factors to explain 95% of the term structure, presented in Table 3.9. The first factor only represents 13% of the variance, which is an apparent reduction from the PCA of futures prices. The plot of factor loadings also shows little to extract from this analysis. It is unclear how to represent the graphs based on simple equations as done in the literature and for the futures, and thus we cannot say that they are stabilizing in the maturity dimension. Further, there are signs of seasonality in the factors. This is clear from the curve where the periods are exactly 50 weeks.

Table 3.9: *Principal Component Analysis (PCA) outcomes of short-term forecast data, with variance from the largest components, explained. The initial four and last two components are shown. To capture more than 95% of the variance, we require 40 components.*

Number of factors	% Variance explained	% Cumulative variance
1	30.38	30.38
2	15.66	46.04
3	12.41	58.45
4	4.53	62.98
⋮	⋮	⋮
39	0.24	94.78
40	0.22	95.00

Figure 3.5: *The three largest factor loadings of the forecast data are plotted.*



One explanation for the outcome of the forecast PCA might be that the seasonality for the futures data did not cover all the seasonality in the forecasts. Therefore, we attempted to fit another seasonality function to the forecasts and subtract this curve, with no better results.

After analyzing the PCA results of forecasts, it is clear that PCA cannot be used to test the hypothesis of a converging forward premium for our data sets.

4 Model

First, we present the method applied when estimating the long-term forward curve, including smoothing the swap contracts and calculating the shifting variable. We apply a deterministic seasonality of the futures price curves, based on the approach of Dietze et al. (2022). We build our approach on the assumption that the forward risk premium will stabilize in the maturity dimension in the long run.

4.1 Extrapolating the Long-Term Forward Curve

The long-term extrapolated forward curve consists of elements, including a long-term seasonality component (LTSC) and a shifting variable. The deterministic seasonality component is given by a truncated Fourier series as defined by Equation 2.4. The truncated Fourier series consists of an equilibrium line of the seasonality and $n = 4$ pairs of sine and cosine terms. We decide on the seasonality function after constructing the elementary forward prices. The shifting variable is a time-varying price level that depends on the long-term forecast, the calculated forward risk premium, and the equilibrium line of the seasonality. The forward risk premium is calculated with three different methods.

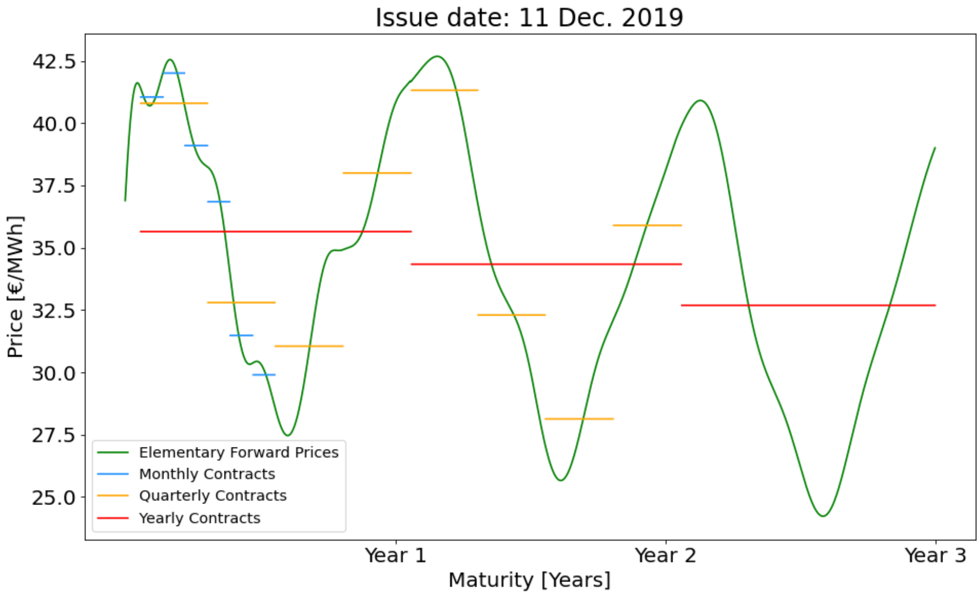
$$
\begin{aligned}
\text{Long-Term Forward} &= \text{Truncated Fourier Series} + \text{Shift Variable} \\
&= \text{Truncated Fourier Series} + \text{Long-Term Forecast} \\
&\quad - \text{Forward Risk Premium} - \text{Equilibrium Line of Seasonality} \\
&= \text{Truncated Fourier Series with Equilibrium Line of Zero} \\
&\quad + \text{Long-Term Forecast} - \text{Forward Risk Premium}
\end{aligned}
$$

4.1.1 Smoothing and Seasonality

To create long-term models for electricity forwards, we need smoothed elementary forward curves that fit the swap contracts of different maturities and with overlapping delivery periods. This is analogous to the approach of Dietze et al. (2022). We split the observable swap contracts into new contracts with as short delivery periods as possible. In a no-arbitrage environment, the price of one of the observed swap contracts should be equal to the weighted average of the elementary forward prices over the delivery period of the observed swap contract.

We generate arbitrage-free prices for the observed swap contracts. In real electricity markets, minor market imperfections and changes in market power could lead to the existence of arbitrage opportunities between the overlapping swap contracts for short periods. Thus, small adjustments are made to the prices of the contracts to minimize the arbitrage between the overlapping contracts. Figure 4.1 shows the elementary forward curve for 11 December 2019, together with the corresponding tradable contracts.

