HSC Research Report

HSC/13/08

Revisiting the relationship between spot and futures prices in the Nord Pool electricity market

Rafał Weron*
Michał Zator*

* Institute of Organization and Management, Wrocław University of Technology, Poland

Hugo Steinhaus Center
Wrocław University of Technology
Wyb. Wyspiańskiego 27, 50-370 Wrocław, Poland
http://www.im.pwr.wroc.pl/~hugo/

Revisiting the relationship between spot and futures prices in the Nord Pool electricity market

Rafał Weron[a], Michał Zator[a]

[a]*Institute of Organization and Management, Wrocław University of Technology, Wrocław, Poland*

Abstract

This work discusses potential pitfalls of applying linear regression models for explaining the relationship between spot and futures prices in electricity markets. In particular, the bias coming from the simultaneity problem, the effect of correlated measurement errors and the impact of seasonality on the regression results. Studying a 13-year long (1998-2010) price series of spot and futures prices at Nord Pool and employing regression models with GARCH residuals, we show that the impact of the water reservoir level on the risk premium is positive, which is to be expected, but contradicts the results of Botterud et al. (2010). We also show that after taking into account the seasonality of the water level, the storage cost theory proposed by Botterud et al. (2010) to explain the behavior of convenience yield has only limited support in the data.

Keywords: Electricity market, Spot and futures prices, Risk premium, Convenience yield

1. Introduction

The Nordic commodity market for electricity, known as Nord Pool, was established in 1992 as a consequence of the Norwegian energy act of 1991 that formally paved the way for deregulation. In the years to follow Sweden (1996), Finland (1998) and Denmark (2000) joined what became the world's first international power exchange. In 2002 the physical electricity market *Elspot* was separated from the derivatives market and renamed Nord Pool Spot. The last few years saw the Baltic states join Nord Pool Spot. As of 2012 over 70% of the total power consumption in the Nordic-Baltic region is traded in the spot market, a fraction that has steadily been growing since the inception of the exchange in the 1990s (Nord Pool Spot, 2013). In 2010 the financial derivatives market Nord Pool, also known as *Eltermin*, changed its name to NASDAQ OMX Commodities Europe after an acquisition by NASDAQ OMX. In this market a range of Nordic power derivatives are being traded: monthly, quarterly and annual forwards, daily and weekly futures, options and contracts for difference. However, the product range is much wider now and includes Dutch, German and UK power futures and forwards, UK Natural Gas futures and carbon products (EUA, CER). The Nordic *Eltermin* market has been highly successful, with churn ratios – the number of times a product is traded above its physical consumption – between 4 and 7 in the last decade (NASDAQ OMX, 2012; Ofgem, 2009).

Email addresses: `rafal.weron@pwr.wroc.pl` (Rafał Weron), `michal.zator@gmail.com` (Michał Zator)

October 1, 2013

Yet regardless of this commercial success it is not clear that the forward market is operating efficiently. Christensen et al. (2007) report that significant forward premia existed at Nord Pool in the period 2003-2006 and that they were related both to spot market volatility and abuse of market power and manipulation in the spot and forward markets by one of the dominant producers in Western Denmark. In a study focusing on the Nord Pool *Eltermin* market, Kristiansen (2007) finds inefficiencies in the pricing of synthetic seasonal contracts constructed by monthly contracts. Also Gjolberg and Brattested (2011) find evidence of market inefficiency. Studying Nord Pool data in the period 1995-2008 they reach a conclusion that the differences between futures prices and subsequent spot prices are very significant and their high magnitude can hardly be explained by the level of risk. Furthermore, Redl and Bunn (2013) argue that while forward markets in general promote market completeness, facilitate risk management and induce greater competitive behavior in the spot markets, the transaction costs (including premia) that prevail in the markets may well eliminate some of these benefits in practice.

It is therefore important to be able to identify and estimate the components of the premia implied by forward electricity prices. However, in spite of an increasing amount of literature (see also Benth et al., 2008b; Bessembinder and Lemmon, 2002; Bunn and Chen, 2013; Diko et al., 2006; Douglas and Popova, 2008; Handika and Trueck, 2013; Haugom and Ullrich, 2012; Huisman and Kilic, 2012; Janczura, 2013; Longstaff and Wang, 2004; Karakatsani and Bunn, 2005; Kolos and Ronn, 2008; Redl et al., 2009; Ronn and Wimschulte, 2009; Weron, 2008), this topic remains a challenging and relatively unresolved area of research. Much of this has to do with the confusion around the terminology in published research (more details in the next Section). The terms *risk premium*, *forward premium*, *forward risk premium* and *market price of risk* are not uniquely defined and is some cases used interchangeably. Furthermore, some authors analyze *ex-post* (or *realized*) premia, others construct expectations of the spot price to compute *ex-ante* premia. While being conceptually attractive, the latter are highly dependent on the subjective choice of a model for the spot price, and therefore tend to be less comparable between different studies. Finally, different authors use different datasets, not only in terms of the generation stack and the power market where the data originates from, but – more importantly – also in terms of the time scale considered: short-term (days) vs. mid-term (weeks, months) forward prices.

In this paper we focus on ex-post (realized) risk premia in the Nord Pool market. We recover them from the prices of weekly futures contracts of maturities ranging from 1 to 6 weeks. Hence, as in Botterud et al. (2010), Gjolberg and Brattested (2011) or Lucia and Torro (2011), the time scale used is weekly. Overall, the sample comprises 679 weekly data points in the 13-year long period: January 1998 – December 2010. When analyzing Nord Pool data we should bear in mind two things. First, this is a hydro-dominated market with roughly 50% of the total generation capacity coming from this renewable source. In Norway alone the share of hydropower exceeds 95%. The precipitation in the mountains and the filling of the water reservoirs during the Spring flood are therefore a crucial factor for the functioning of the Nord Pool market and for explaining the relationship between futures and spot prices (Torro, 2009; Weron, 2008). Second, the Nord Pool market is characterized by significant seasonal variations in weather conditions (including water inflow) and in consumption. We pay special attention to the analysis of these seasonal effects and their influence on risk premia.

The contribution of our paper is twofold. First, we point out some problems with the risk premium model proposed by Botterud et al. (2010) and show that after they are taken care of, the observed relation of the water level and the risk premium is actually of opposite sign. We emphasize potential pitfalls of making no distinction between ex-ante and ex-post risk premia. We also analyze the convenience yield model proposed by these authors and show that existing evidence gives less unambiguous support to the storage cost theory than initially claimed by the authors. Second, we revisit the Nord Pool market with a longer, more recent 13-year dataset (1998-2010), extending the former study by four years, and employ GARCH components in the regression models for the risk premium and the convenience yield. We show that the latter approach leads to a better description of the studied phenomenon.

The remainder of the article is organized as follows. In Section 2 we discuss the spot-forward price relationship and the concepts of the risk premium and the convenience yield. We also review the literature and emphasize the similarities and differences between the studies and the terminology used. In Section 3 we comment on the pitfalls of regression analysis and discuss possible ways to avoid them. In Section 4 we describe the conducted empirical study, compare our results with those of Botterud et al. (2010) and provide evidence in favor of the regression models with GARCH residuals for the risk premium. Finally, in Section 5 we wrap up the results and conclude.

2. Risk premia in electricity markets

2.1. Definitions of the risk premium

For commodities, the relationship between spot and forward prices (and between prices of futures or forward contracts with different maturities) is often explained in terms of the *convenience yield*, an approach dating back to Kaldor (1939). The convenience yield is defined as the premium to a holder of a physical commodity as opposed to a futures or forward contract written on it (see e.g. Geman, 2005; Weron, 2006). However, electricity is a ‘flow’ rather than a ‘stock’ commodity. It is produced and consumed continuously and is essentially non-storable, at least not economically. So does the notion of the convenience yield make sense in the context of electricity? Can we quantify the benefit from ‘holding’ electricity, not to mention the storage cost? As there is no consensus on this issue in the literature (we will return to this discussion in Section 2.3) let us now focus on the second economic theory, which considers equilibrium relationships between futures prices and expected spot prices. Within this approach, which can be traced back to Keynes (1930), the forward price is viewed as being determined as the expected spot price plus an *ex-ante risk premium*. In other words, the ex-ante risk premium is the difference between the spot price forecast, which is the best estimate of the going rate of commodity (e.g. electricity) at some specific time in the future, and the forward price, i.e. the actual price a trader is prepared to pay today for delivery of this commodity in the future (Botterud et al., 2010; Diko et al., 2006; Hirshleifer, 1989; Janczura, 2013; Pindyck, 2001; Weron, 2006, 2008):

$$\mathrm{RP}^*_{t,T} = \ln\left\{\mathbb{E}_t(S_{t+T})\right\} - \ln(F_{t,T}) = \ln\left\{\frac{\mathbb{E}_t(S_{t+T})}{F_{t,T}}\right\}, \tag{1}$$

where $\mathbb{E}_t(S_{t+T})$ is a forecast made today (time t) regarding the the spot price at a future date $(t + T)$ and $F_{t,T}$ is the price of a futures (or forward) contract quoted today with delivery period starting at this future date. Note that the above definition of the risk premium as a log difference and the notation for the forward price is used here for consistency with the paper of Botterud et al. (2010). However, it is more common in the literature to consider a simple difference and the second subscript in $F_{t,T}$ to define the delivery date, not the time to delivery. Note also that the expectation $\mathbb{E}_t(S_{t+T})$ in eqn. (1) is taken at time t with respect to the 'real-world' or 'risky' probability measure, say $\mathcal{P}$, and concerns the spot price S_{t+T} at a future date $(t + T)$. On the other hand, the futures price $F_{t,T}$ is the expectation made also at time t of the spot price S_{t+T} but with respect to the 'risk-neutral' or 'risk-adjusted' measure, say $\mathcal{P}^\lambda$ (see Weron, 2008); more formally: $F_{t,T} = \mathbb{E}_t^\lambda(S_{t+T})$.

This consideration leads us to the so-called *market price of risk*, a notion popular in the financial mathematics literature (Benth et al., 2008a,b; Geman, 2005; Janczura, 2013; Kolos and Ronn, 2008; Ronn and Wimschulte, 2009; Weron, 2006, 2008). The market price of risk can be seen as a drift adjustment (a constant – λ, a deterministic function of time – λ_t) in the stochastic differential equation (SDE) governing the spot price dynamics to reflect how investors are compensated for bearing risk when holding the spot, i.e. the drift adjustment when moving from the original 'risky' probability measure $\mathcal{P}$ to the 'risk-neutral' measure $\mathcal{P}^\lambda$, like in the Black-Scholes-Merton model. By virtue of the Girsanov theorem there exists a probability measure $\mathcal{P}^\lambda$, equivalent to the original measure $\mathcal{P}$, such that the process

$$B_t^\lambda \equiv B_t + \int_0^t \lambda(s)ds = B_t + \lambda_t, \tag{2}$$

is a Brownian motion (i.e. a Wiener process) under $\mathcal{P}^\lambda$, see e.g. Musiela and Rutkowski (2005). Using Itô calculus this change of measure can be applied to different kinds of SDEs, including mean reverting processes which are commonly used for modeling commodity prices. Although different in value, a constant market price of risk $\lambda_t \equiv \lambda t$ defined above is of the same sign as the risk premium in eqn. (1).

