Derivative Price Information use in Hydroelectric Scheduling

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Abstract

Hydropower producers face the challenge of scheduling the release of water from reservoirs under uncertain future electricity price and reservoir inflow. Using weekly data from thirteen Norwegian power plants during 2000–2006, we find that electricity derivatives prices affect the scheduling decisions significantly. Hence, consistent with recommendations by several theoretical Operations Management studies, financial market information is used in the everyday production planning practice. As expected, production is high at relatively high reservoir levels and is low at high electricity price volatility. When the reservoir level is low, the production is less dependent on the electricity price. Since our empirical model explains about 88% of the realized variation in the power plant scheduling, the model can be used to simplify the scheduling in practice.

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1 Introduction

Hydroelectric scheduling entails managing a set of inventories so as to release water through the turbines at times when it is most beneficial [Massé, 1946]. Reservoirs have a fixed size and inflow is random and, therefore, care must be taken not to spill too much of the water. Producers have some flexibility given by the water reservoirs. They can benefit from the volatile electricity price and produce at high price levels and save water when the price is low. Given a spot price forecast, the producer establishes a feasible production plan that maximizes its value, see e.g. Conejo et al. [2002]. Thus, the producers want to make a strategy so that the present value of production cash flows is maximized.

The OR and engineering literature on hydroelectric scheduling is vast and addresses different decision models and algorithms to solve this. In order to ease the computational burden, a hierarchy of models is often used: long-term studies typically employ monthly or weekly time increments over a one to five year horizon and short-term studies consider granularity from 15 minute to daily intervals with a planning horizon of several days. The long-term models give input to the short term models in the form of e.g. target production levels. The OR/engineering literature is surveyed by Yeh [1985], Labadie [2004] and, for stochastic programming specifically, by Wallace and Fleten [2003]. The economic theory of hydro scheduling is studied in Førsund [2007].Tipping et al. [2004] uses aggregate reservoir data from New Zealand as a part of an electricity pricing model and find that hydropower production increases when inflow is higher than expected and when the reservoir level is higher than normal.

Fleten et al. [2002], Näsäkkälä and Keppo [2008] point out that electricity forward prices should be used in the optimization of hydropower plants. More generally, Ding et al. [2007], Caldentey and Haugh [2006] show that firms should optimize their financial positions and production simultaneously. However, according to empirical studies by Guay and Kothari [2003], Bartram et al. [2006] non financial firms use derivatives only little and, thus, there seems to be a gap between the theoretical papers and the industry practices.

In the present paper we show empirically that this gap does not exist with Norwegian hydroelectric producers, i.e. the producers use information from the electricity derivative market in their hydropower scheduling. Thus, even though they do not necessary use significantly the electricity derivatives they seem to utilize the electricity swap prices in the scheduling of hydro plants. Usually the hydro scheduling in Norway is done by using stochastic dynamic programming where electricity spot price and inflow forecasts are used Fosso et al. [1999]. Our linear regression model explains about 88% of the variation in the realized scheduling decisions even though the scheduling is solved by using sophisticated mathematical programming methods. Thus, this regression model can simplify the practical production planning considerably.

Our data consists of weekly production data from thirteen Norwegian hydropower producers and it includes the electricity generated, reservoir level, and inflow. In addition, we use electricity prices from Nord Pool, both weekly-average spot prices and forward (swap) prices. Both these data sets are from the period February 2000 to December 2006. With the help of our unique data from individual producers, the article contributes to the literature by providing an empirical

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analysis of how commodity storage is operated in a situation where well-functioning markets for spot and forward transactions are available.

Empirical and theoretical dynamics of commodity storage was pioneered by Kaldor [1939], Working [1949], Brennan [1958] and Telser [1958]. These explain how equilibrium inventories relate to competitive spot- and futures prices and perform empirical analyses on agricultural commodities such as cotton and wheat by using aggregate inventory data. High convenience yield is main reason for holding inventory, it is a flow of implicit value that accrues to those who hold the commodity. Agricultural commodities are relevant in the context of electricity, since they are perishable. However, electricity is a flow commodity that can not be stored, so convenience yield need to be interpreted as the benefit of delivering it sooner rather than later. The relationship between commodity storages and price volatility has been studied in several papers, see e.g. Geman and Nguyen [2005] and the references there. Geman and Nguyen [2005] show that soybean price volatility rises when the aggregate soybean inventory falls. Thus, when "scarcity" is high then the price uncertainty is also high. Fama and French [1987, 1988] and Litzenberger and Rabinowitz [1995] show that rising price volatility decreases inventories. Fama and French [1987, 1988] and Litzenberger and Rabinowitz [1995] use a proxy for inventories.