Figure 4.1: *The elementary forward curve for 11 December 2019, along with the tradable futures contracts at the corresponding issue date. There are in total six monthly, eight quarterly, and three annual futures contracts.*



As explained in Section 2 using Equation 2.3, Dietze et al. (2022) assume the elementary forward prices to be equal to the deterministic seasonality component plus the residual term. The residual terms are subject to the maximum smoothness criterion in both the time and maturity dimensions. This allows for a smoother interpolation in the presence of missing data points. We model the deterministic seasonality function using a truncated Fourier series with four terms as suggested by Benth, Benth, et al. (2008). This seasonality function contains one intercept term and four sets of sine and cosine terms, and it only depends on the maturity and the trading date. Due to the deterministic nature of the seasonality function, we can easily extrapolate it in the maturity dimension.

Looking at the long-term extrapolation of forwards, we observe that the amplitude of the seasonality remains constant throughout the maturity range. One alternative model could be to scale the amplitude of the seasonality relative to the price level for that maturity. In this case, the amplitude would increase in absolute terms, while the relative variations would be constant. We could implement this by observing the relative size of the amplitude compared to the price level in-sample. This relationship could then be used to scale the coefficients related to the amplitudes of the Fourier series relative to the appropriate price level for each maturity. A relevant discussion is if changes in the amplitude would make sense. Electricity prices change over time because of deviations in the relationship between supply and demand. More specifically, sources of change can be in the fundamental variables for production, e.g., an increase in CO_2 quotas or a decrease in LCOE of new wind production. One could have implemented an anticipated change differently, e.g., by considering the linear, logarithmic, or exponential relationship between the amplitude and the forward price level. We have chosen to keep the amplitude constant across the series as we think this is a good proxy for the fundamental factors. Changes in supply and demand drive the amplitude observed in the market, and for simplicity we assume that this relationship is kept constant.

4.1.2 Shift Variable

The shift variable is the coefficient that shifts the seasonality function relative to changes in the long-term forecast. The shift is time-varying nominated in $€/MWh$ and dependent on the forward risk premium between the elementary forward prices and the long-term forecasts. We propose three different ways to calculate the forward risk premium. We calculate the premium for maturities between one and two years ahead. Consequently, when calculating the averages, we sum from 365 to 730 and divide by 365.

1. Level Premium

Defined as the difference between the average forward and average forecast of maturities from one to two years for each of the respective trading dates. We see this in Figure 4.2 as taking the difference between the light blue and the pink curve for each trading date t:

$$FRP_t^{Level} = \frac{\sum_{i=365}^{730} F_{t,i}}{365} - \frac{\sum_{i=365}^{730} E\left[S_{t,i}\right]}{365} \tag{4.1}$$

2. Log-Return Premium

Defined as the log-return between the average forward and the average forecast between maturity one and two years for each of the respective trading dates. In Figure 4.2 this can be seen as taking the log-return between the light blue and the pink curve for each trading date t:

$$FRP_t^{Log-Return} = ln\left(\frac{\sum_{i=365}^{730} F_{t,i}}{365}\right) - ln\left(\frac{\sum_{i=365}^{730} E\left[S_{t,i}\right]}{365}\right) \tag{4.2}$$

3. Rate Premium

We base the Rate premium on a slightly different expression of the relationship between the forward contracts and the forecasts. The log-return between the forward and forecast is calculated for every maturity between one and two years ahead. In Figure 4.2, this can be seen as finding the log-return between each point on the red curve and the equivalent point on the black curve. Each of these premia is discounted with maturity, and then the average of these discounted premia is calculated for each trading date t.

The forward and the forecast are related through the forwards being risk-neutral predictors of the future spot price and the forecasts being risk-adjusted predictors. As a result, there should be an equivalence relationship between the two. The forward contract $FW_{t,T}$ discounted by the risk-free interest rate, $r_{t,T}$, equals the forecast $FC_{t,T}$ discounted by an appropriate discount rate $\rho_{t,T}$. Below are the expressions when the interest rates are discretely discounted annually.

$$\frac{FW_{t,T}}{(1 + r_{t,T})^T} = \frac{FC_{t,T}}{(1 + \rho_{t,T})^T}$$

The appropriate discount rate for the forecast is defined as the risk-free rate minus the forward risk premium. The forward risk premium is assumed to stabilize in the maturity dimension in the long run, and thus it will only vary with issue date t.