While the ex-ante risk premium is often the main object of interest, there is a difficulty in quantifying it. This difficulty stems from the fact that in empirical applications $\mathbb{E}_t(S_{t+T})$ is not a well defined object. The expected value operates on a random variable (here: S_{t+T}) defined on a specific probability space $(\Omega, \mathcal{F}, \mathcal{P})$. Just by analyzing one historical price trajectory it is hard to gain any consensus on what actually is the probability space. Some assumptions or approximations have to be made. For instance, that a certain SDE (i.e. model) describes the spot price dynamics very well (see e.g. Janczura, 2013; Weron, 2008). By computing the expectation within this model, $\mathbb{E}_t(S_{t+T})$ becomes model dependent and, hence, hardly comparable between papers using different models. An alternative approach is to approximate the ex-ante premium $\mathrm{RP}^*_{t,T}$ by the *ex-post* (or *realized*) *risk premium*:

$$\mathrm{RP}_{t,T} = \ln(S_{t+T}) - \ln(F_{t,T}) = \ln\left\{\frac{S_{t+T}}{F_{t,T}}\right\}. \tag{3}$$

In the ex-post risk premium we simply substitute the expectation $\mathbb{E}_t(S_{t+T})$ by its realized value at time $t + T$ value, i.e. S_{t+T}.

There is mixed evidence on the sign and variability of the risk premium in power markets. Generally, the premium can be both positive and negative; it can vary throughout the year or even throughout the day. The results can also differ from market to market. To some extent, however, the mixed evidence has been caused by inconsistent definitions of the risk premium. In particular, some authors (Bessembinder and Lemmon, 2002; Bunn and Chen, 2013; Christensen et al., 2007; Douglas and Popova, 2008; Handika and Trueck, 2013; Longstaff and Wang, 2004; Redl and Bunn, 2013; Redl et al., 2009, among others) use the notion of the *forward premium* or *forward risk premium* defined as the negative of the risk premium:

$$\mathrm{FP}_{t,T} = -\mathrm{RP}_{t,T} = \ln(F_{t,T}) - \ln\left\{\mathbb{E}_t(S_{t+T})\right\} = \ln\left\{\frac{F_{t,T}}{\mathbb{E}_t(S_{t+T})}\right\}, \tag{4}$$

here the ex-post risk premium; analogously we can define the ex-ante forward premium as the negative of the ex-ante risk premium: $\mathrm{FP}^*_{t,T} = -\mathrm{RP}^*_{t,T}$. Other authors (Benth et al., 2008a,b; Bessembinder, 1992; Eydeland and Wolyniec, 2003; Geman, 2005; Gjolberg and Brattested, 2011; Haugom and Ullrich, 2012; Huisman and Kilic, 2012; Ronn and Wimschulte, 2009, among others) use the term risk premium, but define it like the forward premium, i.e. as the difference between the forward price and the expected spot price. Note that Benth et al. (2008a) also define the market price of risk with a minus instead of a plus sign, hence their market price of risk has the same sign as their risk premium, i.e. the forward premium as defined by eqn. (4). Benth et al. (2008b) define a more complicated market price of risk, composed of a diffusion and a jump part which can have opposite signs and different contributions to the forward price. As a result there is no straightforward dependence between their market price of risk and their risk premium (which they also call the *forward bias*). On the other hand, Ronn and Wimschulte (2009) define the market price of risk with a plus sign – as we do in eqn. (2) – but use the term risk premium for the forward premium in eqn. (4) and their market price of risk has the oppposite sign as their risk premium. Finally, Lucia and Torro (2011) and Torro (2009) use the forward premium but call it interchangeably the risk premium, the futures/forward premium or the futures/forward bias.

2.2. Empirical evidence and risk premia

The risk premium theory underlines that the relationship between the futures price and the expectation of the spot price, as defined in eqn. (1), depends on the degree of risk aversion among market participants. If sellers are more risk-averse than buyers, which is the case in most commodity markets where producers want to secure their sales, they are ready to accept a lower price of the futures contract and thus the risk premium is on average positive. On the other hand, when buyers are more risk averse, they are ready to pay a higher price for the contract and the risk premium becomes negative. During peak hours electricity markets are more likely to be described by the second situation, since buyers on the wholesale market are at the same time suppliers in the retail market and must be ready to provide sufficient amount of energy. During off-peak hours, however, the demand is low and retailers are not willing to pay high prices for futures contracts. Producers want to avoid the costs of shutting down base-load generation and thus are willing to accept lower prices for securing their sales. As a result, negative risk premia are often observed during peak hours and positive in the off-peak hours, see e.g. Bunn and Chen (2013), Diko et al. (2006), Karakatsani and Bunn (2005) and Longstaff and Wang (2004). Note that Diko et al. (2006) study risk premia, while in the other three papers forward premia are analyzed. Furthermore, Ronn and Wimschulte (2009) work in the market price of risk context and conclude that it is significant and negative, usually higher (more negative) for peakload than for baseload. Although the conclusions from these studies seem contradictory at first, after taking into account the different premia used they are not.

The specific nature of electricity markets and the inapplicability of the storage cost theory gave rise to the model of Bessembinder and Lemmon (2002) in which risk-averse electricity producers and retailers maximize expected profits by making decisions on their activity in the spot and forward markets. In equilibrium, the observed risk premium is positively related to the expected variance of the spot price, but negatively related to its expected skewness. This may be interpreted less formally in terms of assessing the probability of price spikes. When market participants believe that there is high probability of a price spike (i.e. they expect high skewness), they are willing to buy more forward/futures contracts and thus drive the price up and the risk premium down.

Bessembinder and Lemmon (2002) also provide some initial evidence of model applicability in the PJM market, but due to the short (1997-2000) and not fully representative sample the evidence cannot be considered as strong. Using PJM real-time (called 'spot') and day-ahead ('forward') data, Longstaff and Wang (2004) generally confirm the findings of the Bessembiner-Lemon (B-L) model. Diko et al. (2006) come to similar conclusions using European data. Other works, on the other hand, confirm the implications of the B-L model only partially or do not confirm them at all. Douglas and Popova (2008) obtain results for the PJM market which are in line with the predictions of the B-L model expanded to include the availability of stored gas, which they claim to be an important factor in determining the size of the risk premium. Also Redl and Bunn (2013) confirm the importance of gas and oil for the determination of the risk premium. Haugom and Ullrich (2012) repeat the study of Longstaff and Wang (2004) for a longer dataset (2001-2010). They observe that the premia are still negative (in their setup – positive) and significant but that they have decreased in the more recent period. They analyze the stability of the parameters of variance and skewness in the risk premium regression. Their conclusion is that the parameters vary significantly and that the results are not consistent with the B-L model. Handika and Trueck (2013) do not confirm the B-L model for Australian data, with coefficients being often insignificant or of other sign than expected. Redl et al. (2009), who analyze EEX and Nord Pool data give very weak support of the B-L model obtaining, as expected, a positive skewness coefficient for EEX, but insignificant coefficients of mixed signs in all other cases. Ronn and Wimschulte (2009) check whether investors are willing to pay a premium for securing the price earlier in the day by buying power in the Austrian EXAA market which trades 2 hours earlier than the German EEX market. Then they try to relate this premium to the variance and skewness in the market, but the results are insignificant and do not support the B-L model.

As emphasized by Huisman and Kilic (2012), the risk premium may behave differently depending on the characteristics of the market. Botterud et al. (2010) analyze Scandinavian data from the Nord Pool power exchange and argue that in this hydro-dominated market the level of water in the reservoirs plays a crucial role in determining the spot-forward price relationship. They analyze both the risk premium and the convenience yield (which we discuss in Section 2.3), showing that they are on average negative. The authors make an argument in favor of the storage cost theory which – they claim – can be indirectly applied to the Nord Pool market through the storage of water. Concerning the risk premium, Botterud et al. (2010) use weekly spot and futures data from the period 1996-2006 to estimate the following model (see eqn. (6) in their article):

$$\mathrm{RP}_{t,T} = \alpha_0 + \alpha_1 \mathrm{RES}_t + \alpha_2 \mathrm{INFD}_{t,T} + \alpha_3 \mathrm{CONSD}_{t,T} + \alpha_4 S_t + \alpha_5 \mathrm{VAR}_t + \alpha_6 \mathrm{SKEW}_t + \epsilon_t, \quad (5)$$

where RES_t is the level of water reservoirs in Norway as a fraction of total capacity, INFD_t and CONSD_t are respectively the total deviations of the inflow of water and electricity consumption from long-term (1996-2006) averages between week t and $t + T$, S_t is the average spot price in week t and VAR_t and SKEW_t are variance and skewness of the spot price, respectively.

The coefficient of the water reservoir level, RES_t, is estimated to be significant and negative – a result which Botterud et al. (2010) claim to be expected. In Section 4.2 the authors write: *For instance, the demand for futures contracts is likely to be higher when reservoir levels are low, since this increases the likelihood of price spikes in the spot market. Hence, there should be a negative relationship between risk premium and reservoir levels*. In our opinion, the second sentence should be the opposite – since demand for futures contracts (and thus their price) is higher when reservoir levels are low, there should be a positive relationship between the risk premium and the reservoir level. But how come Botterud et al. (2010) arrive at a significant coefficient with the sign opposite to the one predicted by theory? We believe this is because of model misspecification. This issue is more deeply analyzed in Section 3.

Finally, it should be mentioned that Botterud et al. (2010) analyze ex-post (or realized) risk premia. At the same time equation (2) in their article defines the risk premium as an ex-ante premium. We believe that a sharp distinction between those two concepts should be drawn, especially because the regression results obtained by Botterud et al. (2010) cannot be interpreted in terms of the ex-ante risk premium model, as shown below in Section 3.2.