The remainder of this article is structured as follows. The institutional background is explained in Subsection 1.1. Reservoir operations is the topic of Section 2, and Section 3 explains the data. Section 4 displays the regression results, and Section 5 concludes.

1.1 Nordic Electricity Market

The consumption of electricity in the Nordic countries is characterized by seasonal variation, mainly due to a high degree of direct electrical heating. Low temperatures and short day-lengths lead to higher consumption in the winter than in the summer [Johnsen, 2001].

The Nordic power market, particularly the Norwegian part, is hydropower dominated. In Norway almost 99% of electricity generation comes from hydropower, and in the whole of the Nordic region hydropower constitutes over 50% of the power production [Nordel, 2007].

Norway has a water reservoir capacity of about 84 TWh which roughly constitute 70% of annual generation in Norway. This gives the producers some degree of flexibility and the possibility to schedule generation to the periods with the highest electricity prices. Retailers who buy in the market and deliver electricity to the consumers naturally do not have this opportunity.

Limitations in reservoir capacities and variation in precipitation contribute to price variations between seasons. Since most of the inflow comes during late spring and summer when the snow in the mountains melts, the reservoir capacity is sometimes not sufficient: The limited storage capacity makes it impossible to transfer enough water into the winter season which normally faces high demand and low inflow. Due to the constraints the plants must produce at high level during summer time in order to avoid costly spillage from overflow in the reservoirs [Fleten and Lemming, 2003].

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Nord Pool ASA is the Nordic power exchange. It has developed from being solely a Norwegian power exchange to be a multinational exchange for electrical power which serves Denmark, Finland, Sweden and Norway. In addition to being an exchange, Nord Pool also publishes important market information such as total reservoir content in the Nordic countries and outages for maintenance and repair.

In the Nordic market Elspot is the market for physical contracts and it is an auction-based day-ahead market, where electrical power contracts are traded for each hour the following day. About 70% of the Nordic consumption is traded at Elspot. The system price is the average of the 24 hourly day-ahead prices calculated assuming no bottlenecks in the transmission grid. Its annual volatility is about 189% [Lucia and Schwartz, 2000].

Nord Pool's Eltermin is the main Nordic marketplace for financial electricity contracts having the Elspot price as the main underlying index. Popular products include futures contracts for the next few weeks, and forward contracts for the next few months, quarters and years. Although these are termed forwards at Nord Pool, they correspond best to textbook definition of swaps, since they exchange a floating electricity price with a fixed one [Benth et al., 2008]. There are both baseload contracts and peak load contracts, where the latter is based on peak hours only, i.e. from 8 am. to 8 pm. Baseload contracts are based on all 24 hours of the day. Other traded products are European options, contracts for differences that pay off depending on how much different area prices differ from Elspot system prices, and futures/swaps for other underlying indices such as the German EEX electricity price, the Dutch APX price, and CO_2 emission derivatives.

The forward curve captures the risk adjusted expected value of the future spot price. According to e.g. Lucia and Schwartz [2000], the seasonal systematic pattern throughout the year is of crucial importance in explaining the shape of the forward curve. The shape of the forward curve displays one peak and one valley per year, in total accordance with the behavior of the system price. The trade in financial contracts is more than four times the energy load in the Nordic area.

The Norwegian Water Resources and Energy Directorate (NVE) collects continuous water level data from almost 600 metering locations all over the country. This information is recorded in the national database Hydra II and is used in their power and flood forecasts [Engeset et al., 2003]. Some of this information is publicly available; Svensk Energi, Nord Pool and NVE publish water reservoir statistics regarding the percentage filling in three zones of Norway and the whole of Sweden. The statistics are published on a weekly basis and gives the producers important information on the hydrologic balance in Scandinavia.

2 Hydropower Scheduling

Hydropower plants typically have quite complex topologies with several cascaded reservoirs or power stations in the same river system. We will focus on simple topologies with no hydraulically coupling to other stations. Hence, when the term hydropower station is used in this article, it is assumed to be a hydropower station with only one reservoir connected to it[1].