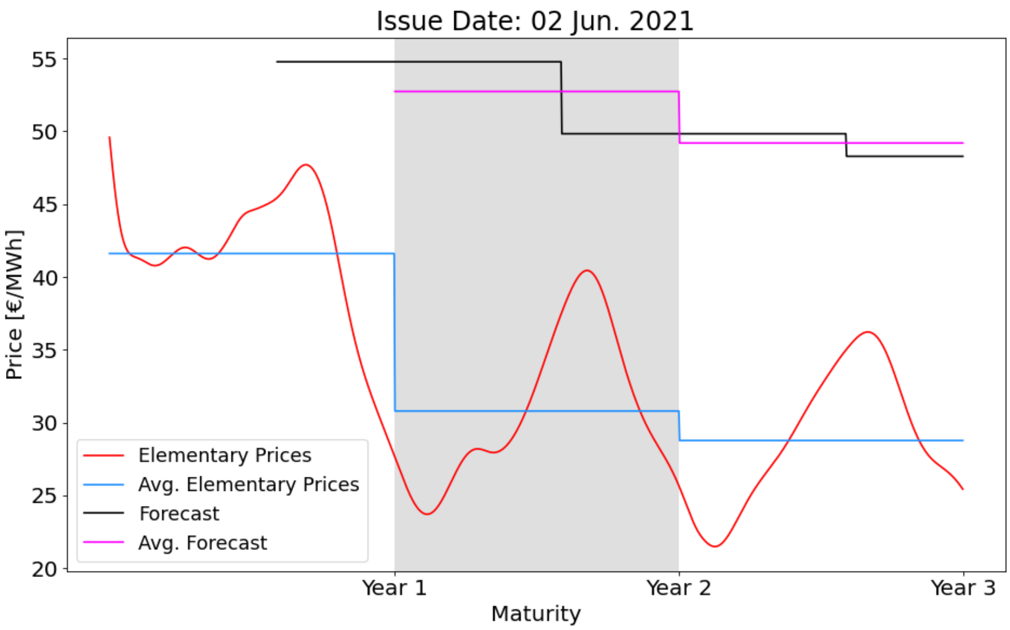
$$\rho_{t,T} = r_{t,T} - FRP_t$$

This is the theoretical starting point for the rate premium approach. Using this premium, one can derive an expression for the forward risk premium to measure the premium in-sample and then derive an expression for the forward contract. A complete derivation can be found in Appendix C.

$$FRP_t^{Rate} = \frac{\sum_{i=365}^{730} \frac{ln\left(F_{t,i}\right) - ln\left(E\left[S_{t,i}\right]\right)}{i}}{365} \tag{4.3}$$

We measure the forward risk premium from the elementary forward prices and the long-term forecasts. It is assumed that the methods consist only of the seasonality component and the shifting coefficient. Instead of the residual terms, we shift the forwards to the price corresponding to the measured premium and the relevant forecast. The out-of-sample modeling starts 730 days ahead, i.e., maturity of 2 years. The shifting is performed by finding the closest long-term forecast and the forward premium corresponding to that forecast. From this, we can find the shifting coefficients of the forward price curves beyond the maturities of the tradable contracts, being only limited by the length of the long-term forecasts.

Figure 4.2: *Calibrating the in-sample forward risk premium for the issue date 2 June 2021. The shaded area indicates the maturity for which the forward premium is computed. This is between the maturity of one and two years ahead. We determine the premia by calculating the average premium over the maturity period using different approaches. The plot shows the elementary forward curve and the long-term forecast alongside average prices over every one-year maturity period.*



5 Results

This section presents the extrapolated forward curve. We show graphs and describe the three distinct forward risk premium strategies. Further, out-of-sample performance and accuracy analysis is conducted to determine the best approach. Finally, we discuss our results and elaborate on how they can be applied by market participants.

5.1 Long-Term Forward Estimation

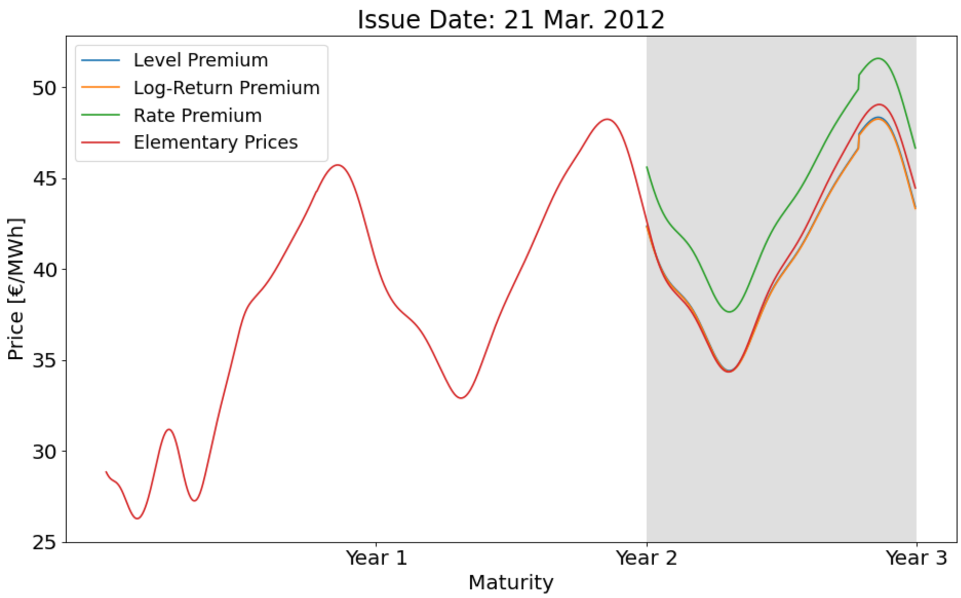
Figure 5.1 presents elementary forward prices with maturities of up to three years and the estimated forward prices for two different issue dates, 21 March 2012 and 02 June 2021. The three forward risk premium techniques are presented for maturities between two and three years. The difference between the Level and Log-Return curves is marginal in this maturity range. The Rate premium curve deviates slightly from the others. This can be explained by the Rate approach differing slightly more from the others.

The curves are not smooth across the predicted forward curves; there are jumps at specific maturity points. The provider of long-term predictions provides annual forecasts. The forecast curve will show one price for each calendar year before jumping to a new price for the following year. The shift of the estimated forward curves is dependent on both the observed risk premium and the forecasting level. Consequently, the estimated forward curves will include price jumps when the curve reaches a maturity date when a price jump occurs.