2.3. Convenience yields and storage

In addition to the risk premium analysis, Botterud et al. (2010) conduct an analysis of the second commonly used measure of the spot-forward price relationship – the convenience yield:

$$\mathrm{CY}_{t,T} = \ln(S_t) - \ln(F_{t,T}) = \ln\left(\frac{S_t}{F_{t,T}}\right), \quad (6)$$

where S_t is the spot price at time t and $F_{t,T}$ is the price of a futures contract with delivery period starting at time $t + T$, quoted at time t. Botterud et al. (2010) argue that this relation between today's spot and forward price may be explained by storage cost theory and the storage of water. Depending on how costly it is to store the water (the total cost is determined by potential cost of water spillover which is high when reservoir levels are high) and what are the benefits of storing the water (they are determined by the future value of the water, which depends on expectations about prices in the future; in particular, high reservoir levels decrease the probability of high prices in the future and thus decrease the future value of the water), producers may decide to produce now or to store the water for a later generation. As a result, the observed convenience yield should negatively depend, among else, on the level of water in the reservoirs. This hypothesis is confirmed by regression results with a negative and significant coefficient of water reservoir levels.

The provided evidence is, however, insufficient and cannot be used to convincingly argue for storage cost theory. By a simple algebraic transformation we can see that the convenience yield is

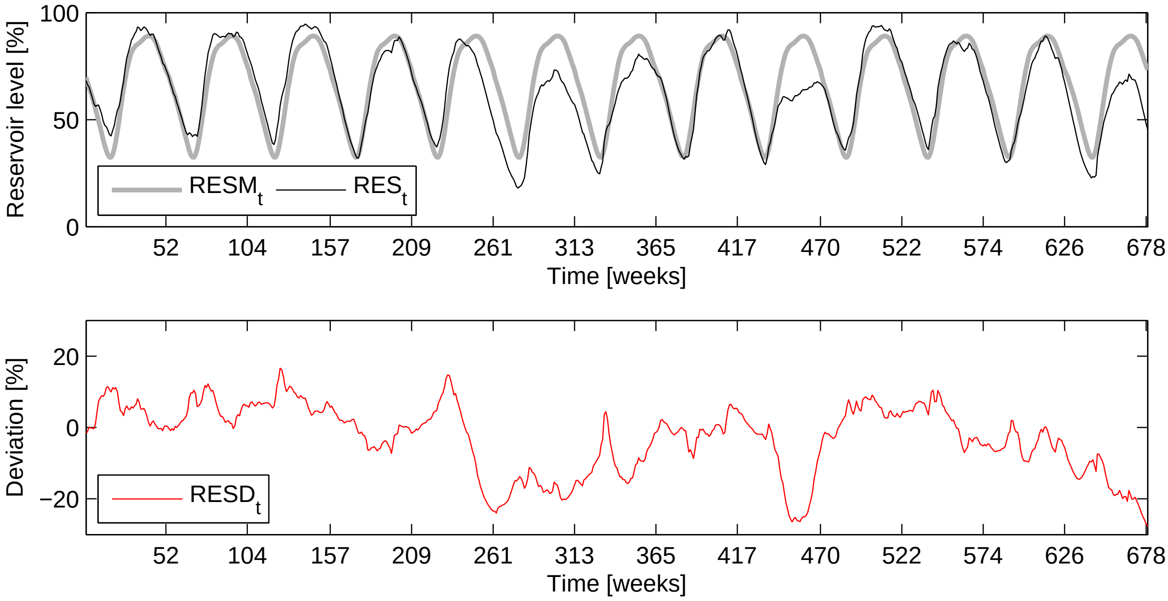

Figure 1: *Top panel*: The water reservoir level, RES_t, in the period from week #1 of 1998 to week #52 of 2010. The median reservoir level, RESM_t, for each week of the year in the 1971-2005 period is provided for reference. Note, that the reservoir levels reach the minimum in the Spring, in weeks #16-#17. *Bottom panel*: The deviation, RESD_t, of the reservoir level (RES_t) from the median level (RESM_t). Note that the values in both panels are given in percent of total reservoir capacity.

nothing else but the realized risk premium minus a component representing the relative change of the spot price in the period from t to $t+T$:

$$\mathrm{CY}_{t,T} = \ln\left(\frac{S_t}{F_{t,T}}\right) = \ln\left(\frac{S_{t+T}}{F_{t,T}} \cdot \frac{S_t}{S_{t+T}}\right) = \mathrm{RP}_{t,T} - \ln\left(\frac{S_{t+T}}{S_t}\right) \approx \mathrm{RP}_{t,T} - \%\Delta S_{t,T}, \tag{7}$$

where $\%\Delta S_{t,T}$ denotes the percentage change of the spot price in the period from t to $t+T$. As already discussed, the relationship between the risk premium and the reservoir levels should be positive. Therefore, if we obtain a negative coefficient of the water level in the regression for the convenience yield, it must be due to the positive relationship of the water level and the component representing the change of price, i.e. $\%\Delta S_{t,T}$.

A reason for this positive relationship can be a similarity of seasonal patterns in both variables. It is well known that the Nord Pool spot price is the lowest in the Summer. This means that the seasonal component of the expected change of price, approximately, reaches the minimum in the Spring: if the spot price has a (roughly) sinusoidal pattern with the minimum in the Summer, then its derivative also has a sinusoidal pattern with the minimum $\frac{1}{4}$ of the annual period, ca. 13 weeks, earlier. Reservoir levels, as shown in Figure 1, also reach the minimum in the Spring. Therefore there may be a positive correlation between seasonal components, which obviously does not mean any causality and which can explain the negative coefficient of the water level in the regression for convenience yield. Nevertheless, storage cost theory may be another, plausible explanation. In such a case, one should check whether the deseasonalized reservoir levels also have a significant, negative impact on the observed convenience yield. If the answer is positive, it will be evidence in favor of the storage cost theory. We address this question in Section 4.4.

3. Pitfalls of regression analysis

Ordinary Least Squares (OLS) is the most commonly used tool in the analysis of econometric data. Although very simple, the method continues to be the workhorse of econometrics because of its simplicity and favorable properties, i.e. unbiasedness, consistency and efficiency, which are achieved in many circumstances. Those properties, however, are guaranteed only if certain assumptions regarding the data are fulfilled. In social sciences, where the data rarely comes from controlled experiments, those assumptions are often not met. This section briefly discusses some pitfalls of regression analysis in the context of electricity markets and the risk premium. For a more detailed discussion of OLS properties see Hayashi (2000) or Wooldridge (2002) and references therein.

For the purpose of this section we define a basic regression model as follows:

$$y = \beta_1 x_1 + \beta_2 x_2 + u, \tag{8}$$

where y is the dependent variable, $x = (x_1, x_2)$ are the regressors and u is a random disturbance. We define and analyze the model in terms of a unit from underlying population but it can easily be translated to the sample counterpart.

The OLS formula allows for obtaining an unbiased and consistent estimate of the coefficients vector $\beta = (\beta_1, \beta_2)'$ as long as $\mathbb{E}(x'x)^{-1}$ exists (which almost never poses a problem and will not be discussed further) and $\mathrm{Cov}(x, u) = 0$. The latter assumption is always fulfilled when we are willing to make a popular, stronger assumption of $\mathbb{E}(u|x) = 0$. The violation of this assumption is called *endogeneity* of regressors. There are three potential reasons of endogeneity: (i) omitted variables, (ii) simultaneity and (iii) measurement errors. In what follows we discuss the latter two reasons.

3.1. Simultaneity

Let us use the model for y as given by equation (8) and assume that at the same time x_1 satisfies:

$$x_1 = \alpha_1 y + \alpha_2 x_3 + v. \tag{9}$$

Under this assumption x_1 is partially determined by y but at the same time y is partially determined by x_1. Such a situation is called *simultaneity* and precludes using OLS for obtaining consistent estimates of any coefficient in (8). This is because under simultaneity x_1 and u are correlated; observe that u is part of y and y determines x_1. We can say that we fail to estimate the real effect of x_1 on y because we cannot distinguish whether an observed high value of x_1 is the reason for the high value of y or whether we observe a high value of x_1 only because y is large for some other reason.

The bias caused by simultaneity is proportional to $\mathrm{Cov}(x, u)$ and it potentially influences all model coefficients if the independent variables are correlated. In case of equation (8), if

$\mathrm{Cov}(x_1, u) \neq 0$, we cannot consistently estimate β_1 and we can consistently estimate β_2 only if $\mathrm{Cov}(x_1, x_2) = 0$, which is rarely the case in typical problems. The magnitude of the simultaneity bias is often very difficult to assess. In economic systems very few variables can be treated as unambiguously exogenous, i.e. not determined by the response variable in any way. We often apply OLS even in the potential presence of endogeneity, hoping that the induced bias will be very small. However, in some cases simultaneity is more evident and a significant bias may occur.

What is the potential source of the simultaneity bias in model (5)? In the first place, it is the spot price. We can easily imagine that the spot price S_t may be influenced by the current situation in the futures market and therefore by the futures price $F_{t,T}$ and the risk premium $\mathrm{RP}_{t,T}$. In reality, the prices in the spot and futures markets are determined at the same time and are subject to common shocks. Botterud et al. (2010) in Section 5.5 note that the spot price follows futures prices very closely. Potential problems with a simultaneous determination of spot and futures prices are also mentioned by Redl et al. (2009). All this suggests that direct inclusion of the spot price in the model may be a potential source of bias.

3.2. Correlated measurement errors

Another potential reason for endogeneity are measurement errors. What is usually meant under this term is the error in measuring an independent variable which causes the regressors to be correlated with the random disturbance; see Wooldridge (2002) for the analysis of the behavior of the OLS estimator in this case. Here, however, we analyze simultaneous, correlated measurement errors both in the dependent and the independent variable. To this end, we introduce a notation which is consistent with the notation for the risk premium in Section 2.1. Namely, the true or 'ex-ante' values are denoted by a star, while the observed or 'ex-post' values have no superscript.

Let us assume that we want to analyze the impact of true value x_1^* on the true value y^*, controlling for the observed value x_2:

$$y^* = \beta_1 x_1^* + \beta_2 x_2 + u. \tag{10}$$

However, instead of observing the true values y^* and x_1^* we can only observe $y = y^* + \epsilon_0$ and $x_1 = x_1^* + \epsilon_1$, where ϵ_0 and ϵ_1 are zero-mean and uncorrelated with any variable from the structural model; we allow for non-zero correlation between ϵ_0 and ϵ_1, though. By construction we also have the correlation between ϵ_0, ϵ_1 and y, x_1. We can rewrite model (10) in terms of the observed variables:

$$y = \beta_1(x_1 - \epsilon_1) + \beta_2 x_2 + u + \epsilon_0 = \beta_1 x_1 + \beta_2 x_2 + w, \tag{11}$$

where $w = \epsilon_0 - \beta_1\epsilon_1 + u$. If there is no endogeneity in model (10), x_2 is not correlated with the new error. However, as long as ϵ_0 and $-\beta_1\epsilon_1$ do not cancel each other out (for which there is no reason to happen in general), x_1 is correlated with the new error. Therefore we cannot consistently estimate regression coefficients by OLS.

