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Effektene av implisitt volatilitet på predikasjon av realisert volatilitet på forwards i det nordiske kraftmarkedet

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Innlevert: mai 2014
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Oppgavens (foreløpige) tittel **Effektene av implisitt volatilitet på predikasjon av realisert volatilitet på forwards i det nordiske kraftmarkedet**	
Oppgavetekst/Problembeskrivelse The purpose of this master thesis is to investigate the ability of implied volatility in forecasting realized volatility using a Heterogeneous Autoregressive model for the Nordic Power Forward Market at the Nord Pool Exchange. Main contents: (1) Description of the problem (2) Description of the Nordic power market (3) Development of relevant theories and models (4) Description of the data (5) Discussion of the results, the usefulness of the model (6) Results and discussion of further research	
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Trondheim 23.05.14

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Oppgavetekst/Problembeskrivelse
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4. Bedømmelse

Kandidatene skal ha *individuell* bedømmelse	☐
Kandidatene skal ha *felles* bedømmelse	☒

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The Effects of Implied Volatility on Forecasts of Realized Volatility in the Nordic Power Forward Market

Martin Opdal and Ole Henrik Birkelund*

May 23, 2014

Abstract

In this thesis we study implied and realized volatility in the Nordic power forward market. We first create an implied volatility index with a fixed time to maturity. We then specify several forecasting models in order to test the information content in implied volatility for forecasting. Our results show that the implied volatility index improves the daily, weekly and monthly forecasts. These results are consistent with previous research in other markets, notably WTI futures and S&P futures.

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1 Introduction

Understanding and managing risk is crucial for all participants involved in financial transactions. In order to price assets, hedge production or hedge financial positions, the risk characteristics need to be understood. The risk dynamics for electricity markets are different from other commodities. This is because there is yet to exist a technology that lets us economically store electricity. Therefore, mismatches in electricity demand and generation must be covered immediately, resulting in short spikes or troughs in prices and transient periods of high volatility. This non-storability makes understanding risk more important, but also increases complexity. Financially settled forwards and options on these forwards help market participants manage risk. They also create the opportunity of making models that describe and predict the market's expectation of future volatility.

Volatility, as implied from option prices, is a commonly used measure of the market's expectation of future risk and has been extensively studied, particularly for equities. Previous research shows that implied volatility (IV) indices provide better forecasts for volatility than traditional time series methods such as GARCH (Martens and Zein, 2004). Christensen and Prabhala (1998) show this for the VIX index for S&P500 volatility and Molnar et al. (2013) for WTI futures. However, Agnolucci (2009) found that a Component-GARCH model performs slightly better than IV in forecasting volatility for crude oil futures. This indicates that implied volatility for the power market could hold important information.

Since the liberalization of the Nordic power market, several studies have investigated volatility in the Nordic power forward market. Haugom et al. (2011b) compared forecasts of day-ahead volatility obtained from GARCH models with forecasts obtained with traditional time series models of realized volatility (RV). They found that the latter approach outperforms the GARCH framework. Haugom et al. (2011a) was the first paper to utilize high-frequency data to analyze the Nord Pool forward market and to apply known market measures to forecast future volatility. They created a simple Heterogeneous Autoregressive (HAR) model to forecast volatility and found that the inclusion of exogenous variables improved the forecast performance.

These papers are concerned with realized volatility only, and do not make any use of implied volatility. In fact, implied volatility from options on power forwards in the Nordic market has not yet been studied, but there is some indication that it is used by practitioners. In this paper a unique dataset on bid and ask prices of options from market makers allow us to calculate the implied volatility from options on forwards in the Nordic power forward market. Our goal is to create a risk measure from implied volatilities that captures information previously not available in the Nordic power forward market. Furthermore, by using well-known models such as the Black-Scholes option pricing formula, we put emphasis on practicality and applicability over methodological complexity to ensure this thesis' relevance for practitioners.

We create an implied volatility time series with a constant time to maturity constructed from the 1pos and the 2pos contracts. To test this *ex ante* risk measure we calculate realized volatility. Furthermore, we vary the way by which we calculate realized volatility to find the best sampling method. We find that the implied volatility on average is greater than realized volatility, and hence that there is evidence of a volatility risk premium in the Nordic power market.

This is, to the best of our knowledge, the first academically created IV-index for the Nordic power market. To test the proposition that IV contains information that can improve the predictive power of forecasting models we specify several Heterogeneous Autoregressive models (Corsi, 2009). The comparison of these models reveal that the inclusion of IV improves the forecasts.

The rest of this thesis is organized as follows. Section 2 describes derivatives trading in the Nordic power market and in section 3 we concentrate on general theory and methodology. Section 4 describes all information pertaining to data sampling and selection and section 5 describes the results. Finally, in section 6 we conclude.

2 The Nordic Power Market

Many countries have liberalized their power markets in the past 30 years and the Nordic countries are no exception. The deregulation of the power market resulted in competitive markets and sometimes large movements in spot prices. With prices fluctuating, a healthy and increasingly liquid derivatives market sprung from the need to control risk. Consequently, academic research studying the pricing of electricity derivatives also emerged, *inter alia* Vehvilainen (2002), Benth et al. (2007), Weron (2008) and Kiesel et al. (2009).

Norway and Sweden established the Nord Pool electricity and power market exchange in 1996, as the world's first multinational exchange for trading and clearing of financial power contracts. Clearing of standardized financially settled contracts was introduced in 1997, and standardized options on forward and futures contracts were introduced in 1999. Nord Pool Clearing was in 2008 acquired by Nasdaq OMX, and the exchange changed name to Nasdaq OMX Commodities Europe in 2010. Nord Pool remains in existence today as an independent exchange for spot electricity.

The Nasdaq OMX Commodities Europe exchange is open for trading on power derivatives between 08:00 and 15:30 (CET) and both the underlying forward and the option contracts are cleared within this time span. Options on forwards are mostly traded over-the-counter (OTC) at various brokerage firms, such as ICAP Energy, and trades are cleared the same day as long as they are submitted before the deadline of 15:30. Trading after the deadline is cleared the next day. Closing prices are fixed at a random time between 15:25 and 15:30. Forwards are available for daily, weekly, monthly, quarterly and yearly contracts.

A forward at the exchange is an obligation to buy or sell a predetermined amount of power at a given price with delivery each hour for the time covered by the forward. The minimum size of the contract is 1 MW and the minimum ticker is 0.01 EUR. In other words, the forward price in the Nordic power market represents the market's expectation for the average price over the delivery period plus a premium. The contracts are settled financially.

An option on a forward is the purchase or sale of the right to buy or sell a forward contract at a fixed put/call price, at some time in the future. The maturity of the power option is the Wednesday before delivery, 10 working days before the maturity of the underlying forward. The payoff is a function of the forward price only (Vehvilainen, 2002). Forwards and options on those forwards are standardized agreements, making comparisons possible without introducing unnecessary variables.