2.1 Power Generation

The process of generating hydroelectric power is quite simple and involves converting the kinetic energy in the moving water into mechanical energy by the turbines. Then in turn the turbines spin a generator rotor which produces electrical energy. The power generated at the hydropower station is generally a nonlinear function of water release and the station's net head which is the difference between the headwater elevation and the tail water elevation. The release of water is in turn a function of the volume of the reservoir.

Depending on the size of the reservoir and the time horizon, it is sometimes reasonable to make the assumption that there is a fixed energy coefficient, saying how many kWh of electricity one m^3 of water produces. This approximation is standard in long-term scheduling and in systems where production is a near linear function of release, e.g., because the head variation is small compared to the average head [Lamond and Sobel, 1995]. We will use this approximation throughout.

Due to the Nordic power market's dependence on hydropower, the reservoir content and the inflow to the reservoirs are factors that are expected to influence the market prices and the electricity production. Therefore, producers follow regularly information on these variables [Johnsen, 2001]. Naturally, the inflow is expected to increase the production. Furthermore, seasonal variation may affect how the production decision depends on inflow.

Since water can be lost through overflow, it is important to model inflow as a stochastic variable. In Norway there are long time series of historical observed inflow from a large amount of metering locations that enables inflow analysis. The risk of overflow is particularly considerable when the snow melts in the spring. This risk can be reduced if the producer has information about the snow reservoir. Then the future inflow will consist of a known part, the melted snow, and an unknown part, the future precipitation minus possible evaporation [Hindsberger, 2005]. Many producers follow all these factors and try to forecast them in order to improve their production scheduling.

2.2 Production Factors

There are several factors that affect the hydropower scheduling. First, if the expected future electricity price is high relative to the current spot price then it is optimal to postpone the production (see e.g. [Näsäkkälä and Keppo, 2008]). Thus, price forecasts are needed in estimating the water values and the optimal production strategy.

Second, we expect that a positive deviation from the average reservoir level results in increased production. Furthermore, when a reservoir is nearly empty or nearly full, the inflow is the main driver in the production decisions and electricity prices do not affect the decisions significantly.

[1]If there are more than one reservoir connected to the power station(s), we aggregate the system into one equivalent reservoir and power station.

Third, if there is an unexpected increase in the spot price or inflow volatility then, by the real option theory [Dixit and Pindyck, 1994], we expect a decrease in the production since the value of waiting for more information is high.

From the above discussion we can form the following hypotheses on the hydropower scheduling:

- If the expected future prices are high relative to the current spot price then the current production is low.
- Electricity production rises in reservoir level.
- Electricity production falls in electricity price and inflow volatilities.

These hypotheses are studied more in the empirical analysis. Before that we next introduce the data used.

3 Data

The empirical analysis presented in this paper is mainly based on data from thirteen Norwegian hydropower producers. The selected producers are introduced in Table 1. The power stations have different production capacity, reservoir size and other physical conditions. For example, the smallest producer has a capacity of 23 MW and the largest producer has a capacity of 210 MW.

Table 1: Descriptive data from the thirteen hydropower plants. Some notion require clarification; Inflow is the expected yearly inflow, relative regulation is defined as reservoir size divided by annual expected inflow and capacity factor is defined as annual expected inflow divided by the rated power station capacity. Here the capacity factor is given as a percentage of a year.

Producer	*Rated capacity* [MW]	*Energy coefficient* [kWh/m^3]	*Reservoir size* [GWh]	*Annual inflow* [GWh/yr]	*Relative regulation* [yr]	*Capacity factor* [%]
1	128	1.16	228.1	641.2	0.356	57.2
2	120	1.32	624.4	380.8	1.640	36.2
3	30	1.15	47.1	106.6	0.442	40.5
4	40	1.27	51.8	139.9	0.370	39.9
5	28	0.67	118.9	87.8	1.350	35.8
6	23	0.16	14.0	153.0	0.092	76.0
7	68	1.25	255	272.3	0.937	45.7
8	167	1.09	272.5	414.4	0.642	28.3
9	210	1.46	1270	1250.5	1.015	68.0
10	62.1	1.50	142	231.8	0.613	42.6
11	41	0.95	42.6	81.3	0.953	22.6
12	29	0.91	12.4	147.2	0.084	57.9
13	140	1.36	380.8	662.9	0.574	54.0

In the modeling of the producers we make the following assumption:

- All the producers are price takers. That is, the producers are small relative to the aggregate market volume and, therefore, they are not able to affect the market prices.
- If the producers have bilateral contracts that obligate them to deliver power to a contracted price, they can purchase the contracted volume at the spot market. Therefore, the contracts do not change the scheduling problem.