Using the Frisch-Waugh-Lovell Theorem (FWL; see Lovell, 1963), from equation (11) we can obtain the expressions for the probability limits of the OLS estimates:

$$\hat{\beta}_1^n = \beta_1 + \frac{\mathrm{Cov}(\epsilon_0, \epsilon_1) + \beta_1 \mathrm{Var}(\epsilon_1)}{\mathrm{Var}(u_{x_1^*|x_2})}, \quad \hat{\beta}_2^n = \beta_2 + \frac{\mathrm{Cov}(x_1^*, x_2) \cdot \left\{\mathrm{Cov}(\epsilon_0, \epsilon_1) + \beta_1 \mathrm{Var}(\epsilon_1)\right\}}{\mathrm{Var}(u_{x_2|x_1^*})}, \tag{12}$$

see Zator (2013) for details. Here $\mathrm{Var}(u_{x_1^*|x_2})$ and $\mathrm{Var}(u_{x_2|x_1^*})$ denote variances of residuals from regressing x_1^* on x_2 and x_2 on x_1^*, respectively. What is important is that the denominators are always positive but signs of the numerators are unknown and depend on correlations observed in the data. This means that if the correlations between measurement errors and between regressors are sufficiently large, the regression coefficients obtained by OLS from equation (11) may be significantly different from the original coefficients from equation (10).

How is this discussion related to the model of Botterud et al. (2010)? Recall the definition of the ex-ante risk premium $\mathrm{RP}^*_{t,T}$. In equation (1), S_{t+T} is the spot price at time $t + T$ and $F_{t,T}$ is the price of a weekly futures contract quoted at time t with delivery starting at time $t + T$. Therefore the risk premium defined in such a way, i.e. the ex-ante risk premium, is a function of the futures price $F_{t,T}$ and the expectation $\mathbb{E}_t(S_{t+T})$ at time t of the spot price at time $t + T$. Unfortunately, the expectations of the future spot price cannot be observed in the market and we can only collect the data on the ex-post (or realized) risk premium $\mathrm{RP}_{t,T}$, see equation (3). If we are willing to assume that expectations of market participants are on average correct (which is often done), the ex-post premium should be on average a good proxy for the ex-ante one. This may be formalized in a measurement error setup as:

$$\mathrm{RP}_{t,T} = \mathrm{RP}^*_{t,T} + \epsilon_t, \quad \text{with } \mathbb{E}(\epsilon_t) = 0. \tag{13}$$

Among other regressors, Botterud et al. (2010) use realized deviations in consumption and water inflow, $\mathrm{CONSD}_{t,T}$ and $\mathrm{INFD}_{t,T}$, defined as the sum of deviations from the long-term average in the period between trade and delivery. If those realized values of deviations were to be interpreted in the context of modeling the ex-ante risk premium, they could be treated as a proxy for the forecasts that market participants have at day t. We could formalize it as:

$$\mathrm{CONSD}_{t,T} = \mathrm{CONSD}^*_{t,T} + e_{1,t} \quad \text{and} \quad \mathrm{INFD}_{t,T} = \mathrm{INFD}^*_{t,T} + e_{2,t}, \tag{14}$$

where the starred variables denote the forecasts. It is straightforward to argue that ϵ and $e_{1,2}$ are correlated – if the realized consumption is higher or realized inflow is lower than predicted, it is likely that S_{t+T} will be higher than expected at time t. The correlation of those measurement errors implies that the obtained coefficients cannot be interpreted in the context of the ex-ante risk premium model.

Observe, however, that forecasts of deviations of consumption and water inflow can have some power in explaining the ex-ante risk premium, therefore including them in the model is desirable. The only problem is that including realized at time $t+T$ values as proxies for the forecasts made at time t can lead to biased estimates. One viable alternative may be to use realized at time t values of deviations of consumption and inflow as they do not possess this unwanted property. Since the series of both deviations are likely to be persistent, realized at time t values may be treated as proxies for the expectations made at time t about these values at a not very distant future time point, say $t + T$.

3.3. Seasonality

In the context of time series analysis we need more assumptions to obtain meaningful estimates of the regression coefficients. First, we need the process to be stationary – so that the distribution of the series stays constant across time – and second, to be ergodic – so that an observation becomes approximately independent of its lagged values when we increase the length of the lag; for a detailed discussion of these issues see e.g. Davidson and MacKinnon (1993). In the analysis of economic data, and perhaps especially in the context of electricity markets, the assumption of stationarity is often violated because of the visible seasonal behavior of the series. The topic of seasonality and seasonal adjustments of the data is very broad and has been heavily investigated in the literature, see e.g. the original papers by Lovell (1963) and Sims (1974), and the more recent reviews by Brendstrup et al. (2004) and Hylleberg (1986). Here we briefly discuss only selected aspects of this problem.

We employ a framework similar to that in Section 3.2, decomposing the two independent variables x_1 and x_2 into the seasonal (x_i^s) and stochastic (x_i^d) parts:

$$x_1 = x_1^s + x_1^d \quad \text{and} \quad x_2 = x_2^s + x_2^d. \tag{15}$$

This lets us rewrite the original regression model, see eqn. (8), in the following form:

$$y = \beta_1^s x_1^s + \beta_1^d x_1^d + \beta_2^s x_2^s + \beta_2^d x_2^d + u. \tag{16}$$

We assume that the seasonal components have no effect on the dependent variable y, so that it does not exhibit a seasonal pattern, and that the seasonal components are not correlated with the stochastic ones but are correlated with each other. Since we know that seasonal components have no effect on y, we have $\beta_1^s = \beta_2^s = 0$.

We are interested in estimating the coefficients of the stochastic components but in reality we do not observe the seasonally decomposed variables. Instead, we only observe x_1 and x_2 and can only estimate the original regression model. But how are the parameters of the original regression model related to those of the seasonal model in eqn. (16)? Using the OLS formula for the coefficients vector and the above seasonal decomposition, we can derive the probability limits of the coefficients in the original model (for details see Zator, 2013):

$$\begin{aligned} \hat{\beta}_1^n &= \frac{\left\{\mathrm{Var}(x_2^s) + \mathrm{Var}(x_2^d)\right\}\mathrm{Cov}(x_1^d, y) - \left\{\mathrm{Cov}(x_1^d, x_2^d) + \mathrm{Cov}(x_1^s, x_2^S)\right\}\mathrm{Cov}(x_2^d, y)}{\mathrm{Var}(x_1)\mathrm{Var}(x_2)(1 - r_{x_1,x_2}^2)}, \\ \hat{\beta}_2^n &= \frac{\left\{\mathrm{Var}(x_1^s) + \mathrm{Var}(x_1^d)\right\}\mathrm{Cov}(x_2^d, y) - \left\{\mathrm{Cov}(x_1^d, x_2^d) + \mathrm{Cov}(x_1^s, x_2^s)\right\}\mathrm{Cov}(x_1^d, y)}{\mathrm{Var}(x_1)\mathrm{Var}(x_2)(1 - r_{x_1,x_2}^2)}, \end{aligned} \tag{17}$$

where r_{x_1,x_2} is the correlation coefficient between x_1 and x_2. Similarly, we can derive expressions for the probability limits of the coefficients in the seasonal model:

$$\begin{aligned} \hat{\beta}_1^{d,n} &= \frac{\mathrm{Var}(x_2^d)\mathrm{Cov}(x_1^d, y) - \mathrm{Cov}(x_1^d, x_2^d)\mathrm{Cov}(x_2^d, y)}{\mathrm{Var}(x_1^d)\mathrm{Var}(x_2^d)(1 - r_{x_1^d,x_2^d}^2)}, \\ \hat{\beta}_2^{d,n} &= \frac{\mathrm{Var}(x_1^d)\mathrm{Cov}(x_2^d, y) - \mathrm{Cov}(x_1^d, x_2^d)\mathrm{Cov}(x_1^d, y)}{\mathrm{Var}(x_1^d)\mathrm{Var}(x_2^d)(1 - r_{x_1^d,x_2^d}^2)}. \end{aligned} \tag{18}$$

Note that both the numerators and the denominators in (18) are different than in (17). However, since the denominators are always positive, the crucial difference is the lack of $\mathrm{Cov}(x_1^s, x_2^s)$ in eqn.

(18). When the covariance between seasonal components is large (which is very likely), this term may dominate the entire expression and thus, in general, the coefficients of the original regression model are not very much related to those of the seasonal model.

In the model of Botterud et al. (2010) two variables – the level of water and the spot price – have a strong seasonal component. The above analysis shows that the obtained coefficient of the water reservoir level can be very different from the coefficient of its stochastic part. But why are we interested in the coefficient of the stochastic part and not of the total reservoir level in the first place? The reason is that the seasonal component of water level captures the influence of the seasonal behavior of all omitted variables, the most important being probably the demand for electricity. In econometric terms we could say that the seasonal component of the water level is correlated with omitted variables and thus its coefficient cannot be consistently estimated. The stochastic component, on the other hand, is less likely to be correlated with any omitted variable and its coefficient should reflect the real influence of the varying water level. Therefore, if we want to capture the real effect of the water level on the risk premium, we either have to control for all potentially significant variables with a seasonal pattern (which seems to be nearly impossible) or to concentrate on the effect of the stochastic part of the water level.

All three reasons discussed in this Section – simultaneity, correlated measurement errors and seasonality – may have introduced bias in the coefficients obtained by Botterud et al. (2010) and may explain why their coefficient of water level is of different sign than predicted by theory. This discussion also casts some doubt on the regression results for the convenience yield obtained by using exactly the same set of regressors. In the following Section we revisit the Nord Pool market and try to go around the mentioned problems in the analysis of empirical data.

4. Empirical analysis

4.1. The data

In this paper we focus on ex-post risk premia in the Nord Pool market. We recover them from realized spot prices and the prices of weekly futures contracts of maturities 1W, 2W, 3W, 4W, 5W and 6W (W≡weeks). Note that in most cases we report the results only for some of the maturities (typically 1W, 3W and 6W). As in Botterud et al. (2010), Gjolberg and Brattested (2011) and Lucia and Torro (2011) the time scale used is weekly. More precisely, for each time point or week t, the weekly spot price S_t is calculated as the arithmetic (unweighted) average of the 168 hourly prices in week t. Likewise, the weekly spot price S_{t+T} is calculated as the average of the 168 hourly prices in week $t + T$. On the other hand, the futures prices $F_{t,T}$, with $T = 1, 3$ or 6 weeks, are closing prices from the last trading day in week t and with delivery in week $t + T$. All prices are quoted in Norwegian kroner (NOK). Since in the later part of the studied period EUR became the primary quotation currency, we convert EUR prices to NOK using the official exchange rate of the Norges Bank for a given day. Overall, the sample comprises 679 weekly data points in the 13-year long period: January 1998 – December 2010.