3 Literature and Methodology

This study is to the best of our knowledge the first academic investigation of implied volatility and its use in forecasting in the Nordic power forward market. However, many studies on other markets examine implied volatility.

Taylor and Xu (1997) find that there is significant incremental information in implied volatility when compared to ARCH forecasts on the DM/$ exchange rate. The results are confirmed out-of-sample.

Using a long time series and nonoverlapping, monthly data on the S&P100, Christensen and Prabhala (1998) find that implied volatility predicts future realized volatility better than past realized volatility. They use Black-Scholes implied volatilities and test the predictive power by running a regression of IV on RV. The results are robust to the addition of lagged implied volatilities as well as lagged realized volatilities. Christensen and Prabhala (1998) conclude that implied volatility subsumes the information in past RV.

Ederington and Guan (2002) studied a 10-year period of the S&P500 index futures comparing a large variety of differently weighted implied volatility measures to realized volatility using the same linear regression as Christensen and Prabhala (1998). They find a positive bias in implied volatility compared to realized volatility and suggest correcting for this by using an adjusted implied volatility measure in forecasts.

Martens and Zein (2004) use high-frequency data on the S&P500, YEN/USD and Light, Sweet Crude oil to test the forecasting ability of implied volatility compared to the time-series forecasts of ARFIMA and GARCH. In the latter test, implied volatility subsumes most of the forecasting information for all cases and a positive bias is found. The results obtained with the long-memory ARFIMA model show forecasts performing better than implied volatility forecasts, particularly on S&P500 and Crude Oil.

Lastly, for WTI futures, Molnar et al. (2013) used implied volatility with a HAR-RV model and found that daily and weekly forecasts were improved with the inclusion of implied volatility. For the same market, Agnolucci (2009) found that a Component-GARCH model performs slightly better than implied volatilities in forecasts, but he ultimately suggests incorporating IV-measures into forecasts. He does not find a significant bias in implied volatility measures.

These studies show the prevalence of implied volatility as an important and often used measure and input to forecasting models. It therefore motivates our choice of studying and explaining the dynamics of implied and realized volatility for electricity.[1]

[1] A comprehensive review of volatility modelling and forecasting is found in Taylor (2005).

3.1 Realized Volatility

For our study we create three measures of realized volatility. Firstly, we use the daily observed returns and the volatility of returns is denoted RV_{Daily}. Secondly, we use intradaily observations of frequency N to create RV_{Intra}, and lastly we include the overnight return to find a measure of realized volatility for the whole day, RV_{24h}. In section 5 we chose the method that best captures the volatility dynamics.

The theoretical foundation for using realized volatility is strong. Following the standard assumptions in financial theory, returns are assumed to be i.i.d[2] normally distributed with mean μ, variance σ^2, and following a brownian motion (Alexander, 2008a). Mean daily and intradaily returns are assumed to be zero. We assume returns to follow brownian motion, with sample path σ_t. The theory of quadratic variation (Karatzas and Shreve, 1991) then gives us the following:

$$\rho \lim_{N\to\infty} \left(\int_0^1 \sigma^2_{t+\tau} d\tau - \sum_{j=1}^{N} r^2_{t,j} \right) \to 0, \tag{1}$$

where $r_{t,j}$ is the intradaily return, measured at an intradaily frequency of N. Volatility is unobservable in the market, but the last term in equation 1 is understood to be the realized variance. We denote intradaily realized variance in the following way:

$$RVar_t = \sum_{j=1}^{N} r^2_{t,j}, \quad t = 1, \ldots, T. \tag{2}$$

Anderesen and Bollerslev (1998) showed that a well behaving estimator of volatility is realized volatility as measured by the square root of realized variance,

$$RV_{Intra} = \sqrt{RVar_t} \tag{3}$$

3.1.1 A 24-hour measure of volatility

In order to obtain an estimate of the volatility over the whole day, we use the method developed by Hansen and Lunde (2005) and used by Haugom et al.

[2]Independent and identically distributed.

(2013) to create RV_{24h}. The method finds the realized volatility as a weighted sum of the intradaily and overnight return by finding weights that minimize the squared error between the realized volatility and the true volatility.

Let or_t denote the overnight return between the last price on day t-1 and first price on day t, and $RVar_t$ as specified above. We then define the following measures:

$$\hat{\mu}_0 = \frac{1}{n}\sum_{t=1}^{n}(or_t^2 + RVar_t) \tag{4}$$

$$\hat{\mu}_1 = \frac{1}{n}\sum_{t=1}^{n} or_t^2 \tag{5}$$

$$\hat{\mu}_2 = \frac{1}{n}\sum_{t=1}^{n} RVar_t \tag{6}$$

$$\hat{\eta}_1^2 = Var(or_t^2) \tag{7}$$

$$\hat{\eta}_2^2 = Var(RVar_t) \tag{8}$$

$$\hat{\eta}_{12}^2 = Cov(or_t^2, RVar_t) \tag{9}$$

And a relative importance factor which is calculated the following way:

$$\hat{\varphi} = \frac{\hat{\mu}_2^2\hat{\eta}_1^2 - \hat{\mu}_1\hat{\mu}_2\hat{\eta}_{12}}{\hat{\mu}_2^2\hat{\eta}_1^2 + \hat{\mu}_1^2\hat{\eta}_2^2 - \hat{\mu}_1\hat{\mu}_2\hat{\eta}_{12}} \tag{10}$$

The optimal weights can then be found:

$$\hat{\omega}_1^* = (1-\hat{\varphi})\frac{\hat{\mu}_0}{\hat{\mu}_1} \quad and \quad \hat{\omega}_2^* = \hat{\varphi}\frac{\hat{\mu}_0}{\hat{\mu}_2} \tag{11}$$

In our model, 24 hour realized volatility for day t is then calculated by the following formula:

$$RV_{24h,t} = \sqrt{\hat{\omega}_1^* or_t^2 + \hat{\omega}_2^* RVar_t} \tag{12}$$

3.1.2 Sampling

Choosing the right sampling method and frequency is important for the validity of our estimates. We sample by extracting ticker prices prior to every minute as suggested by Wasserfallen and Zimmermann (1985) and discussed by Hansen and Lunde (2006). From equation 1 we see that to fully capture the information content in high frequency data, the sampling frequency should be as high as possible. On the other hand, higher sampling frequencies give biased measures of RV due to microstructure effects such as bid-ask bounce (Alexander, 2008b; Taylor, 2005). Andersen et al. (2001) suggests using 5 minute intervals, a frequency that has been used by many researchers in other markets (Molnar et al., 2013; Patton, 2011; Martens, 2002). To resolve the tradeoff between statistically high information content and microstructure problems we use a volatility signature plot as suggested by Anderson et al. (2000) and used by Bollerslev et al. (2008) and Haugom et al. (2013). It shows the average realized volatility such that

$$\overline{RV}^{(N)}_{t_0,T} = \frac{1}{T} \sum_{t=t_0}^{t_0+T} RV_t, \tag{13}$$

where N is the number of samples per day from equation 2, and T is the number of days. The plot is obtained by varying N. The highest number of N where the plot is flat, is the point where the RV measure is approximately free of microstructure bias (Andersen et al., 2000).