The three different forward premium approaches are plotted together with the long-term forecast in Figure 5.2. Since the long-term forecasts have different horizons, the extrapolations are also different. The upper plot extrapolates the curves until maturity year 23 (2035), and the lower plot extrapolates until maturity year 29 (2050). We see that the premium approaches deviate more in the long run. We observe the Log-Return premium method deviates downwards from the other methods in the upper graph. In the second graph, we observe the Log-Return and Rate premium methods to follow the same direction, while the Level premium is diverging upwards. The further away the forecast gets from the initial price level, the more significant deviation between the different models is expected.

Another interesting point to notice is that for the lower plot in Figure 5.2 the estimated forward curves are clearly below the long-term forecast. The elementary forward curve is substantially lower than the forecast between maturity years one and two, yielding a significantly negative forward risk premium. As a result, the estimated forward curve for this issue date will stay below the forecast.

Figure 5.1: *Extrapolation of forward curves for two different issue dates. The top graph displays data from 21 March 2012, while the graph below displays data from 2 June 2021. The elementary forward prices are seen from the date of issuance. The extrapolated forward curves begin at maturity year 2, which is denoted by the grey region indicating the out-of-sample maturity range.*



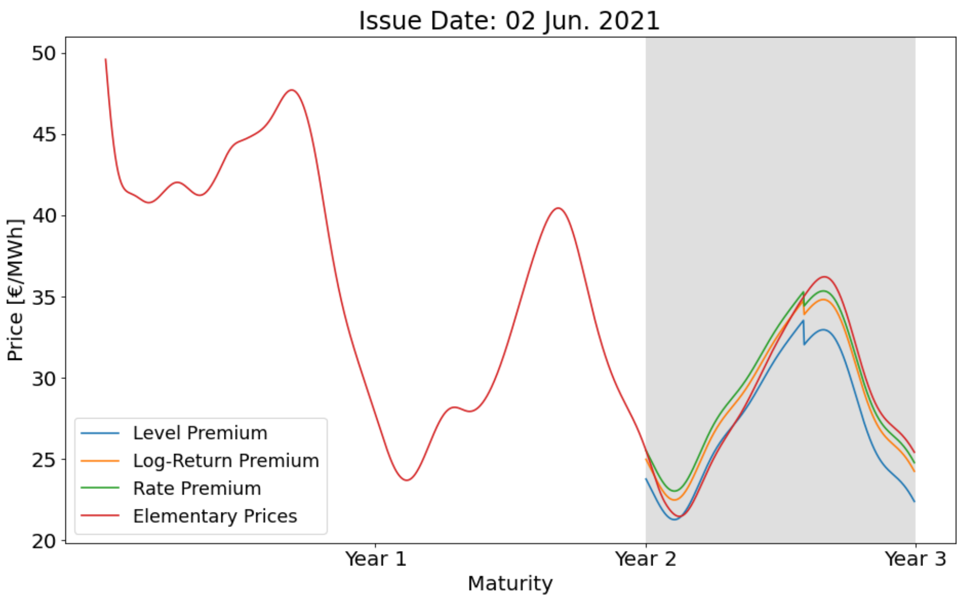
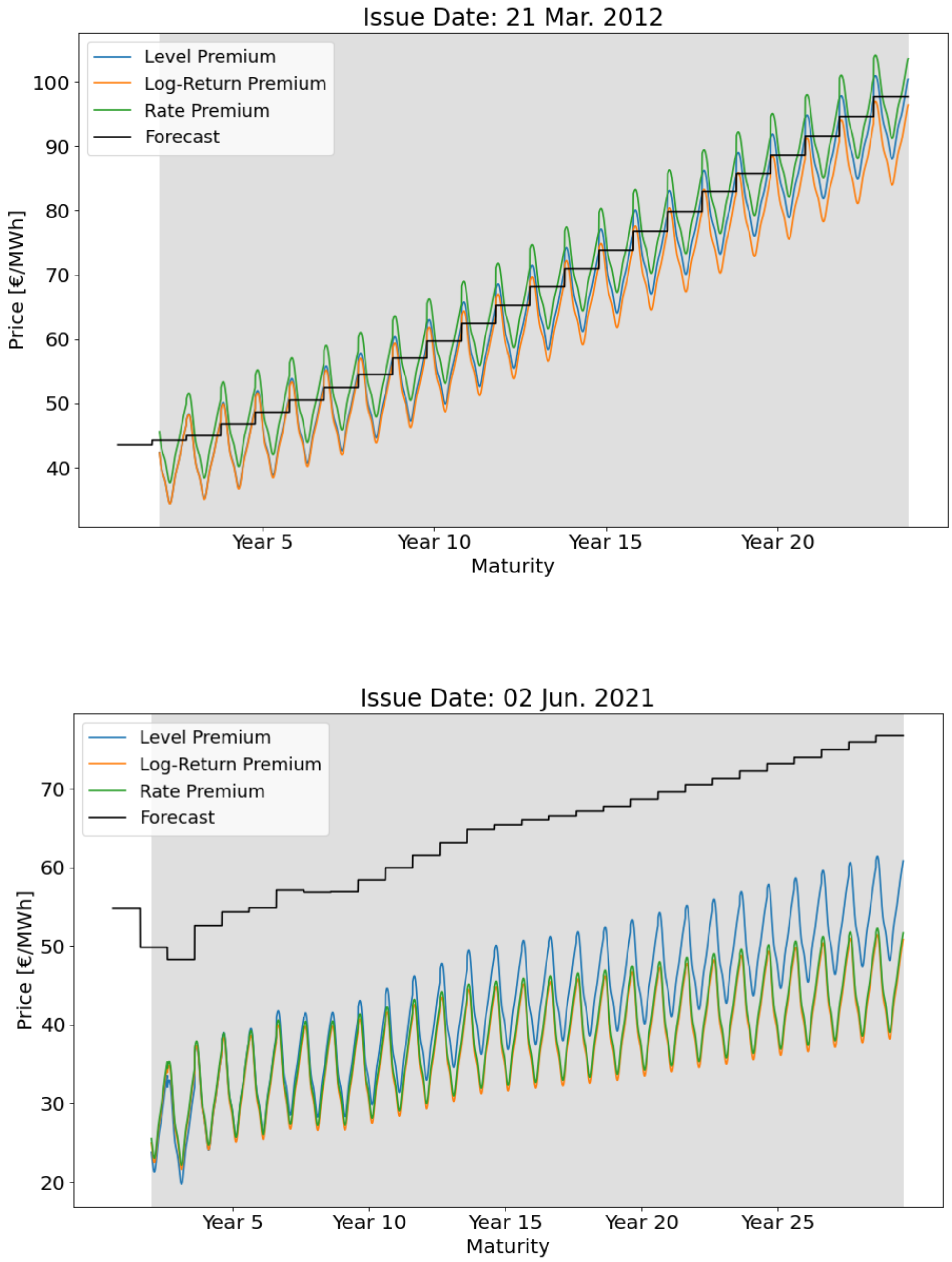