Spot and futures prices are used to calculate the ex-post risk premia, as defined by eqn. (3), and convenience yields, as defined by eqn. (6), which are our response variables. Our main explanatory variable is the water level in the Norwegian reservoirs as a fraction of total capacity, RES_t. Next, we define the seasonal and stochastic parts of the reservoir level. The seasonal one,

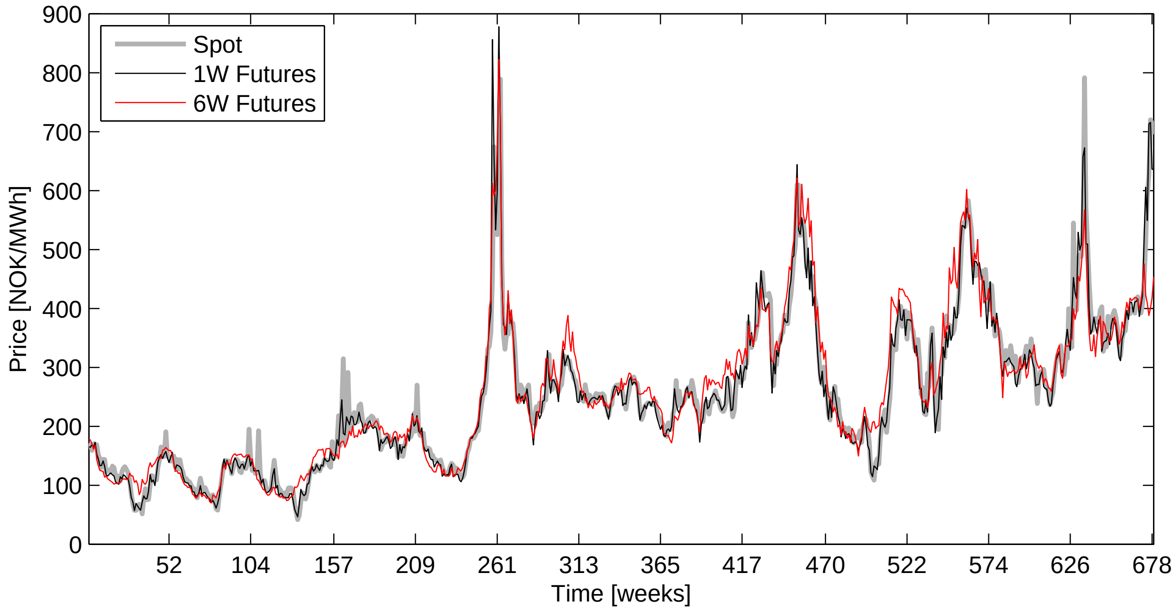

Figure 2: Spot price, 1W and 6W futures prices in the studied period (January 1998– December 2010). Note that 1W futures prices closely follow the spot price and are hardly visible at this scale. Futures prices are end of week values (quoted 1 or 6 weeks earlier) and the spot price is the arithmetic average of the 168 hourly prices in a given week.

RESM_t, is defined as the median water level in a particular week of a year in the 1971-2005 period. The stochastic component is defined as the difference between the observed value and the seasonal component, i.e. $\mathrm{RESD}_t = \mathrm{RES}_t - \mathrm{RESM}_t$. To compare our results with those of Botterud et al. (2010), we create variables representing deviations of energy consumption and water inflows from long term averages: $\mathrm{CONSD}_{t,T}$ and $\mathrm{INFD}_{t,T}$, respectively. They are defined as sums of deviations in the period between t and $t + T$ from the 1998-2010 average for a given week in the year. The notation CONSD_t or INFD_t represents the deviations from week t alone. We refer to Section 3.2 for the discussion of selecting proxies for the forecasts of market participants.

As suggested by Bessembinder and Lemmon (2002), we include the variance and skewness of the spot price in the regression model. While the B-L model suggests that the risk premium should depend on the forecast of future variance and skewness, market participants may use the last realized values of variance and skewness in the process of creating expectations. Therefore we include the realized variance and realized skewness of hourly prices from week t, denoted as VAR_t and SKEW_t.

The descriptive statistics are presented in Table 1. As we can see, both risk premia and convenience yields can vary significantly which is a consequence of high volatility of prices. In Figure 2 we graphically present selected prices and dependent variables. The reservoir levels with their seasonal and stochastic components were plotted in Figure 1.

Table 1: Descriptive statistics of the main considered variables. Two last columns are the 5th and 95th percentiles of the sample. *Upper part*: Spot and futures prices for 1, 3 and 6 week contracts, see also Figure 2. All futures prices are end of week values, while the spot price is the average of the 168 hourly prices in a given week. *Middle part*: Corresponding realized risk premia and convenience yields, see Figure 3. Note that premia and yields are calculated as log differences and, hence, values exceeding ±100% are attainable. *Bottom part*: Reservoir level (RES_t) and deviation (RESD_t) of the reservoir level from the long-term median level, see Figure 1. The values are given in percent of total reservoir capacity.

Variable	Mean	Median	Min	Max	St.dev.	5 perc.	95 perc.
			Spot and futures prices [NOK/MWh]				
S_t	253.78	239.18	41.59	791.57	126.68	88.99	484.87
$F_{t,1}$	250.90	236.40	46.26	877.93	129.31	84.28	498.76
$F_{t,3}$	256.99	244.00	63.88	875.00	128.47	87.50	511.13
$F_{t,6}$	257.87	244.63	70.00	822.50	124.91	88.75	483.65
			Realized risk premia and convenience yields [%]				
$\mathrm{RP}_{t,1}$	1.83	1.26	-37.97	43.47	7.37	-8.23	14.33
$\mathrm{RP}_{t,3}$	-0.73	0.08	-89.47	62.88	16.35	-26.77	23.66
$\mathrm{RP}_{t,6}$	-1.17	-1.93	-83.68	87.89	22.29	-38.61	35.18
$\mathrm{CY}_{t,1}$	1.64	1.61	-63.24	51.49	8.87	-12.75	15.51
$\mathrm{CY}_{t,3}$	-1.27	-1.05	-63.79	50.76	12.14	-20.26	17.08
$\mathrm{CY}_{t,6}$	-2.17	-2.04	-85.97	58.94	16.38	-28.05	19.73
			Water reservoir levels [%]				
RES_t	63.67	65.15	18.12	94.64	19.40	30.72	91.66
RESD_t	-2.96	-0.90	-27.78	16.60	9.67	-21.22	10.02

4.2. OLS estimates for the risk premium

We start our analysis by neglecting all remarks made in Section 3 and simply re-estimating the model proposed by Botterud et al. (2010), see eqn. (5), both for the full 13-year dataset and for a dataset similar to the one used by the cited authors, i.e. limited to years 1998-2006. The results for 1W and 6W maturities are presented in Table 2. As we may observe, the findings of Botterud et al. (2010) are robust with respect to extending the sample by four years. Although there are some differences in values of the coefficients and significance, the main conclusion remains the same and the coefficient of water level is negative.

As discussed in Section 3, the model of Botterud et al. (2010) may suffer from at least three problems. In order to solve them, in what follows we try to respecify the model and obtain new, hopefully more credible estimates of the water level coefficient. First, we eliminate the realized deviations of consumption and inflow from the model. As argued in Section 3.2, their presence prevents us from interpreting the coefficients in terms of the ex-ante risk model, which is of our main interest. At the same time, however, we agree that forecasts of abnormal consumption or water inflows can play a role in determining the risk premium. What could be a reasonable proxy for these forecasts? Exploiting the fact that there exists a relatively high degree of persistence in both series – the partial autocorrelation function (PACF) for the first lag varies from 0.5 to 0.95 – we may use realized values of deviations from week t: CONSD_t and INFD_t.

Second, to solve the problem with the seasonality of water level, which captures the influence

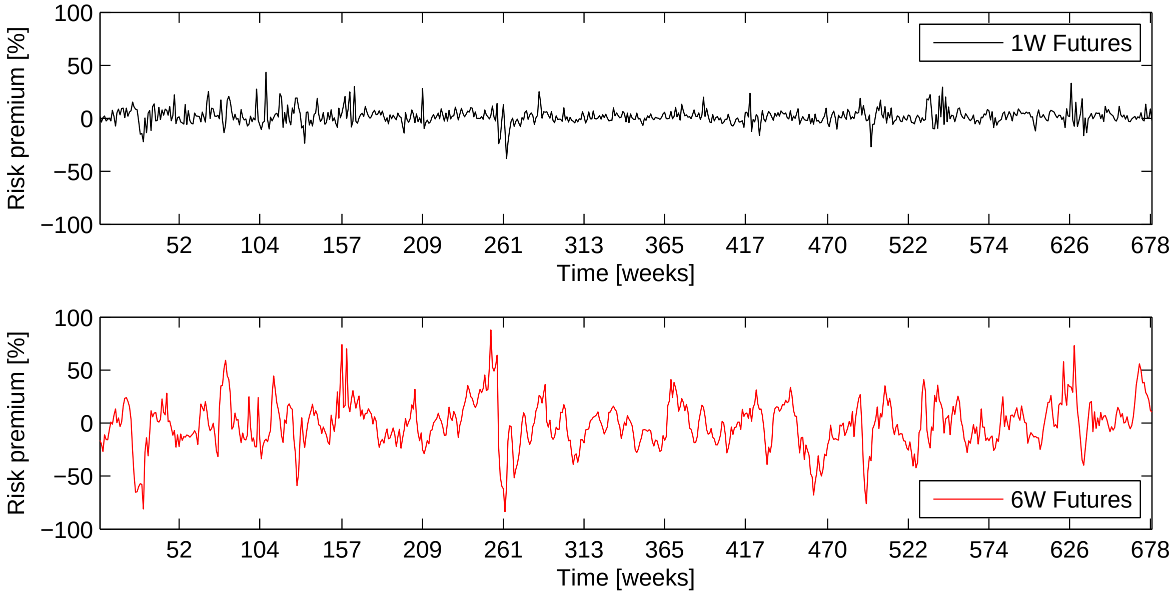

Figure 3: Ex-ante (realized) risk premia for the 1W and 6W futures contracts depicted in Figure 2. Weekly data in the period 1998-2010.

of other seasonal variables, we divide the water level into seasonal and stochastic parts, as discussed in Section 4.1. Both of them are included in the regression. Third, the endogeneity of the spot price is probably the hardest to tackle. It is difficult to come up with a convincing instrumental variable for the spot price and therefore the only remaining solutions are (i) to eliminate spot price from the model or (ii) to simply leave it there. The first approach may lead to the omitted variables bias while the second may cause the simultaneity bias. Nevertheless, if estimates from these two approaches are consistent with each other, we can hope that the conclusions from the analysis are reliable. Finally, after the above adjustments, our regression **Model 1** for the realized risk premium is as follows:

$$\mathrm{RP}_{t,T} = \beta_1 + \beta_2 \mathrm{RESD}_t + \beta_3 \mathrm{RESM}_t + \beta_4 \mathrm{INFD}_t + \beta_5 \mathrm{CONSD}_t + \beta_6 \mathrm{VAR}_t + \beta_7 \mathrm{SKEW}_t + \beta_8 S_t + u_t. \quad (19)$$

All variables are as previously defined: $\mathrm{RP}_{t,T}$ is the risk premium for a T-week futures contract, RESD_t and RESM_t are the stochastic and seasonal components of water level, INFD_t and CONSD_t are the deviations of water inflow and energy consumption from long-term averages in a given week, VAR_t and SKEW_t are the variance and skewness of the spot price, and S_t is the average spot price in week t. **Model 2** is obtained by setting $\beta_8 \equiv 0$, i.e. by discarding the spot price from the regression.