3.2 Implied Volatility

Soon after the introduction of the option pricing model of Black and Scholes (1973), and Merton (1973)[3] it was clear that the fomula could be reversed to calculate implied volatility (Latane and Rendleman, 1976). All of the input variables in the BSM model, except for volatility, are observable in the market. This makes it possible to calculate the volatility based on the current option price, current forward price, the strike price, the time to maturity and the risk free interest rate. Such a method has been used to create several implied volatility indices, most notably the VIX from the Chicago Board Options Exchange (CBOE) in 1993. However, the assumptions inherent in

[3]Hereafter called the BSM model.

the BSM model are dubious and lately different methods of finding implied volatility have been presented.

In 2003 the CBOE decided to change the method for calculating the VIX. The previous model, based on the BSM-IV, was replaced by model-free implied volatility developed by Britten-Jones and Neuberger (2000) for the VIX on the S&P500 stock index (CBOE, 2003).[4] This method makes the implied volatility independent of any option price model and calculates IV from the full set of available strikes for European puts and calls (Andersen and Bondarenko, 2007). Jiang and Tian (2005) generalized the method to include jumps and showed that model-free implied volatility subsumes all information contained in BSM implied volatilities and that it gives a more efficient forecast of future realized volatilities. Zhang et al. (2013) confirmed this with Monte Carlo simulations.

Andersen and Bondarenko (2007) provide the first comparison of model-free implied volatility and BSM implied volatility with a corridor implied volatility. This method benefits from not truncating the tails of the distribution as the model-free approach does when there are few far out/in-the-money options. They show that corridor implied volatility may be the best "market-based implied volatility measure for volatility prediction" and argue that this is because it has a strong link to the underlying volatility process.

In light of these recent developments, the choice of implied volatility model for our index then becomes a tradeoff between practicality and precision. Information content is indeed key, but our goal is to create a measure that is readily understood by practitioners and which fits their current models. Therefore, we choose to use BSM implied volatilities. This choice is supported by the fact that brokerages report BSM implied volatilities instead of more complex models that incorporate factors such as jumps or stochastic volatility.

3.2.1 Creating the implied volatility index

Options with different moneyness,[5] but with the same maturity will in practice give different implied volatilities. This runs contrary to the expectation of volatility being independent of strike price. Without further discussion of

[4]The old BSM implied volatility method is still in use, but with the ticker VXO for the S&P100 index.

[5]$Moneyness = \frac{F_0}{K}$

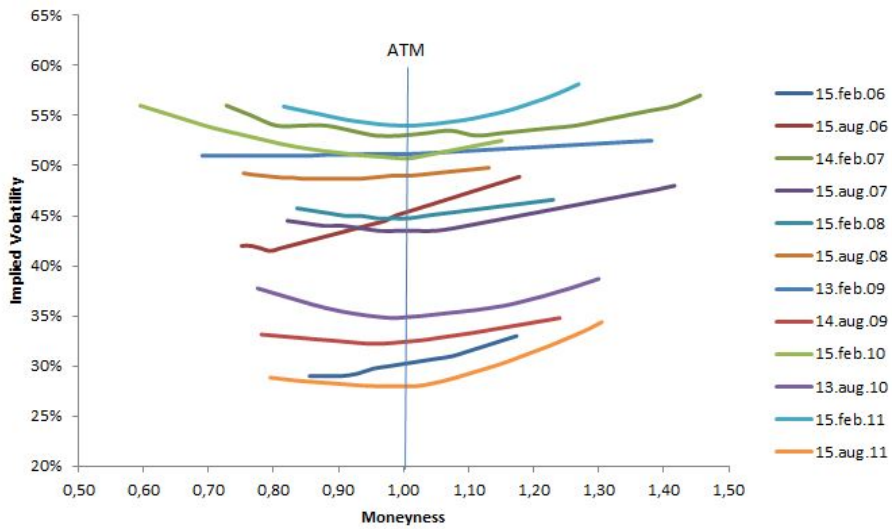


Figure 1: Illustration of volatility smile and its development throughout our sample

the sample period, figure 1 shows this for different dates in our data. Two factors should be highlighted; the concavity and the variability over time.

Firstly, we observe how the IV varies depending on the moneyness, it is concave and we call this concavity the smile effect (Taylor, 2005; Alexander, 2008c). The explanation for this effect varies, but some suggest transaction costs or traders including a risk premium for in/out-of-the-money options as possible reasons (Peña et al., 1999; Taylor, 2005). Our index should mimic the actual volatility and we therefore want to exclude the inherent risk premia in volatility smiles. Hence, we use at-the-money (ATM) option prices.

Many methods exist to find or use ATM option prices when an exact ATM option is not available and Taylor (2005) suggests that the most liquid option nearest ATM is a natural choice. As liquidity in the Nordic power option market is limited, we must use bid prices and therefore this method is not feasible. An alternative is to use weighting as suggested by Siriopoulos and Fassas (2009) and Ederington and Guan (2002). The IV for each day is then computed from bid prices of the two nearest out-of-the-money put options and the two nearest out-of-the-money call options. More options could be used in the weighting, but Ederington and Guan (2002) showed that this is not necessary. Hence, equation 14 describes our model for calculating the implied volatility for a given date.

$$IV = \frac{1}{M}(m_a IV_a + m_b IV_b + m_c IV_c + m_d IV_d), \tag{14}$$

where m_i is the moneyness of option i, with volatility IV_i and M is the sum of moneyness for all four options. Option a and b are put options with $m \leq 1$ while option c and d are call options with $m \geq 1$. All IV's are calculated on the same day with the same time to maturity. Hence this weighting is equal to the weighting in the traditional VIX methodology as described by Fleming et al. (1995). When the method in equation 14 is used for options in the front forward we get the 1pos implied volatility.