Figure 5.2: *Extrapolated forward curves for the long term. The top graph displays the forward curve from 21 March 2012 through 2035. The graph below displays the forward curve from 2 June 2021 through 2050. The black curves indicate the long-term forecast. The extrapolated forward curves for the Level, Log-Return, and Rate premium techniques are represented by blue, yellow, and green curves. The shaded portion of the curve represents the extrapolated range of maturity.*



5.2 Accuracy Measurements and Out-of-Sample Testing

To evaluate the performance of the three models, we perform out-of-sample accuracy measurements comparing the estimated forward curves with the validation set of elementary prices. These accuracy measurements are performed on data with maturity between two and three years, marked as the shaded area in Figure 5.1. This is the range where we have both the estimated forward curves and the elementary forward prices.

The accuracy measurements applied are Mean Absolute Error (MAE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). As we estimate the forward curve for each issue date, we get a set of accuracy measures for every date. We calculate the average accuracy for each of the three forward premium techniques. The formulae for the accurate measurements are presented in Appendix D.

The results from the accuracy measurements are presented in Table 5.1. We only find a small difference in the performance between the Level and Log-Return premium approaches. On average, the Log-Return approach yields marginally better performance than the Level approach. The MAPE of Log-Return is 8.256%, while Level has a slightly higher value of 8.364%. The Rate premium approach yields, on average worse results with 11.439%. The results of MSE are similar to the findings of MAPE, with Level and Log-Return yielding 8.859$(€/MWh)^2$ and 8.503$(€/MWh)^2$ respectively. The Rate premium results in an average MSE score of 13.896$(€/MWh)^2$. Finally, the MAE of Log-Return gives 2.138 $€/MWh$, slightly less than the 2.170 $€/MWh$ of the Level premium method. The MAE is larger for the Rate premium method, which has value of 2.930 $€/MWh$.

Table 5.1: *Accuracy tests of the three methods for risk premium. We perform Mean Absolute Percentage Error (MAPE), Mean Squares Error (MSE), and Mean Absolute Error (MAE).*

	MAPE %	MSE $(€/MWh)^2$	MAE $€/MWh$
Level Premium	8.364	8.859	2.170
Log-Return Premium	8.256	8.503	2.138
Rate Premium	11.439	13.896	2.930

We analyze the difference between the accuracy measurements by performing paired t-tests to test whether the samples are significantly different. The results of this are shown in Table 5.2. We see no statistically significant difference between the accuracy scores of the Level and Log-Return approach. This means that we cannot conclude that the Log-Return approach is better than the Level approach. The Rate approach is significantly different from the Level and Log-Return approaches for all three accuracy measures. We can conclude that both the Level and Log-Return approach appears to be superior to the Rate approach when considering fitting the elementary forward prices out-of-sample.

Table 5.2: *Significance tests of the outcomes of the accuracy tests. The p-values of the paired t-tests are presented with Newey-West (HAC) standard errors. At $\alpha = 0.05$, the blue color indicates a significant difference, whereas the red color indicates no significant difference.*

	MSE (p-value)	MAE (p-value)	MAPE (p-value)
Level vs. Log-Return	0.859	0.773	0.810
Level vs. Rate	0.015	$5.67 \cdot 10^{-10}$	$9.23 \cdot 10^{-10}$
Log-Return vs. Rate	0.009	$6.20 \cdot 10^{-11}$	$1.50 \cdot 10^{-10}$

5.3 Discussion

The extrapolated forward curves can be useful for several purposes. Knowledge of the futures price on a long-term horizon could be of great value for production planning and hedging, by lowering risk and making resources available for other objectives. It will be beneficial for suppliers to assess the value of power plants and potential new projects more precisely. For instance, net present value estimates for both onshore and offshore wind projects are often close to zero. Small changes in the valuations of the underlying assets might ultimately alter the project's planning, transforming it from successful to unprofitable or vice versa. Therefore, accurate estimates of the price of long-term forwards will be of great interest to agents involved in power production and consumption.