Estimation is performed in GRETL using Ordinary Least Squares (OLS). The literature does not provide a clear guidance as to the order of integration of spot prices and other considered variables (Torro, 2009). Since for our sample the unit root hypothesis is rejected, we do not consider first differences but work with raw data. This approach is also consistent with the one of Botterud et al. (2010). Heteroskedasticity is clearly present, as is autocorrelation. We therefore use

Table 2: Regression results for the risk premium model (5) estimated using the full dataset studied in this paper (1998-2010, *upper part*) and a truncated dataset (1998-2006, *middle part*). The dependent variable is the realized risk premium for weekly contracts with different maturities ($T = 1$ and 6W). p-values based on HAC standard errors are given in parentheses. Stars *,** and *** denote significance at the usual levels of 10%, 5% and 1%, respectively. Note that model (5) ignores the critique of Section 3 and therefore the coefficients can be biased. The original results of Botterud et al. (2010), Table 6, are presented for comparison in the *bottom part* of the table.

T	Const.	RES_t	$INFD_t$ ($\times 10^5$)	$CONSD_t$ ($\times 10^5$)	VAR_t ($\times 10^4$)	$SKEW_t$	S_t ($\times 10^4$)
Years 1998-2010 (full sample)							
1W	0.084^{***}	-0.054^{***}	-1.064^{***}	4.935^{***}	-2.300^{*}	0.016	-1.506^{***}
	(0.000)	(0.000)	(0.000)	(0.001)	(0.123)	(0.845)	(0.000)
6W	0.098^{**}	-0.095	-2.024^{***}	5.544^{***}	-3.033	-0.298	-3.826^{***}
	(0.050)	(0.112)	(0.000)	(0.000)	(0.355)	(0.266)	(0.002)
Years 1998-2006							
1W	0.105^{***}	-0.070^{***}	-1.241^{***}	5.114^{***}	-1.516	0.016	-2.347^{***}
	(0.000)	(0.000)	(0.000)	(0.006)	(0.264)	(0.826)	(0.000)
6W	0.154^{**}	-0.130^{**}	-1.989^{***}	6.410^{***}	-2.114	-0.386	-6.718^{***}
	(0.010)	(0.044)	(0.000)	(0.000)	(0.495)	(0.144)	(0.002)
Years 1996-2006, results from Botterud et al. (2010), Table 6							
1W	0.062^{***}	-0.053^{***}	-1.900^{***}	7.300^{***}	-0.001^{**}	-0.001	-1.900^{***}
6W	0.210^{***}	-0.179^{***}	-1.800^{***}	8.100^{***}	-28.000	-0.000	-7.100^{***}

Newey-West standard errors to account for them. The models have a rather low explaining power, resulting in R^2 between 0.05 and 0.08. The high variance of the error term makes it difficult to observe significant coefficients. Nevertheless, some statistically significant results are obtained, see Table 3. As we can observe, the coefficient of $RESD_t$ (the stochastic component of the water level) is positive, which is to be expected, but contradicts the results of Botterud et al. (2010). The significance of the coefficient is low, especially when we include the spot price (Model 1) but nonetheless this clearly does not support the hypothesis of a negative relationship between the risk premium and the reservoir level. Please note that the general picture does not change if we analyze only the first or the second half of the sample, although the coefficients become then highly insignificant and some of them are negative (not reported here).

The weak evidence in favor of a positive relationship between the risk premium and the reservoir level is a bit disappointing. However, the relatively low fit of Models 1 and 2 suggests that a large amount of variation is unexplained. Possibly due to omitted but important factors, the linearity of the model or drawbacks related to the used variables. We have tried to include non-linear terms in the model, i.e. squares and interactions of the variables, but this has not led to any significant improvement. However, when we test for the presence of ARCH effects, the hypothesis of no effect is unambiguously rejected for all contract maturities. In the following Section we therefore turn to the estimation of regression models with GARCH residuals.

4.3. Models with GARCH residuals

We expand Models 1 and 2 by taking u_t in eqn. (19) to be a GARCH(p, q) process. For all contract maturities we find that GARCH(1,1) is the best choice in terms of minimizing standard

Table 3: Regression results for **Models 1** and **2**, see eqn. (19), and the full 1998-2010 dataset. The dependent variable is the realized risk premium for weekly contracts with different maturities ($T = 1, 3$ and 6W). p-values based on HAC standard errors are reported in parentheses. Stars denote significance at usual levels of 10%, 5% and 1%.

T	Const.	RESD$_t$	RESM$_t$	INFD$_t$ ($\times10^5$)	CONSD$_t$ ($\times10^5$)	VAR$_t$ ($\times10^4$)	SKEW$_t$	S_t ($\times10^4$)
Model 1								
1W	0.077^{***}	0.042	-0.050^{***}	-0.672^{***}	1.853	-2.833^{*}	0.021	-1.019^{**}
	(0.000)	(0.288)	(0.000)	(0.005)	(0.114)	(0.065)	(0.812)	(0.012)
3W	0.071^{**}	0.044	-0.060	-1.214^{*}	5.596^{*}	1.362	0.205	-1.795
	(0.023)	(0.722)	(0.134)	(0.055)	(0.942)	(0.835)	(0.405)	(0.132)
6W	0.076	0.007	-0.052	-0.829	12.662^{**}	-1.376	0.519	-2.823
	(0.143)	(0.977)	(0.433)	(0.388)	0.017)	(0.777)	(0.140)	(0.119)
Model 2								
1W	0.052^{***}	0.134^{***}	-0.046^{***}	-0.651^{***}	1.128	-2.796^{*}	-0.003	–
	(0.000)	(0.002)	(0.000)	0.007)	(0.329)	(0.062)	(0.969)	
3W	0.027	0.206	-0.053	-1.176^{*}	4.320	1.427	0.163	–
	(0.256)	(0.119)	(0.202)	(0.065)	(0.197)	(0.824)	(0.500)	
6W	0.007^{**}	0.262	-0.041	-0.770	10.654^{**}	-1.273	-0.453	–
	(0.854)	(0.241)	(0.551)	(0.420)	(0.037)	(0.789)	(0.187)	

information criteria. The resulting models are called **Model 3** and **4**, respectively. We estimate them in GRETL using robust QML standard errors. The results are presented in Table 4, this time for all six futures contracts – from one week (1W) to 6 week (6W).

The coefficient of RESD$_t$ is always positive, though not always significant, no matter if we include (Model 3) or exclude (Model 4) the spot price. This result is also robust with respect to the time range – separate analyzes of the truncated subsamples, i.e. the first or second half of the 13-year period, yield qualitatively the same results (not reported here). This confirms the hypothesis that the impact of water level on the risk premium is actually positive, which is consistent with our expectations, but contradicts the results of Botterud et al. (2010). The coefficient of water level generally lies between 0.1 and 0.25, depending on the contract maturity and on whether we control for the spot price or not. Is it economically significant? If the reservoir level changes by 10% of its total capacity – which is a reasonable value, even if we do not count seasonal changes, see Table 1 – the risk premium changes by 0.01 to 0.025, i.e. 1-2.5 percentage points. Since the average risk premium, depending on contract maturity, is more or less -1.5%, the deviation of reservoir level may change the risk premium quite significantly.

Furthermore, the deviation of the consumption, CONSD$_t$, usually has a positive sign, as opposed to the deviation of the inflows, INFD$_t$. However, the coefficients are insignificant in most of the cases. The higher is the expected consumption (the lower the inflow of water), the higher the realized spot price, which suggests that the market does not fully incorporate all the information into futures prices (see e.g. Gjolberg and Brattested, 2011, for a discussion of the risk premium and market inefficiency). The coefficients of variance and skewness are of mixed sign and low significance. Therefore our results cannot provide evidence in favor of the Bessembinder-Lemon model. However, they also cannot be treated as evidence against the model.

Table 4: Regression results for **Models 3** and **4** with GARCH residuals, see Section 4.3, and the full 1998-2010 dataset. The dependent variable is the realized risk premium for weekly contracts with different maturities ($T = 1, ..., 6$W). p-values based on robust QML standard errors are reported in parentheses. Stars denote significance at usual levels of 10%, 5% and 1%.