The second factor to notice in figure 1 is how the smile varies with time. This is because the risk factors in the market changes over time. To include this in a time series we propose to create an index, similar to the VIX, the IV_{Index}, with a constant time to maturity. To achieve this Taylor (2005) suggests creating term structures. Instead we follow Martens and Zein (2004) and adjust IV to the desired time horizon by using linear interpolation between options of different maturities. Therefore, for two options with maturities at T_1 and T_2 on day t, and with $T_1 < H < T_2$ we create an IV measure with time horizon H from equation 15.

$$IV_{t,H} = IV_{t,T_1} + \frac{H - T_1}{T_2 - T_1}(IV_{t,T_2} - IV_{t,T_1}) \tag{15}$$

This method of creating an IV-index is analogous to the previously mentioned original method for VIX on the S&P Index (Martens and Zein, 2004).[6] For our index we combine IV_{1pos} and IV_{2pos}, therefore T_1 and T_2 will be the maturity date of the 1pos and 2pos options at day t.

3.3 Forecasting volatility

In an effort to test if the IV-index adds predictive power to models of realized volatility, we specify a Heterogeneous Autoregressive model, the HAR-RV (Corsi, 2009). As shown by Fradkin (2007), the addition of implied volatility to HAR models almost always improves forecasts. Therefore, comparing several HAR models, with and without IV, is a suitable test for information content and the usefulness of our IV-index.

[6] The VIX-methodology has changed to use model free volatility. Interested readers are referred to page 388 in Taylor (2005).

The Heterogeneous Market Hypothesis developed by Müller et al. (1993) describes a world where motivations, actions and time-horizons differ among traders. The result of this is that the traders react to different components of volatility, a fact supported by empirical observations (Corsi, 2009). The HAR-RV model builds on this idea and creates a cascading model that includes different components of volatility.

Compared to methods like GARCH, the HAR-model is in its infancy of application, but empirical evidence point to robust replication of the stylized facts of volatility. In out-of-sample forecasts, Corsi (2009) showed that the HAR model outperforms short memory models[7] and performs similarly to an ARFIRMA(5,d,0) model, on USD/CHF, S&P500, and T-Bonds. Similar results are found on Nord Pool Forwards when HAR-RV is compared to FIGARCH and EWMA (Haugom et al., 2011b). For these reasons we prefer the simple HAR model over complicated fractional integration models as it presents an acceptable tradeoff between practicality and precision.

To specify the HAR-RV model we note the daily measure of volatility, $RV_t^{(d)}$. Weekly realized volatility is defined as the average RV over the past five observations:

$$RV_t^{(w)} = \frac{1}{5}\left(RV_t^{(d)} + RV_{t-1d}^{(d)} + \ldots + RV_{t-4d}^{(d)}\right), \tag{16}$$

and by extension, monthly realized volatility is the average over the past 22 days. We then get the HAR-RV model, where i represents the forecast horizon.[8]

$$\overline{RV}_{t+1,t+i}^{(i)} = \beta_0^{(i)} + \beta_1^{(i)} RV_t^{(d)} + \beta_2^{(i)} RV_t^{(w)} + \beta_3^{(i)} RV_t^{(m)} + \epsilon_{t+1} \qquad i \in [d, w, m] \tag{17}$$

This lag structure, (1, 5, 22), is equal to the one suggested by Corsi (2009) in his original paper and there is evidence that flexible lag lengths do not improve the forecasting abilities of the HAR model (Craioveanu and Hillebrand, 2010).

Haugom et al. (2011a) show that exogenous variables can improve the forecasting ability of the HAR-RV model on volatility of Forwards at Nord Pool. They suggest adding time-to-maturity to account for the Samuelson

[7] AR(1) and AR(3).

[8] The betas are different for the different forecast horizons in equation 18, 19 and 20 also, but the notation is omitted for presentation purposes.

effect (Samuelson, 1965), a measure of volume, as evidence point to it affecting volatility (e.g. Karpoff, 1987; Jones et al., 1994), and a dummy variable (FQ) for days with return in the first quartile to account for the leverage effect (Alexander, 2008b). Empirical studies, notably (French, 1980) and Haugom et al. (2011a), have found volatility to be greater on Mondays than on other weekdays. This effect is termed 'Monday effect' and is assumed to be caused by the fact that more information arrives over the weekend than between two consecutive days. We therefore include the weekdays as exogenous variables.[9] This gives us the HAR-RV-EX model:[10]

$$\begin{aligned} RV_{t+1} = \beta_0 + \beta_1 RV_t^{(d)} + \beta_2 RV_t^{(w)} + \beta_3 RV_t^{(m)} + \beta_5 Vol_t + \beta_6 TTM_t \\ + \beta_7 FQ_t + \beta_8 MON + \beta_9 TUE + \beta_{10} WED + \beta_{11} THU + \epsilon_{t+1} \end{aligned} \tag{18}$$

Molnar et al. (2013) also apply the HAR model, but to the U.S. Oil Market. They add both the oil volatility index as a proxy for implied volatility and various exogenous variables and find that the HAR-RV model is significantly improved when IV and EX-variables are included. To test if this is the case with our IV-index we specify a HAR model with IV (HAR-RV-IV) in equation 19 and a model with both IV and EX (HAR-RV-IV-EX) in equation 20.

$$RV_{t+1} = \beta_0 + \beta_1 RV_t^{(d)} + \beta_2 RV_t^{(w)} + \beta_3 RV_t^{(m)} + \beta_4 IV_t + \epsilon_{t+1} \tag{19}$$

$$\begin{aligned} RV_{t+1} = \beta_0 + \beta_1 RV_t^{(d)} + \beta_2 RV_t^{(w)} + \beta_3 RV_t^{(m)} + \beta_4 IV_t + \beta_5 Vol_t \\ + \beta_6 TTM_t + \beta_7 FQ_t + \beta_8 MON + \beta_9 TUE + \beta_{10} WED + \beta_{11} THU + \epsilon_{t+1} \end{aligned} \tag{20}$$

We deviate from Haugom et al. (2011a) in that we also include $RV_t^{(m)}$ in our forecasts, whereas they only include $RV_t^{(d)}$ and $RV_t^{(w)}$ in their basic HAR-RV model. Furthermore, we model the average realized volatility over

[9] The weekdays variables are not included for weekly and monthly forecasts.

[10] Other exogenous variables were considered but found irrelevant. The slope of the forward curve does not have any meaningful interpretation in the power market due to non-storability. Liquidity measures were also tested. The effective tick method (Goyenko et al., 2009) gave spurious results and the roll estimator (Roll, 1984) could not be used since the autocorrelation in price changes during the day was positive on more than 50% of the days.

the next week and month by estimating separate coefficients for the weekly and monthly models respectively. With these specifications we will be able to gauge the benefits of adding our IV measure to forecasting models.