Considering these applications, it is essential to evaluate the accuracy of our extrapolations. The three forward premium approaches yield MAPE scores of 8.364%, 8.256%, and 11.439% for the Level, Log-Return, and Rate premium. Evaluating MAPE scores is challenging, but 8% is generally not a substantial error score. However, one should consider that these accuracy measurements were performed one year out of sample due to data limitations for long-term futures. Thus, we would expect the errors to be even larger in the long run. For some consumers where the cost of electricity is only a small portion of their production costs, this might be sufficiently accurate. The accuracy may also suffice for existing power producers with no additional investment costs and low operating costs, e.g., hydropower plants (Statkraft, 2021). However, for consumers for whom the price of electricity is a more prominent cost factor and for producers that are close to break-even, this is not the case. Therefore, the extrapolations may not be accurate enough to be used directly in these cases. Nevertheless, they provide some insight into the approximate price levels, and can thus add some value to all market participants.

Moreover, power purchase agreements are over-the-counter (OTC) contracts whose pricing is frequently kept secret between the parties involved. Consequently, knowledge of the agreed-upon rates is lacking, while the market power of large industrial actors participating in many agreements has strengthened in recent years. This can lead to weakening the assumptions of market efficiency. Market players with better information can secure superior deals, obtaining rates below forward market prices. Therefore, acquiring information on the price of long-term futures could be advantageous for all parties involved in these negotiations.

As mentioned earlier in Section 5.1, the difference between the forecast and futures curves is larger for some issue dates than for others. This difference in forward premium can be observed by examining Figure A.1 in Appendix. The graph shows time series plots of the futures, forecast, and forward risk premium for the Y+1 contract. We see that the premium between 2012 and 2015 was consistently moving around zero. Then there appears to have been a change around the summer of 2015, with the premium becoming significantly negative. The volatility also seems to have increased from the same point in time. For 2021 we see a forward risk premium measured in log-return values between −20% and −40%. Thus, it is vital to measure the forward risk premium for each forecast issue date as this is not stable over time in the issue date dimension. Our assumption of a stable long-term forward risk premium is based on convergence in the maturity dimension. Thus a change in the premium over time will not affect this assumption.

A possible criticism of our hypothesis of a stabilizing forward risk premium in the maturity dimension could include the possibility of a correlation between futures prices and the price level of power purchase agreements. The expected future cash flows are carefully evaluated when planning new investment projects. As stated in Section 2.5, new projects often require a large proportion of the production to be sold through long-term power purchase agreements. These contracts provide a guaranteed amount for the output and dramatically reduce the project's risk. The remaining production capacity can then be sold through futures contracts or on a more immediate market, such as the spot market.

Following a discussion with Lasse Torgersen, Head of the Department of Energy Market at Norsk Hydro, an interesting case is suggested. In general, the long-term forecasts show an appreciation of the spot price, see Table 3.5. Based on our assumption of a constant forward premium, this should also result in higher futures prices. Nonetheless, as the spot price is expected to increase, the expected cash flows resulting from the portion of power sold on the spot market will also increase in value. This alleviates the pressure on long-term PPA revenue requirements. Thus, the projects are less reliant on high prices for these agreements and can negotiate lower prices. As a result, the producers can negotiate PPAs lower than futures prices on the financial market.

The buy-side of power purchase agreements is often a power-intensive industry, new data centers, and large corporations with an ESG focus. The purchasers benefit by securing long-term electricity supply at a discount relative to the futures market. Therefore, the depreciation in prices of power purchase agreements is good news for these market participants. Further, PPAs are an increasingly popular alternative to traditional futures. As a direct result, the financial market lacks a fundamental buy-side for the traditional futures contracts, although the conventional sell-side of hydropower producers is still there. As presented in Section 2.5, the traded volumes of PPAs have increased while the corresponding volumes of futures have fallen over the last years (Copenhagen Economics, 2020). This creates an imbalance in the equilibrium of the market, resulting in a change in hedging pressure. This pressure will pull the prices of longer future contracts down towards the prices of power purchase agreements. This is supported by the findings of a declining forward risk premium, as seen in Table 2.2. If this assumption holds, power purchase agreements play a key role in leading the forward curve. This will eventually increase the spread between futures and expected spot, contradicting our assumption of a steady forward risk premium.

However, given the limited data on PPA pricing, there is no empirical evidence of this potential relationship between the pricing of these agreements and the forward curve. Moreover, if such a relationship exists in the current market, it is likely a lagging relationship. This lag is affected by the contract length of the existing agreements. Also, negotiating new contracts takes some time, the flow of information is minimal, and the delay associated with acting on this information. Consequently, it will take time for changes in the long-term forecasts to be incorporated into the price of the PPAs and then for the price of the agreements to affect the futures prices. As a result, it will likely be several years before the effect can be observed. Therefore, in our research we assume that these effects are slow and that changes in the price of power purchase agreements have no measurable direct impact on futures prices over a few years horizon.