T	Const.	RESD_t	RESM_t	INFD_t ($\times 10^5$)	CONSD_t ($\times 10^5$)	VAR_t ($\times 10^4$)	SKEW_t	S_t ($\times 10^4$)
				Model 3				
1W	0.071***	0.041	−0.043***	−0.463**	1.931	−0.087	0.056	−0.773***
	(0.000)	(0.311)	(0.000)	(0.023)	(0.115)	(0.980)	(0.706)	(0.004)
2W	0.071***	0.109**	−0.052**	−0.649**	2.215	−10.241***	0.156	−1.305**
	(0.000)	(0.046)	(0.025)	(0.019)	(0.200)	(0.002)	(0.275)	(0.015)
3W	0.096***	0.087	−0.127***	−0.341	4.220*	4.712	−0.082	−1.003
	(0.021)	(0.234)	(0.000)	(0.298)	(0.065)	(0.218)	(0.622)	(0.198)
4W	0.095***	0.177**	−0.165***	−0.338	4.923**	4.605	−0.319	−0.271
	(0.000)	(0.035)	(0.000)	(0.376)	(0.029)	(0.281)	(0.105)	(0.737)
5W	0.155***	0.192*	−0.254***	0.636	6.323**	−5.758	0.337	−0.470
	(0.000)	(0.096)	(0.000)	(0.222)	(0.018)	(0.346)	(0.146)	(0.704)
6W	0.126***	0.245	−0.221***	0.616	6.087**	−1.103	0.252	−0.388
	(0.001)	(0.104)	(0.000)	(0.196)	(0.031)	(0.759)	(0.316)	(0.729)
				Model 4				
1W	0.052***	0.104***	−0.041**	−0.426***	1.676	0.167	0.057	–
	(0.000)	(0.004)	(0.010)	0.032)	(0.142)	(0.960)	(0.697)	
2W	0.047***	0.190***	−0.059***	−0.601**	1.739	−10.045	0.126	–
	(0.001)	(0.000)	(0.008)	0.022)	(0.305)	(0.004)	(0.384)	
3W	0.078***	0.150**	−0.133***	−0.314	4.178	4.366	−0.108	–
	(0.000)	(0.033)	(0.000)	0.324)	(0.078)	(0.250)	(0.522)	
4W	0.091***	0.194**	−0.168***	−0.323	4.914**	4.566	−0.324*	–
	(0.000)	(0.016)	(0.000)	0.402)	(0.030)	(0.288)	(0.093)	
5W	0.147***	0.213	−0.258***	0.656	6.270**	−6.014	0.341	–
	(0.000)	(0.125)	(0.000)	0.211)	(0.022)	(0.352)	(0.134)	
6W	0.118***	0.267	−0.223***	0.636	5.951**	−1.236	0.239	–
	(0.000)	(0.109)	(0.000)	0.169)	(0.040)	(0.724)	(0.334)	

4.4. *Regression results for the convenience yield*

As mentioned in Section 2.3, in our opinion the storage cost theory, proposed by Botterud et al. (2010) to explain the behavior of the convenience yield in the Nord Pool market, needs stronger empirical evidence than provided. The significant, negative coefficient of water level in the regression model for the convenience yield observed by Botterud et al. (2010) can be explained by the correlation of seasonal components and may not reflect any real, causal relationship between the convenience yield and the level of water. In addition, the model may suffer from similar problems as the risk premium model, e.g. simultaneity. To provide less ambiguous evidence one could regress the convenience yield on the stochastic part of the water level, avoiding the problem with the seasonality.

To start the analysis, we estimate the regression model for the convenience yield as proposed by Botterud et al. (2010) in eqn. (4), i.e.:

$$\text{CY}_{t,T} = \alpha_0 + \alpha_1 \text{RES}_t + \alpha_2 \text{INFD}_{t,T} + \alpha_3 \text{CONSD}_{t,T} + \alpha_4 S_t + \alpha_5 \text{VAR}_t + \alpha_6 \text{SKEW}_t + \epsilon_t. \qquad (20)$$

The independent variables are the same as in the risk premium model (5). The results are summarized in Table 5. As we can see, the coefficients of water level are negative and highly significant, just like in the original article.

Table 5: Regression results for the convenience yield model (20) estimated using the full dataset studied in this paper (1998-2010, *upper part*). The dependent variable is the convenience yield for weekly contracts with different maturities ($T = 1$ and 6W). p-values based on HAC standard errors are given in parentheses. Stars *,** and *** denote significance at the usual levels of 10%, 5% and 1%, respectively. Note that model (20) ignores the critique of Section 3 and therefore the coefficients can be biased. The original results of Botterud et al. (2010), Table 4, are presented for comparison in the *bottom part* of the table.

T	Const.	RES_t	INFD_t ($\times 10^5$)	CONSD_t ($\times 10^5$)	VAR_t ($\times 10^4$)	SKEW_t	S_t ($\times 10^4$)
				Years 1998-2010 (full sample)			
1W	0.076^{***}	-0.079^{***}	1.470^{***}	-8.018^{***}	-17.735^{***}	0.340^{***}	-0.117
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.717)
6W	0.198^{***}	-0.407^{***}	0.238	-0.111	25.526^{***}	-0.931^{***}	1.249
	(0.000)	(0.000)	(0.100)	(0.892)	(0.000)	(0.000)	(0.248)
				Years 1996-2006, results from Botterud et al. (2010), Table 4			
1W	0.047^{***}	-0.082^{***}	0.381	-10.1^{***}	0.004^{**}	0.008^{***}	-0.750^{***}
6W	0.260^{***}	-0.461^{***}	0.095	0.033	0.006^{***}	0.054^{**}	-1.5

Analogously as in our analysis of the risk premium, we have examined the relationship after dividing the water level into the stochastic and seasonal parts. Our regression **Model 5** for the convenience yield is as follows:

$$\text{CY}_{t,T} = \beta_1 + \beta_2\text{RESD}_t + \beta_3\text{RESM}_t + \beta_4\text{INFD}_t + \beta_5\text{CONSD}_t + \beta_6\text{VAR}_t + \beta_7\text{SKEW}_t + \beta_8 S_t + u_t. \quad (21)$$

The independent variables are the same as in the risk premium model (19). **Model 6** is obtained by setting $\beta_8 \equiv 0$, i.e. by discarding the spot price from the regression. The results are summarized in the upper part of Table 6. They give only limited support to the storage cost theory. The coefficient of the stochastic component of water level is of mixed sign. Interestingly, it is negative and significant for the contracts with longer maturities. One possible interpretation of this phenomenon is that the risk of reservoir overflow during a 6 week period may be more significant than during a 1 week period and thus storage cost theory may be more appropriate for longer time horizons.

Finally, after rejecting the hypothesis of no ARCH effect, we build regression models for the convenience yield with GARCH residuals. We expand Models 5 and 6 by taking u_t in eqn. (21) to be a GARCH(p, q) process; again we find that GARCH(1,1) is the best choice in terms of minimizing standard information criteria. The resulting models are called **Model 7** and **8**, respectively. We estimate them in GRETL using robust QML standard errors. The results are presented in lower part of Table 6.

The inclusion of GARCH residuals does not change much. The coefficient of RESD_t is generally negative and very close to zero. If the spot price is excluded from the model, the coefficient becomes significant for longer maturities. Therefore the storage cost theory may be an explanation for the longer term behavior of the convenience yield. The mechanism described by Botterud et al. (2010) definitely may exist, but it is not showing up in the data as unambiguously as suggested by the authors. The very strong support that they report was caused by coincidence of the seasonal patterns of water level and the expected change of the spot price. The cost of the potential water spillover, which is an element of the theory, seems to be negligible for short time horizons. In

Table 6: Regression results for the full 1998-2010 dataset and **Models 5** and **6**, see eqn. (21), and for **Models 7** and **8** with GARCH residuals, see Section 4.4. The dependent variable is the convenience yield for weekly contracts with different maturities ($T = 1, 3$ and 6W). p-values are based on robust standard errors (HAC errors for Models 5 and 6, QML errors for Models 7 and 8) are reported in parentheses. Stars denote significance at usual levels of 10%, 5% and 1%.

T	Const	RESD$_t$	RESM$_t$	$INFD_T$ $\times 10^{-5}$	$CONSD_T$ $\times 10^{-5}$	VAR_t $\times 10^{-4}$	$SKEW_t$	S_t $\times 10^{-4}$
				Model 5				
1W	0.067*** (0.000)	0.094* (0.055)	−0.090*** (0.000)	1.376*** (0.000)	−8.804*** (0.000)	17.374*** (0.000)	0.285*** (0.002)	0.781** (0.015)
3W	0.090*** (0.000)	0.056 (0.366)	−0.162*** (0.000)	0.564*** (0.001)	−4.035*** (0.000)	18.818*** (0.000)	0.431*** (0.000)	0.920 (0.047)
6W	0.183*** (0.000)	−0.146 (0.159)	−0.420*** (0.000)	0.216 (0.136)	−4.613 (0.590)	25.208*** (0.000)	0.860*** (0.000)	2.575** (0.015)
				Model 6				
1W	0.085*** (0.000)	0.023 (0.609)	−0.092*** (0.000)	1.346*** (0.000)	−8.468*** (0.000)	17.479*** (0.000)	0.311*** (0.001)	–
3W	0.149*** (0.000)	−0.115 (0.200)	−0.245*** (0.000)	0.233 (0.144)	−1.901** (0.034)	20.126*** (0.000)	0.592*** (0.000)	–
6W	0.246*** (0.000)	−0.378*** (0.008)	−0.428*** (0.000)	0.166 (0.229)	−0.286 (0.749)	25.439*** (0.000)	0.952*** (0.000)	–
				Model 7				
1W	0.075*** (0.000)	−0.001 (0.992)	−0.095*** (0.000)	1.036*** (0.000)	−6.163*** (0.000)	18.947*** (0.000)	0.312*** (0.005)	0.561** (0.042)
3W	0.102*** (0.000)	−0.007 (0.917)	−0.206*** (0.000)	0.346*** (0.003)	−0.9222 (0.167)	22.290*** (0.000)	0.630*** (0.000)	1.099** (0.040)
6W	0.161*** (0.000)	−0.118 (0.227)	−0.327*** (0.000)	0.243*** (0.009)	−0.258 (0.745)	31.630*** (0.000)	1.008*** (0.000)	1.319** (0.030)
				Model 8				
1W	0.086*** (0.000)	−0.042 (0.369)	−0.093*** (0.000)	1.050*** (0.000)	−6.085*** (0.000)	18.920*** (0.000)	0.310*** (0.005)	–
3W	0.131*** (0.000)	−0.088 (0.129)	−0.213*** (0.000)	0.319*** (0.007)	−0.877 (0.205)	22.299*** (0.000)	0.629*** (0.000)	–
6W	0.203*** (0.000)	−0.214** (0.027)	−0.345*** (0.000)	0.213** (0.014)	−0.198 (0.823)	31.476*** (0.000)	1.028*** (0.000)	–

other words, one rarely faces a significant risk of reservoir overflow within the next 1-3 weeks. On the other hand, the overflow is more likely within next 5 or 6 weeks.

5. Conclusions

The motivation and a starting point for this study was a recent article by Botterud et al. (2010) who analyzed weekly Nord Pool futures contracts in the 11-year period 1996-2006. The strong support for the storage cost theory, expressed by a negative and statistically significant coefficient of the water reservoir level in the regression model for the convenience yield seemed very attractive both from a modeling and a theoretical point of view. However, a closer inspection of the data and models revealed some weaknesses in the econometric setup and flaws in the argumentation.