4 Data

Data for implied volatility is collected from ICAP Energy, a commodity brokerage firm that provides OTC brokering and advisory services. It is presented to us in a refined form by Fred Espen Benth of the Center of Mathematics for Applications, University of Oslo. The raw data contains daily prices of options on forwards with different strikes for quarterly and yearly contracts. We use quarterly contracts in our study.[11]

The liquidity of options on forwards is low and it is possible to argue that there are too few trades in the market to successfully study IV. However, ICAP provides the bid and ask prices from the market makers and market participants trust these prices not to be affected by orders below 10 MW. Implied volatilities are calculated by ICAP from the BSM model and we use closing bid prices in our analysis. We create IV_{Index} with a constant time horizon from the 1pos and the 2pos contracts. These contracts have time to maturity T_1 and T_2 respectively, and the choice of H is then naturally the average number of working days in one quarter, 66.

Raw data containing continuously recorded ticker prices of forwards for trades performed in the opening hours of Nasdaq OMX is obtained from Montel. Equations 2 and 3 are used to calculate RV_{Intra} and RV_{Daily},[12] and equations 2 through 12 are used to calculate RV_{24h}. Days where trades are recorded outside of the opening hours are few and the return is treated as overnight return.[13]

Our estimate of realized volatility is based on prices from the nearest

[11] Previous studies find that options with longer time horizons provide the best predictive power for IV against RV (Taylor, 2005). However, we consider the yearly forward contracts to have too low liquidity to be efficiently studied using realized volatility.

[12] For RV_{Daily}, N in equation 2 is 1 and the return is the closing price.

[13] Special circumstances and late clearing explain these examples. The dates include: March 24, 2006, April 25, 2006, May 2, 2006, May 29, 2006, June 23, 2006, July 27, 2006, August 23, 2006, October 30, 2006, December 4, 2006, January 2, 2007, June 29, 2007, August 28, 2007, November 22, 2007, February 28, 2008, March 6, 2008, June 10, 2008, August 28, 2008, December 3, 2008, December 5, 2008, December 10, 2008, March 6, 2009, May 12, 2009, May 14, 2009, July 1, 2009, and December 28, 2009.

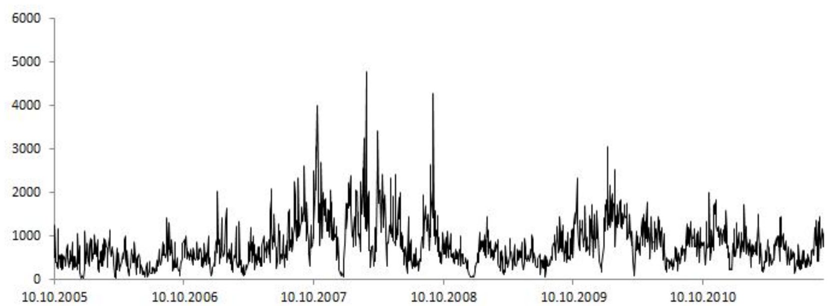


Figure 2: Development of volume per day throughouht the sample

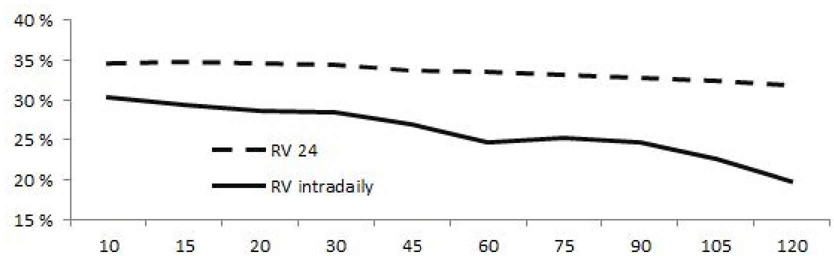


Figure 3: Volatility signature plot

quarter, the 1pos contract. In accordance with Martens and Zein (2004) we roll over to the second nearest contract when the volume of the 2pos contract surpasses that of the 1pos contract. This happens as the contract is close to maturity, and therefore we check for occurrences 10 working days before delivery. At contract rollover we record return as the change in price for the new contract.

Figure 2 shows the volume per day in our sample, an exogenous variable in equations 18 and 20. On average 823 MW is traded each day, distributed on 204 trades per day, a trade every 2 min and 11 seconds. At this level of liquidity the impact of microstructure noise is low. This can be observed in the volatility signature plot in figure 3 on page 15. The expected parabolic decrease in volatility for longer tick intervals is not observed and the plot fails to give a clear indication of the best sampling frequency.

Lien et al. (2012) chose a 30 minute sampling interval when studying the electricity forward market. We see from the volatility signature plot that the volatility in our data is relatively stable at this frequency. We therefore use a sampling frequency of 30 minutes in our study.

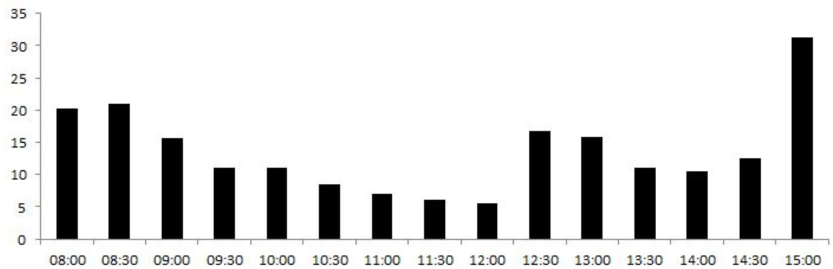


Figure 4: Average number of trades per half hour

Figure 5: Days with return in the first quartile

The choice of this interval in realized volatility calculations has ramifications for what days that should be removed from our sample. With 30 minute intervals, we must sample 15 ticks per day. Figure 4 shows that the trades are not evenly distributed during the day. Hence, to avoid imposing a negative bias in our measurements, we remove days with fewer than 20 trades. Following these adjustments, our sample starts October 10, 2005 and ends September 14, 2011, for a total of 1357 daily observations. Nine outliers or days with low liquidity are removed[14] which leaves us with 1348 days for the empirical study.

Lastly we present the exogenous variable, FQ in figure 5. It shows days with returns in the first quartile. There are clear signs of clustering, as the bars are not evenly distributed throughout the samle. This makes it relevant to include in the HAR model.

[14]The dates include: December 23, 2005, December 28-30, 2005, June 23, 2006, March 26, 2007, January 2, 2008, June 19, 2008, July 23, 2009.

5 Results

5.1 Descriptive statistics

In figure 6 on page 18 we graph the annualized daily observations of realized volatilities under the different sampling schemes. In general we find that volatility varies significantly. Days with volatility of up to 200% illustrate significant uncertainty in the market. Such extreme events are to be expected in power markets where disruption at one large facility will induce large uncertainties about future prices.