To comply with the assumption that the producers act as price takers the largest producers in Norway such as Statkraft and Hydro are not included in our data set. Further, all the companies in Table 1 are producers that participate in the Nordic electricity market. Therefore, for instance industrial companies that produce for their own consumption are not considered. In our data set there are no run-of-the-river plants because they are not as flexible as producers with reservoirs. In addition, to keep the focus on external factors the power stations in Table 1 do not have water connections to other stations that affect the production considerably.

3.1 Producer Panel Data

We have weekly data on the thirteen producers, from February 2, 2000 to December 27, 2006, which totals 361 data points. The producer data includes production, reservoir level and inflow time series. Some of the producers do not directly measure inflow, but calculate it using the change in reservoir level, production and spill. Thus, with these producers the inflow time series is estimated based on their data. Since the data from the different producers have the same time horizon, our data set is a balanced panel data set.

The data from the thirteen producers was gathered through electronic correspondence. We have avoided to alter the time series. In some inflow time series a few data points were negative. Since this is clearly unrealistic and caused by an error in measurements or calculations, these values were set equal to zero. A transformation of the reservoir level data with denomination Mm^3 to MWh using the average energy coefficient was required for some producers. In addition, some of the data we received was on hourly or daily basis. In these cases, we aggregated the data so that it has the form MWh/week or MWh.

3.2 Production Data

In Figure 3.1 the weekly relative production, i.e., the weekly production divided by the maximum weekly production for the producers is plotted against time. As can be seen, the relative production varies considerably. A tendency of an annual periodical trend can be noticed. Further, quite often the data shows zero production over a week. This may be due to the fact that the producer finds it unfavorable to generate or there is maintenance or a breakdown. Unfortunately, information concerning planned and unplanned production interruptions is not available for the analysis. [2]