6 Conclusion

Futures contracts on electricity offer limited insight into the long-term forward curve. This thesis proposes a method for extrapolating the long-term continuous forward curves of electricity in Nord Pool beyond 30 years into the future. First, we employ a smoothing algorithm for the overlapping tradable contracts, creating elementary forward curves. We smooth the contracts by fitting a seasonality function, represented by a four-term Fourier series and a residual term, where the residuals are subject to the maximum smoothness criterion. Then, the discovered seasonality function is utilized to extrapolate the forward curve relative to a long-term forecast from the forecast providers. By computing the long-term forward risk premium for the Nordic electricity market, we find evidence supporting our assumption of long-term premium convergence in the maturity dimension. We calculate the premium using three distinct techniques, resulting in three extrapolation models based on a Level premium, a Log-Return premium, and a Rate premium. Tests of accuracy demonstrate that the Log-Return and Level premium significantly outperform the Rate premium approach. The extrapolated forward prices are approximations of the long-term futures curves and can thus be used by both producers and retailers. Knowledge of the long-term futures could be of great value for long-term production planning and hedging. Another application includes obtaining more accurate evaluations of investments in power plants. The accuracy of the Level and Log-Return premium approaches using out-of-sample testing, measured in MAPE is approximately 8.3%. This accuracy is reasonably accurate and can therefore be utilized for these purposes to some degree.

6.1 Further Work

The assumption of convergence of forward risk premium in the maturity dimension has been tested by examining and comparing the premia of contracts with Y+2 and Y+3 maturities. Additional futures contracts with a longer time to maturity might enhance the study. If Nasdaq OMX provides futures contracts with a longer time to maturity, and the liquidity of the contracts increase, this will be an interesting topic of further investigation. One possible problem in our study is that we rely on a single forecast provider to estimate the expected spot price. Utilizing a forecast consensus curve made of forecasts from many providers will undoubtedly improve the study and analysis. This method might be an excellent topic for future investigation.

The forward risk premium since the summer of 2021 has been highly variable and unpredictable. An interesting area for further work would be to observe these current market conditions' short- and long-term effects on the forward curve. It will significantly affect the forecasts and the forward risk premium. Extending the analyses to incorporate the most recent year's data would likely have impacted the results. To account for the changing market environment, it may be necessary to include a regime-shifting component in our study by the end of 2021. In such an approach, the magnitude of the volatility shift might be included directly, along with the probability of such a shift occurring. Moreover, this price change will increase the volatility, both in terms of forward prices and forward risk premia. This may impact our assumption of a forward risk premium that stabilizes for the long-term maturities.

Extending our research to other markets, such as the German energy market, would be an additional interesting scenario. Often the same market participants are present in multiple markets. Gaining knowledge of interconnected markets could further reduce risk and increase hedging alternatives. It would be interesting to examine if the assumption of a stable forward risk premium holds in other markets. This would require additional long-term market forecasts. Through growing integration, it is expected that the German and Nordic markets have become increasingly correlated over the years. On this basis, we could anticipate similar findings in the German market. On the contrary, the power mix is relatively different from the Nordic, and thus we might find different results for the two markets.

Lastly, one potential study would involve applying other techniques (e.g., Kalman filter) for incorporating the forecast data in extrapolating the forward curve. This could address some of the concerns of our approach, as this would omit the assumption of a stable risk premium in the maturity dimension.

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A Nordic Power Market Graphs

Figure A.1: *Y+1 time series for futures, forecast, and forward risk premium between February 2012 and June 2021. The futures and forecast are measured in €/MWh given by the left-side y-axis, while the premium is measured in % given by the right-side y-axis. The forward premium is calculated as the log-return premium using Equation: 4.2. The premium appears to be closer to zero until between 2015 and 2016. After this the variance appears to be larger and the premium to be more negative.*

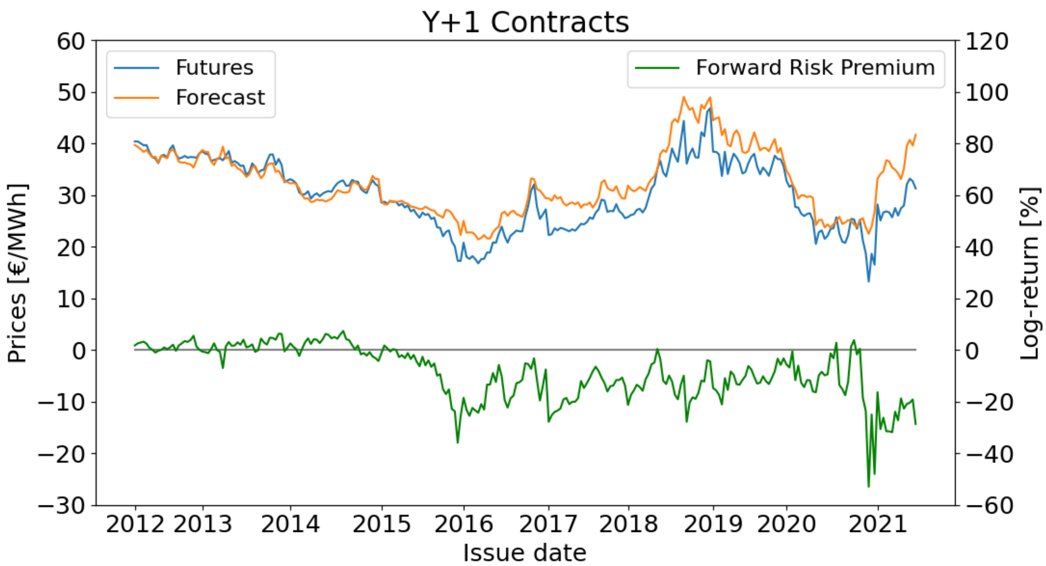
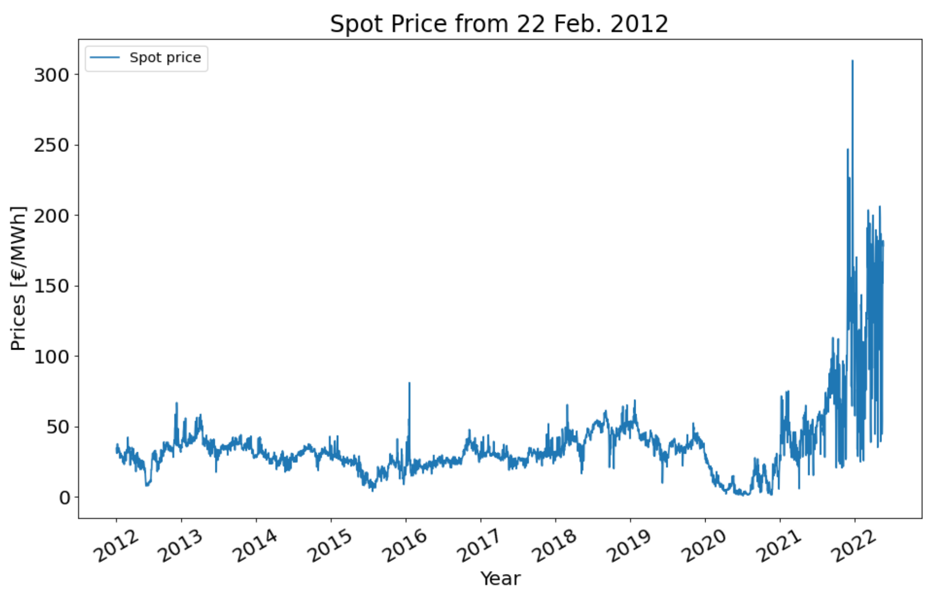