In order to find an appropriate measure of realized volatility, we select the sampling scheme that best captures the underlying volatility dynamic without introducing too much noise. Comparing figure 6a with 6b and 6c we observe that the daily sampling frequency gives a noisy measure of volatility. We find this to be a compelling reason not to use RV_{Daily} in the rest of this study. Furthermore, RV_{24H} is on average larger compared to the intradaily measure. We attribute this to the fact that RV_{24H} captures the full day and therefore contains more information than RV_{Intra}. This becomes clear when figures 6b and 6c are compared. These factors indicate that the full day measure from high frequency data best captures the true volatility dynamics in accordance with Hansen and Lunde (2005) and Anderesen and Bollerslev (1998). Hence, whenever we refer to realized volatility, RV_{24H} is the sampling method we use.

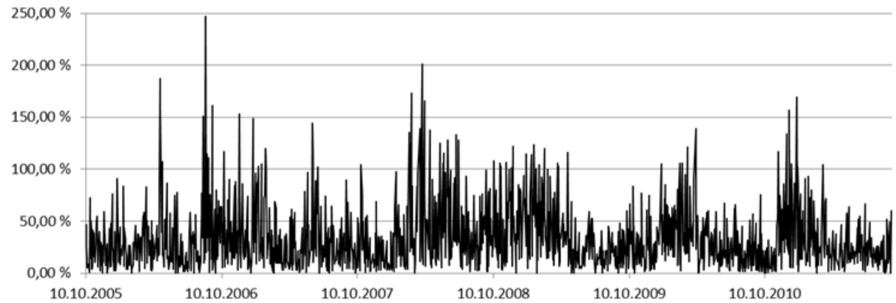
Table 1 on page 19 contains descriptive statistics for our IV and RV measures. Realized volatility is on average lower than the average implied volatility. IV_{Index} is on average 42%, whereas we find an average realized volatility of 37% for the daily values. In general this suggest that there is a risk premium in the option contract prices and the result is similar to Ederington and Guan's findings for S&P 500 futures (2002).

Figure 7 reports the IV-index over the full sample. Note that it is susceptible to shocks as new information arrives in the market. This should indicate that it contains information relevant for forecasts.

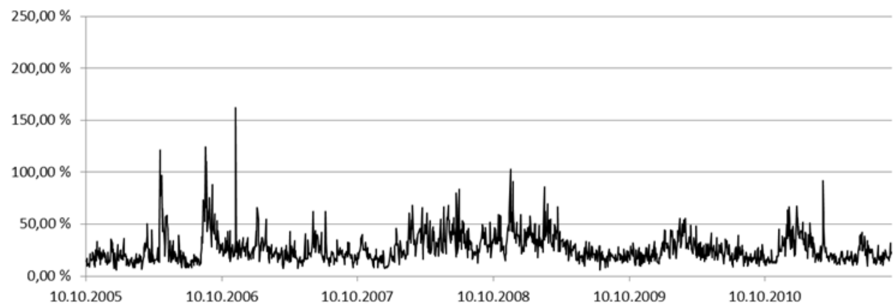
5.2 Volatility forecasts

5.2.1 In-Sample estimates

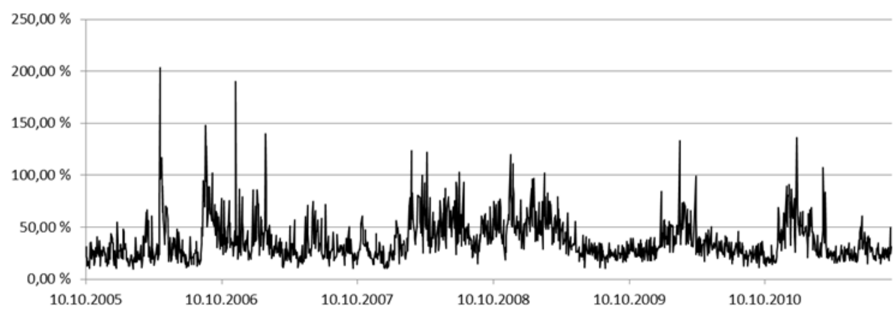
In this section we present the in-sample results of the HAR-RV model and equation 17, 18, 19, and 20. The results are found in table 2, 3 and 4.



(a) Daily observations of RV_{Daily}



(b) Daily observations of RV_{Intra}



(c) Daily observations of RV_{24h}

Figure 6: Daily observations for realized volatility

Table 1: Descriptive statistics for implied and realized volatility

	IV	RV_{24H}
	IV_{Index}	Daily
Mean	0.4178	0.3729
Median	0.4115	0.3187
Maximum	0.6734	2.0341
Minimum	0.2791	0.1009
Std. Dev.	0.0759	0.2016
Skewness	0.4449	2.1030
Kurtosis	2.6689	11.1835
AC(1)	0.9993	0.8929
AC(5)	0.9945	0.8562
AC(10)	0.9899	0.7878
AC(30)	0.9100	0.7457
Observations	1348	1348

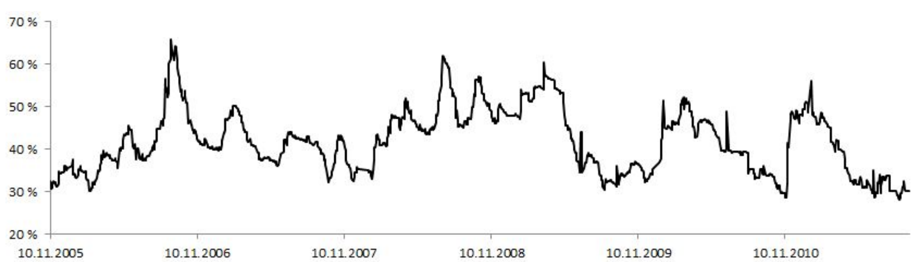


Figure 7: IV_{Index}

Table 2: Daily forecast. The table shows the OSL-regression of RV_{t+1} on $RV_t^{(d)}$, $RV_t^{(w)}$, $RV_t^{(m)}$, IV and exogenous variables for daily forecasts. TTM and Volume are both divided by 10 000 for readability of the coefficients. The sample includes October 10, 2005 through September 14, 2011. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. Robust Newey and West (1986) t-values are used.

	HAR-RV	HAR-RV-IV	HAR-RV-EX	HAR-RV-IV-EX
β_0	0.0538***	-0.0491*	-0.0385***	-0.1085***
$\beta_{1-RV_t^d}$	0.2509***	0.2480***	0.2642***	0.2629***
$\beta_{2-RV_t^w}$	0.4382***	0.4003***	0.3566***	0.3299***
$\beta_{3-RV_t^m}$	0.1666**	-0.0125	0.2366***	0.1061
β_{4-IV_t}	-	0.4425***	-	0.3168**
β_{5-Vol_t}	-	-	0.7041***	0.6750***
β_{6-TTM_t}	-	-	-0.1726	-0.2272
β_{7-FQ_t}	-	-	0.0466***	0.0463***
β_{8-Mon}	-	-	0.1044***	0.1048***
β_{9-Tue}	-	-	0.0064	0.0076
β_{10-Wed}	-	-	0.0162*	0.0178*
β_{11-Thu}	-	-	0.0160	0.0179
Adj. R^2	0.4072	0.4147	0.4935	0.4971

Table 3: Weekly forecast. The table shows the OSL-regression of RV_{t+1} on $RV_t^{(d)}$, $RV_t^{(w)}$, $RV_t^{(m)}$, IV and exogenous variables for weekly forecasts. TTM and Volume are both divided by 10 000 for readability of the coefficients. The sample includes October 10, 2005 through September 14, 2011. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. Robust Newey and West (1986) t-values are used.