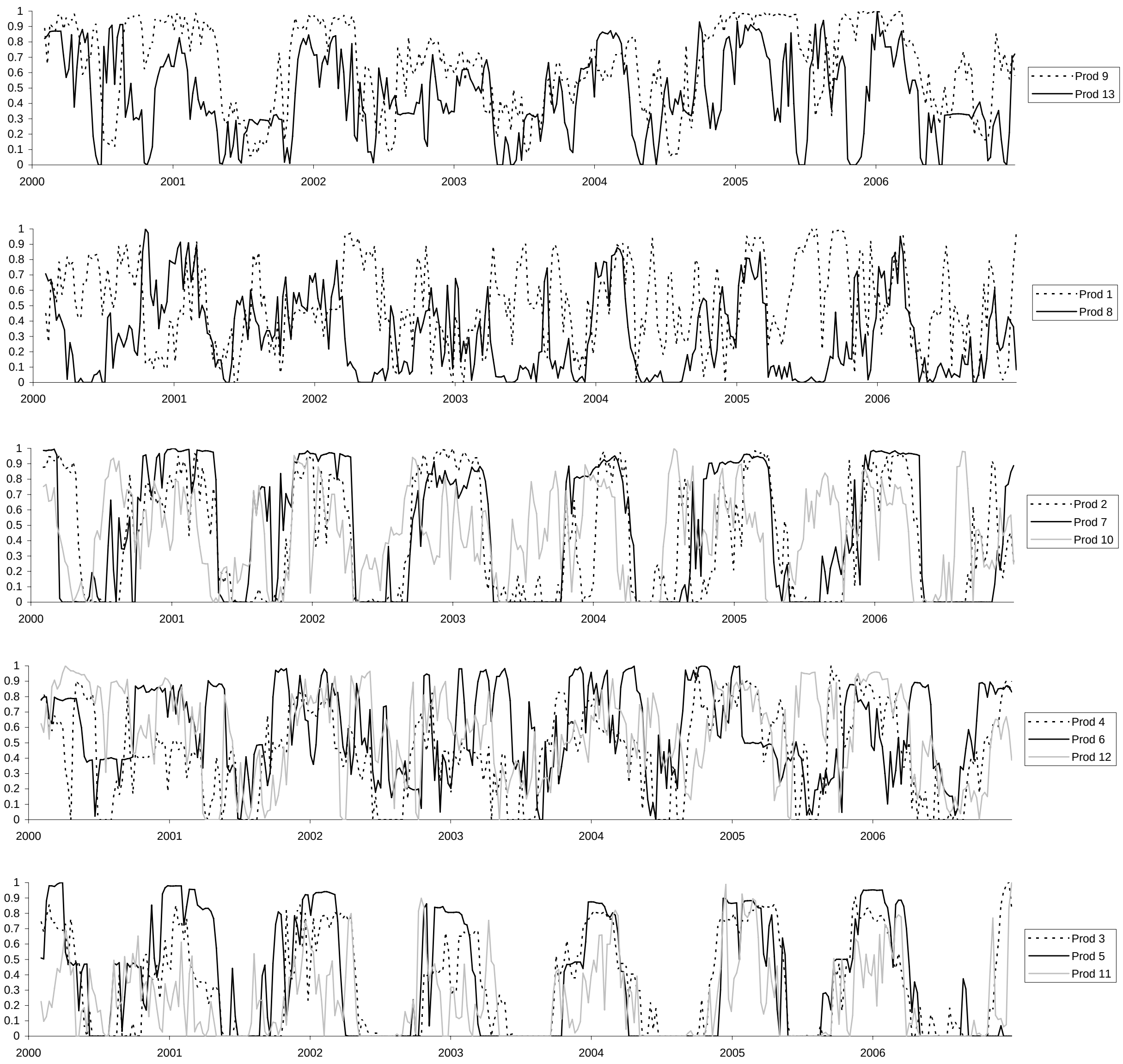

Figure 3.1: Relative production for all producers from 02 February 2000 to 27 December 2006. Time series are sorted according to annual production.

Descriptive statistics for the production data is presented in Table 2. As can be seen, the maximum observed values are high; actually, for most of the producers the maximum value is higher than the theoretical maximum based on the rated capacity presented in Table 1. This indicates that within a short time period the producers have the possibility to produce more than the rated capacity. From Table 2 we also see that the only producer who does not have minimum production of zero is Producer 9.

[2]There is no literature documenting the frequency and duration of outages of hydropower plants but informal investigations among Norwegian firms indicate roughly once a year, with average duration one week.

Table 2: Descriptive statistics for production data. The variables are in MWh/week. ADF is the Augmented-Dickey-Fuller test statistic having a critical value of -2.87 at a 5% significance level [Dickey and Fuller, 1979].

Producer	*Mean*	*Min*	*Max*	*Std. dev*	*ADF*
1	11059	0	21829	5900	-7.583
2	7755	0	18959	7199	-4.441
3	1697	0	5097	1642	-3.820
4	2448	0	5582	1610	-5.333
5	1734	0	4789	1808	-3.949
6	2141	0	3674	1039	-6.539
7	5327	0	11464	4771	-4.132
8	7963	0	26344	7059	-6.086
9	23835	1985	36651	10130	-4.744
10	4662	0	10653	3090	-6.465
11	1448	0	6576	1669	-7.242
12	2616	0	4686	1343	-6.769
13	11863	0	26286	7176	-6.380

3.3 Reservoir Data

Figure 3.2 illustrates the relative reservoir content, i.e., reservoir content as a percentage of the maximum reservoir capacity. A clear periodical variation can be seen. Since many of the reservoirs are emptied once a year, it may be argued that the producers use production scheduling conditional that the reservoirs are at their minimum level at the given date. This agrees with the fact that all of the producers in our sample have a rather low relative regulation. The reservoir data is used in Section 4.1.

3.4 Inflow Data

Inflow time series (weekly inflow in MWh/week) is illustrated in Figure 3.3. It is expected that there are some seasonal variations over a year. However, due to the variations between the years (some of the years are "wetter" than the others), this effect is not clear in the figure. There seems to be significant differences of the spread of inflow during a year. Some of the producers have evenly spread inflow, while others have periods with high and/or low inflow. This is also evident from Table 4 where descriptive statistics for the inflow data is presented.

3.5 Spot Price Data

Electricity price data is obtained from Nord Pool (www.nordpool.com). What we call spot prices in the analysis are weekly average day-ahead system prices in Euro/MWh. Due to the averaging we do not have hourly and daily price variations in our data. In the first row of Table 5 the descriptive statistics of the spot price are presented.