In this paper we have looked at ex-post (or realized) risk premia and convenience yields in the Nord Pool market. At our disposal was a longer and more recent 13-year dataset (1998-2010) of weekly spot and futures prices, consumption figures and water reservoir levels and inflows. As a first step we have reestimated the models of Botterud et al. (2010) and found the results to be consistent with their study and relatively robust with respect to the time period considered, see Tables 2 and 5.

Next we have looked at the potential pitfalls of applying linear regression models for explaining the relationship between spot and futures prices in electricity markets. In particular, the bias coming from the simultaneity problem (Section 3.1), the effect of correlated measurement errors (Section 3.2) and the impact of seasonality on the regression results (Section 3.3). To solve the problem with the seasonality of water level we have divided it into seasonal and stochastic parts. To address the endogeneity of the spot price issue we considered two sets of models – with and without the spot price as an explanatory variable. The first approach may cause the simultaneity bias while the second may lead to the omitted variables bias. Nevertheless, if estimates from these two approaches are more or less consistent with each other, we can hope that the conclusions from the analysis are reliable. After these adjustments the risk premium models (Models 1 and 2) yielded reasonable, but generally not statistically significant results. As a second refinement step we considered GARCH residuals in our regression models; the hypothesis of no ARCH effect was rejected for all contract maturities. Using these models (Models 3 and 4) we have shown that the impact of the water reservoir level on the risk premium is positive, which is to be expected, but contradicts the results of Botterud et al. (2010), and statistically significant. Finally we have shown that after taking into account the seasonality of the water level, the storage cost theory proposed by Botterud et al. (2010) to explain the behavior of the convenience yield has only limited support in the data.

Although we work in a slightly different setup, our results are consistent with a recent study of Lucia and Torro (2011). While they only report that below-average level of water leads to lower risk premium, we show that this effect is more general and there exists a positive relationship between the risk premium and the reservoir level. This is in line with economic theory and supports a more general view that shortage or high prices of 'fuel' (i.e. commodities used for generating electricity) lead to lower risk premia, as shown for gas inventories by Douglas and Popova (2008) or for gas and coal prices by Bunn and Chen (2013).

Our results cannot unambiguously provide an answer as to the character of the observed premia – whether they really represent the price of risk and are not the result of market inefficiency (see e.g. Christensen et al., 2007; Gjolberg and Brattested, 2011; Kristiansen, 2007). However, we show that the evolution of the premia can be partially explained by fundamental factors and thus the premia are likely to be the price of risk. This is in line with the results of Ronn and Wimschulte (2009), who show that investors are indeed ready to pay a premium for securing the price earlier, even if the settlement is only 2 hours apart (EXAA vs. EEX). Nonetheless, the behavior of the premia may differ across markets, as emphasized by Huisman and Kilic (2012), and may change over the years, as reported by Haugom and Ullrich (2012) for the PJM market.

Acknowledgements

We are grateful to Tarjei Kristiansen for sharing with us the Nord Pool database of weekly futures prices. This work was supported by funds from the National Science Centre (NCN), Poland, through grant no. 2011/01/B/HS4/01077 (to RW) and from the Ministry of Science and Higher Education (MNiSW), Poland (to MZ).

Bibliography

Benth, F.E., Benth, J.S., Koekebakker, S. (2008a) Stochastic Modeling of Electricity and Related Markets. World Scientific, Singapore.

Benth, F.E., Cartea, A., Kiesel, R. (2008b) Pricing forward contracts in power markets by the certainty equivalence principle: Explaining the sign of the market risk premium. Journal of Banking & Finance 32(10), 2006-2021.

Bessembinder, H., Lemmon, M.L. (1992) Systematic risk, hedging pressure, and risk premiums in futures markets. Review of Financial Studies 5(4), 637-667.

Bessembinder, H., Lemmon, M.L. (2002) Equilibrium pricing and optimal hedging in electricity forward markets. Journal of Finance 57, 1347-1382.

Botterud, A., Kristiansen, T., Ilic, M.D. (2010) The relationship between spot and futures prices in the Nord Pool electricity market. Energy Economics 32, 967-978.

Brendstrup, B., Hylleberg, S., Nielsen, M.O., Skipper, L., Stentoft, L. (2004) Seasonality in economic models. Macroeconomic Dynamics 8, 362-394.

Bunn, D.W., Chen, D. (2013) The forward premium in electricity futures. Journal of Empirical Finance 23, 173-186.

Christensen, B.J., Jensen, T.E., Molgaard, R. (2007) Market power in power markets: Evidence from forward prices of electricity. CREATES Research Paper 2007-30.

Davidson, R., and MacKinnon, J. G. (1993). Estimation and inference in econometrics. OUP Catalogue.

Diko, P., Lawford, S., Limpens, V. (2006) Risk premia in electricity forward prices. Studies in Nonlinear Dynamics and Econometrics 10(3), Article 7.

Douglas, S., Popova, J. (2008) Storage and the electricity forward premium. Energy Economics, 30, 1712-1727.

Eydeland, A., Wolyniec, K. (2003) Energy and Power Risk Management. Wiley, Hoboken, NJ.

Geman, H. (2005) Commodities and Commodity Derivatives. Wiley, Chichester.

Gjolberg, O., Brattested, T.-L. (2011) The biased short-term futures price at Nord Pool: can it really be a risk premium? Journal of Energy Markets 4(1), 3-19.

Handika, R., Trueck, S. (2013) Risk premiums in interconnected Australian electricity futures markets. SSRN Working Paper. DOI 10.2139/ssrn.2279945.

Haugom, E., Ullrich, C.J. (2012) Market efficiency and risk premia in short-term forward prices. Energy Economics 34, 1931-1941.

Hayashi, F. (2000) Econometrics. Princeton University Press.

Hirshleifer, D. (1989) Determinants of hedging and risk premia in commodity futures markets. Journal of Financial and Quantitative Analysis 24(3), 425-434.

Huisman, R., Kilic, M. (2012) Electricity futures prices: Indirect storability, expectations, and risk premiums. Energy Economics 34, 892-898.

Hylleberg, S. (1986) Seasonality in Regression. Academic Press.

Janczura, J. (2013) Pricing electricity derivatives within a Markov regime-switching model a risk premium approach. Mathematical Methods of Operations Research, forthcoming. DOI 10.1007/s00186-013-0451-8.

Kaldor, N. (1939) Speculation and economic stability. The Review of Economic Studies 7, 1-27.

Kaminski, V. (2004) Managing Energy Price Risk: The New Challenges and Solutions, 3rd ed. Risk Books, London.

Karakatsani, N.V., Bunn, D.W. (2005) Diurnal reversals of electricity forward premia. London Business School Research Paper.

Karakatsani, N.V., Bunn, D.W. (2008) Intra-day and regime-switching dynamics in electricity price formation. Energy Economics 30, 1776-1797.

Keynes, J.M. (1930) A Treatise on Money. Macmillan, London.

Kolos, S.P., Ronn, E.I. (2008) Estimating the commodity market price of risk for energy prices. Energy Economics 30, 621-641.

Kristiansen, T. (2007) Pricing of monthly forward contracts in the Nord Pool market. Energy Policy 35, 307-316.

Longstaff, F.A., Wang, A.W. (2004) Electricity forward prices: A high-frequency empirical analysis. Journal of Finance 59(4), 1877-1900.

Lovell, M. (1963) Seasonal adjustment of economic time series and multiple regression analysis. Journal of the American Statistical Association 58, 993-1010.

Lucia, J.J., Torro, H. (2011) On the risk premium in Nordic electricity futures prices. International Review of Economics and Finance 20, 750-763.

Musiela, M., Rutkowski, M. (2005) Martingale Methods in Financial Modelling (2nd ed.). Springer-Verlag, Berlin.

NASDAQ OMX (2012) Trade at NASDAQ OMX Commodities Europe's financial market (www.nasdaqomx.com/commodities/documentlibrary).

Nord Pool Spot (2013) Annual Report 2012.

Ofgem (2009) Liquidity in the GB wholesale electricity markets. Discussion Paper 62/09 (www.ofgem.gov.uk).

Pindyck, R.S. (2001) The dynamics of commodity spot and futures markets: A primer. The Energy Journal 22(3), 1-30.

Redl, Ch., Haas, R., Huber, C., Böhm, B. (2009) Price formation in electricity forward markets and the relevance of systematic forecast errors. Energy Economics 31, 356-364.

Redl, Ch., Bunn, D. (2013) Determinants of the premium in forward contracts. Journal of Regulatory Economics 43(1), 90-111.

Ronn, E.I., Wimschulte, J. (2009) Intra-day risk premia in European electricity forward markets. Journal of Energy Markets 2(4), 71-98.

Sims, C.A. (1974) Seasonality in regression. Journal of the American Statistical Association 69, 618-626.

Torro, H. (2009) Electricity futures prices: some evidence on forecast power at Nord Pool. Journal of Energy Markets 2(3), 2-26.

Weron, R. (2006) Modeling and Forecasting Electricity Loads and Prices: A Statistical Approach. Wiley, Chichester.

Weron, R. (2008) Market price of risk implied by Asian-style electricity options and futures. Energy Economics 30, 1098-1115.

Wooldridge, J.M. (2002) Econometric Analysis of Cross Section and Panel Data. MIT press.

Zator, M. (2013) Relationship between spot and futures prices in electricity markets: Pitfalls of regression analysis, Master Thesis, Wrocław University of Technology (ideas.repec.org/p/wuu/wpaper/hsc1306.html).

HSC Research Report Series 2013

For a complete list please visit http://ideas.repec.org/s/wuu/wpaper.html

01 *Forecasting of daily electricity spot prices by incorporating intra-day relationships: Evidence form the UK power market* by Katarzyna Maciejowska and Rafał Weron

02 *Modeling and forecasting of the long-term seasonal component of the EEX and Nord Pool spot prices* by Jakub Nowotarski, Jakub Tomczyk and Rafał Weron

03 *A review of optimization methods for evaluation of placement of distributed generation into distribution networks* by Anna Kowalska-Pyzalska

04 *Diffusion of innovation within an agent-based model: Spinsons, independence and advertising* by Piotr Przybyła, Katarzyna Sznajd-Weron and Rafał Weron

05 *Going green: Agent-based modeling of the diffusion of dynamic electricity tariffs* by Anna Kowalska-Pyzalska, Katarzyna Maciejowska, Katarzyna Sznajd-Weron and Rafał Weron

06 *Relationship between spot and futures prices in electricity markets: Pitfalls of regression analysis* by Michał Zator

07 *An empirical comparison of alternate schemes for combining electricity spot price forecasts* by Jakub Nowotarski, Eran Raviv, Stefan Trueck and Rafał Weron

08 *Revisiting the relationship between spot and futures prices in the Nord Pool electricity market* by Rafał Weron and Michał Zator