	HAR-RV	HAR-RV-IV	HAR-RV-EX	HAR-RV-IV-EX
β_0	0.0818***	-0.0569	0.0444**	-0.0725*
$\beta_{1-RV_t^d}$	0.1716***	0.1676***	0.1496***	0.1482***
$\beta_{2-RV_t^w}$	0.3810***	0.3305***	0.3548***	0.3087***
$\beta_{3-RV_t^m}$	0.2282**	-0.0135	0.2718***	0.0518
β_{4-IV_t}	-	0.5966***	-	0.5354***
β_{5-Vol}	-	-	0.4793***	0.4325***
β_{6-TTM_t}	-	-	-0.2512	-0.3439
β_{7-FQ_t}	-	-	0.0326***	0.0319***
Adj. R^2	0.5122	0.5353	0.5471	0.5654

Table 4: Monthly forecast. The table shows the OSL-regression of RV_{t+1} on $RV_t^{(d)}$, $RV_t^{(w)}$, $RV_t^{(m)}$, IV and exogenous variables for monthly. TTM and Volume are both divided by 10 000 for readability of the coefficients. The sample includes October 10, 2005 through September 14, 2011. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. Robust Newey and West (1986) t-values are used.

	HAR-RV	HAR-RV-IV	HAR-RV-EX	HAR-RV-IV-EX
β_0	0.1611***	0.0407	0.1327***	-0.0006
$\beta_{1-RV_t^d}$	0.0869***	0.0827***	0.0730***	0.0714***
$\beta_{2-RV_t^w}$	0.2922***	0.2367***	0.2743***	0.2217***
$\beta_{3-RV_t^m}$	0.1898**	-0.0730	0.2281**	-0.0227
β_{4-IV_t}	-	0.6492***	-	0.6103***
β_{5-Vol_t}	-	-	0.3697***	0.3164***
β_{6-TTM_t}	-	-	-0.1784	-0.2841
β_{7-FQ_t}	-	-	0.0076	0.0067
Adj. R^2	0.3880	0.4289	0.4099	0.4454

Firstly, from the results it is clear that all coefficients of past realized volatility in the HAR-RV model are significant. This is not surprising, but traders in the Nordic power forward market seemingly put more weight on the previous week's volatility than the previous day's volatility.[15] When the forecasting horizon increases, more weight is on the past month's volatility. Also, across the models and for all time horizons $RV_t^{(d)}$ and $RV_t^{(w)}$ remain significant, suggesting their importance in forecasting.

Secondly we observe that the in-sample tests of the HAR models reveal that the inclusion of IV, EX or both increases the explanatory power of the models (adj. R^2). This is true for all horizons. Furthermore, the results reveal that IV adds little explanatory power for the daily horizon, an increase of 0.75 percentage points in adj. R^2, but for the weekly and monthly horizons it increase adj. R^2 by 2.3 and 4.1 percentage points respectively. The opposite is true for the addition of exogenous variables. We find that exogenous variables increases the adj. R^2 with 8.6 percentage points on the daily horizon but only an increase of 3.5 and 2.2 percentage points for the weekly and monthly models respectively. However, for all horizons, the HAR-RV-IV-EX-model exhibits the best fit. In sum we find that the weekly models have have higher adj. R^2 than the daily and monthly models, supporting the results found in (Molnar et al., 2013). The inclusion of IV is important for longer horizons, which is expected since the IV index measures the expectation of volatility over the next quarter. The exogenous variables are more important for the shorter horizons.

In the HAR-RV-IV and HAR-RV-IV-EX models our implied volatility index has a significant impact on future realized volatility at either 1% or 5% level. This is expected as implied volatility measures the markets expectation for volatility over a given horizon. We find the estimated coefficient is larger for longer horizons. However, the inclusion of IV seems to negate the need for the monthly realized volatility variable, $RV_t^{(m)}$. This finding is of some importance.[16] It shows that the IV_{Index} does a better job of predicting the long term component of volatility compared to the past month's volatility. This is true for all forecast horizons tested and with or without the exogenous

[15] This was also found by Haugom et al. (2011a).

[16] A heuristic for multicolllinearity is that if the square of the correlation between two variables is higher than the R^2 of the regression, then multicollinearity is in effect. In our sample the average realized volatility for the past month, $RV_t^{(m)}$, and IV_{Index} are correlated with $\rho = 0.839$, indicating multicollinearity in the regression. Our results indicate that IV should be chosen over $RV_t^{(m)}$.

variables.

Looking at the exogenous variables in both the HAR-RV-EX and HAR-RV-IV-EX models we find that there is a clear and positive relationship between volume and volatility ($\hat{\beta}_{6-Vol_t} > 0$) even at 1% significance level. However, as expected, this effect decreases as the forecasting horizon increases; it starts at 0.6531 and 0.6471 for daily horizon and is reduced to 0.2548 and 0.2475 for monthly horizon in the HAR-RV-EX and HAR-RV-IV-EX models respectively.

Large negative returns increase the realized volatility of the following day ($\hat{\beta}_{7-FQ_t} > 0$) in both daily and weekly forecasts. This confirms the findings of Haugom et al. (2011a) which found a leverage effect for the Nordic power forward market. The effect of returns in the first quartile on the following month's forecast is however not significant. This indicates that the leverage effect is only observable in the short run.

No clear Samuelson effect (Samuelson, 1965) is found for any of the horizons. This should not be surprising given that we cannot find a clear relationship between volatility and time to maturity when they are graphed together. Similar to Haugom et al. (2011a) we find evidence of a Monday effect. $\hat{\beta}_{8-Mon} > 0$ and its effect is significant at the 1% level. We can also observe a higher volatility on Wednesdays at 10% significance level. This is probably due to the fact that the forward contracts are settled on Wednesdays.

The in-sample results indicate that the inclusion of IV does indeed improve the forecasting power of the HAR model, albeit to a lesser extent than the inclusion of exogenous variables. We now move to formally test this out-of-sample.

5.2.2 Out-of-Sample Tests

The purpose of out-of-sample testing is to compare the performance of the models when the actual values are not known in advance. This form of testing is more realistic than in-sample estimation, as it better captures the information available at the time the forecast is being made. The choice of sample size may affect the results substantially. A large sample will make the model robust, but at the same time the model will be less sensitive to regime changes.