Figure A.2: *Average daily base power spot prices in euros per megawatt hour, for delivery at Nord Pool from 22 February 2012 through May 2022.*



B Descriptive Statistics of Forward Risk Premium

Table B.1: *Descriptive statistics of the forward risk premium (FRP) of the Nordic power market. Premia are grouped by five selected maturities and presented both for level and log values. The mean values are the same as presented in the second column of Table 2.2. The standard deviations under the Price S.D. column are the normal standard deviations.*

Series	Nordic FRP from 21 Feb. 2012 to 30 June 2021								
	Mean		Price S.D.		Skewness		Kurtosis		No. of obs.
	Log	Level	Log	Level	Log	Level	Log	Level	
1M	-6.16	-1.03	17.60	3.66	-2.22	-0.59	6.56	0.88	266
1Q	-4.04	-0.81	12.88	2.96	-2.05	-0.65	7.27	1.12	267
1Y	-8.66	-2.48	10.31	2.96	-0.78	-0.51	0.84	-0.36	267
2Y	-12.29	-3.54	10.97	3.17	-0.12	-0.19	-1.19	-0.99	267
3Y	-12.30	-3.54	12.44	3.66	0.16	0.06	-1.18	-0.88	267

C Derivation of the Rate Premium Approach

The rate premium approach is based on the relationship between the forward contracts and the forecasts. The appropriate discount rate for the forecast is defined as the risk-free rate minus the forward risk premium.

$$\rho_{t,T} = r_{t,T} - FRP_t \tag{C.1}$$

Below is the expression of the relationship when the interest rates are discounted annually. This is the theoretical starting point for the Rate premium approach.

$$\frac{FW_{t,T}}{(1 + r_{t,T})^T} = \frac{FC_{t,T}}{(1 + \rho_{t,T})^T} \tag{C.2}$$

This leads to expressions for the forward risk premium and forwards that will depend on the risk-free interest rate. However, this is because the rates are discounted annually. When using continuously compounded interest rates, the rates will cancel in these expressions. Below is the derivation of this:

Initial equations:

$$FW_{t,T}e^{-r_{t,T}T} = FC_{t,T}e^{-\rho_{t,T}T} \tag{C.3}$$

Forward risk premium:

$$FW_{t,T}e^{-r_{t,T}T} = FC_{t,T}e^{-(r_{t,T}-FRP_t)T}$$

$$e^{-(r_{t,T}-FRP_t)T} = \frac{FW_{t,T}}{FC_{t,T}}e^{-r_{t,T}T}$$

$$FRP_t = ln\Big(\frac{FW_{t,T}}{FC_{t,T}}\Big)/T \tag{C.4}$$

Forwards:

$$FW_{t,T}e^{-r_{t,T}T} = FC_{t,T}e^{-(r_{t,T}-FRP_t)T}$$

$$FW_{t,T} = FC_{t,T}e^{-r_{t,T}T+FRP_tT+r_{t,T}T}$$

$$FW_{t,T} = FC_{t,T}e^{FRP_tT} \tag{C.5}$$

From this one can see that continuously compounding the interest rate will cancel the rates in the final expressions. As a result, the Rate premium approach will not depend on the interest rates.

D Formulae for Accuracy Measurements

$$e_{T+h} = y_{T+h} - \hat{y_{T+h|T}} \tag{D.1}$$

Where $y_1, ..., y_T$ is the training data and $y_{T+1}, y_{T+2}, ...$ is the test data

$$\text{MSE} = \sqrt{\text{mean}\left(e_t^2\right)} \tag{D.2}$$

$$\text{MAE} = \text{mean}\left(\left|e_t\right|\right) \tag{D.3}$$

$$\text{MAPE} = \text{mean}\left(\left|\frac{100 \cdot e_t}{y_t}\right|\right) \tag{D.4}$$

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