In table 5 we report the mean squared error (MSE) of different sized rolling-windows. Based on this test, the three year and four year window

Table 5: Test of mean squared error in out-of-sample forecast of daily realized volatility from different window sizes. * indicates the best performing model.

Window Size	HAR-RV	HAR-RV-IV
250	0.0200	0.0198
500	0.0194	0.0193
750*	0.0135	0.0132
1000*	0.0135	0.0132

sizes perform the best. In the choice between the two, we choose the smaller window, the 750-day window. This preserves a higher degree of reactiveness to regime changes and gives 250 more out-of-sample forecasts compared to using a sample size of 1000 days. Therefore, for the out-of-sample tests we construct daily predictions for all models at the different time horizons using a 750-day rolling window. In table 6 we present the mean average error (MAE), the MSE and the root mean squared error (RMSE) for the models out-of-sample.

The conclusions that can be drawn from the error measures in table 6 are similar to our in-sample findings. For the daily time horizons the addition of IV to the HAR-RV model does improve the out-of-sample performance, but to a much lesser extent than for the longer forecasting horizons. Taking MAE as an example, the HAR-RV model improves from 0.0813 to 0.0795 for daily forecasts, a 2.2% improvement, when the HAR-RV-IV model is used. This compares to an improvement of 6.8%, from 0.0684 to 0.0638, for the monthly forecasts.

We find that the largest improvement in out-of-sample performance for daily forecasts comes with the inclusion of the exogenous variables. However, for all error measures, except MAE on daily forecasts, we find that the HAR-RV-EX-IV model produces the best forecast. This is consistent with our findings in-sample and it shows that the IV-index contains information that improves forecasts of volatility.

When the out-of-sample tests are compared to a similar model on the oil-market we find that IV from electricity options improves a HAR model more than IV on WTI futures (Molnar et al., 2013). Comparing the out-of-sample improvements in MAE and MSE of Molnar et al. (2013) HAR-RV and HAR-RV-IV with our out-of-sample MSE and MAE improvements, we

Table 6: Out-of-sample model evaluation from MAE, MSE and RMSE using a 750 day rolling window. * indicates the best performing model.

	HAR-RV	HAR-RV-IV	HAR-RV-EX	HAR-RV-IV-EX
Daily				
MAE	0.0813	0.0795	0.0703*	0.0705
MSE	0.0135	0.0132	0.0113*	0.0113*
RMSE	0.1164	0.1150	0.1065	0.1063*
Weekly				
MAE	0.0597	0.0553	0.0546	0.0514*
MSE	0.0065	0.0060	0.0058	0.0054*
RMSE	0.0809	0.0777	0.0762	0.0738*
Monthly				
MAE	0.0684	0.0638	0.0624	0.0586*
MSE	0.0073	0.0066	0.0066	0.0059*
RMSE	0.0853	0.0811	0.0811	0.0770*

Table 7: Out-of-sample model evaluation from the Mincer and Zarnowitz (1969) regression using a 750 day rolling window. Coefficients close to one indicates the best performing model.

	Daily	Weekly	Monthly
HAR-RV vs. HAR-RV-IV			
$\beta_{0-Intercept}$	0.0152	0.0206	0.0549
$\beta_{1-HAR-RV}$	-0.2044	-0.1996	-0.7655
$\beta_{2-HAR-RV-IV}$	1.1482	1.1151	1.5403
HAR-RV-EX vs. HAR-RV-IV-EX			
$\beta_{0-Intercept}$	0.0324	0.0273	0.0536
$\beta_{1-HAR-RV-EX}$	0.2071	0.0104	-0.4052
$\beta_{2-HAR-RV-IV-EX}$	0.7076	0.9018	1.1961

find that IV improves the HAR model more than in the oil market. The same effect is found in a comparison of HAR-RV-EX and HAR-RV-IV-EX. Hence, this indicates that IV in the Nordic power market is more important for forecasting volatility than IV on WTI futures is for forecasting volatility in the oil market.

Lastly we evaluate the predictive performance of the different models against each other using the regression shown in equation 21 as suggested by Mincer and Zarnowitz (1969). The results are shown in table 7.

$$RV_{t+1} = \alpha + \beta_1 Model1_t + \beta_2 Model2_t + \varepsilon_{t+1} \tag{21}$$

The Mincer-Zarnowitz regressions confirm that the models with implied volatility perform better than the those without our IV_{Index}. This is true for all forecasting horizons and it strengthens our conclusion of information content in the IV-index.

6 Conclusion

With the deregulation of the Nordic power market, risk management became more important. In the ensuing years, several studies have evaluated different forecasting methods for volatility, but none of these papers have made use of implied volatility from options. This is the first paper to calculate an implied volatility index for forwards on the Nordic Power Market and to test its predictive power.

First, based on well-known theories and methods, we construct an IV_{Index} from a unique dataset on option prices. This index is included in a HAR model as described by Corsi (2009) along with other exogenous variables.

Our results show that implied volatility for all models and forecasting horizons has a significant impact on future realized volatility. Furthermore, we show that the IV_{Index} does a better job of predicting the long term component of volatility compared to the past month's volatility. This is true for all forecast horizons tested and with or without the exogenous variables.

Our results confirm those of Haugom et al. (2011a) in that exogenous variables improve the forecasting ability of the HAR model on forwards at the Nord Pool Exchange. This effect is reduced for longer forecasting horizons. Our inclusion of IV improves the adjusted R^2 for all horizons, but this effect is larger for longer forecasting horizons. However, for all horizons, the HAR-RV-IV-EX-model exhibits the highest adjusted R^2. This is formally tested with a rolling window out-of-sample.

The out-of-sample tests confirm the findings in-sample. IV improves the predictions of the HAR model, and the improvement is larger for longer forecasting horizons. The Mincer and Zarnowitz (1969) regressions also reveal that HAR-RV-IV and HAR-RV-IV-EX outperform HAR-RV and HAR-RV-EX respectively. These findings are similar to previous studies on the electricity market (Haugom et al., 2011a) and on WTI futures (Molnar et al., 2013). However, we find indications that the IV from options at the Nordic power market improves the volatility forecasts more than IV from options on WTI futures.

The IV-index improves forecasts of future volatility, and could be used as input for pricing of other derivatives. Moreover, many power companies hedge part of their production, which provides another use for our index. Lastly, traders in the option market can use it to benchmark option prices in a market with low liquidity.

Further research could focus on dividing the realized volatility into a continuous and a jump component and test the model against traditional time series forecasts. Several modifications to the construction of the IV-index can also be made, where using a midway range of bid and ask prices for IV's or to calculate IV from a different model seem the most relevant.

Acknowledgements

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