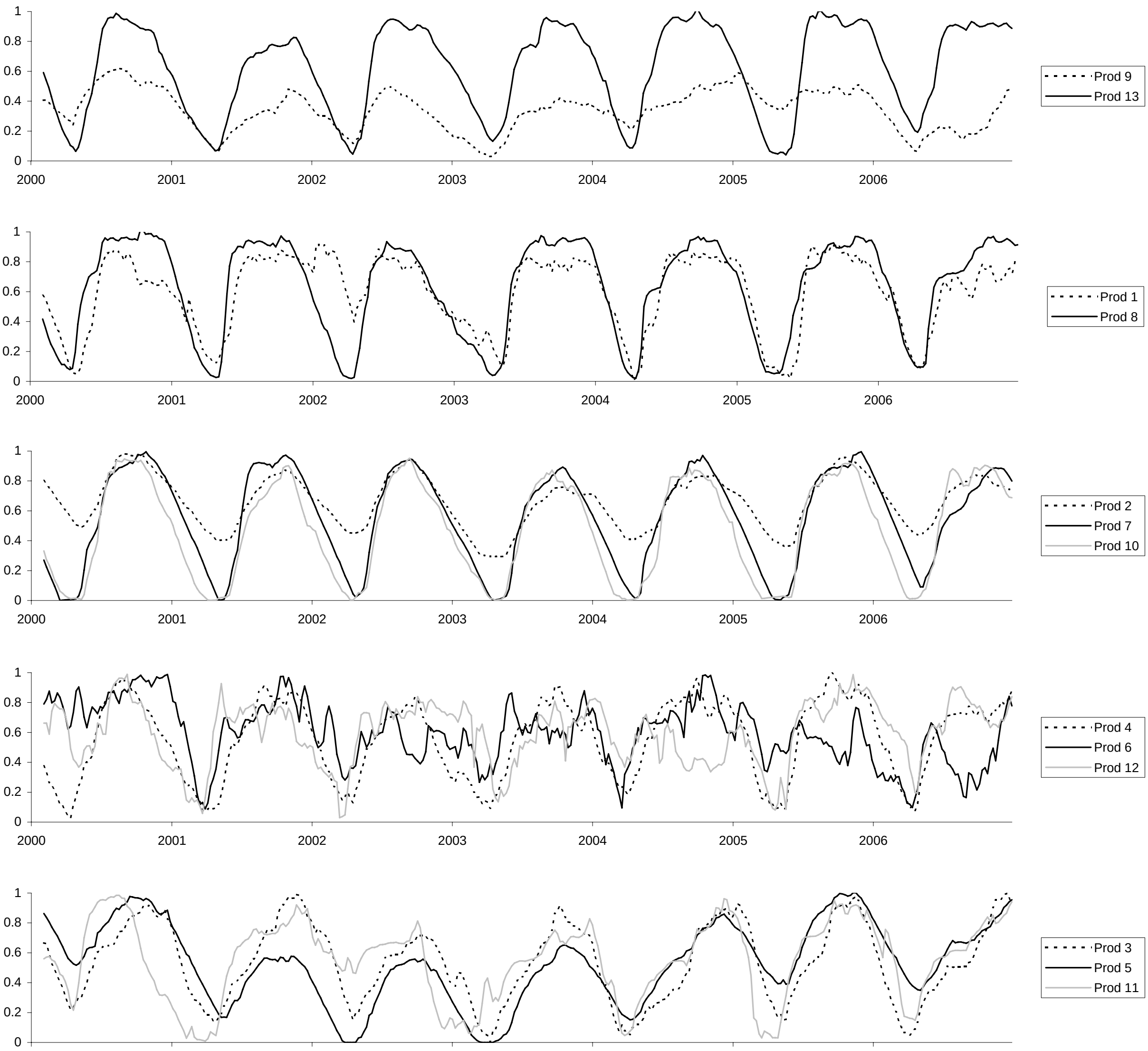

Figure 3.2: Reservoir content for all producers from week 5 in 2000 until week 52 in 2006.

Table 3: Descriptive statistics reservoir data. All data are in MWh. ADF is the Augmented-Dickey-Fuller test statistic having a critical value of -2.87 at a 5% sign. level.

Producer	*Mean*	*Min*	*Max*	*Std. dev*	*ADF*
1	135517	558	208347	58219	-1.923
2	412736	183562	612497	109436	-1.334
3	25229	300	46900	12264	-1.180
4	28829	1617	51721	13620	-1.537
5	63145	0	119113	31008	-0.7387
6	8338	1242	13823	2897	-3.172
7	141294	50	253800	81101	-1.368
8	171573	5380	276221	87367	-1.570
9	433929	37500	786100	173834	-1.212
10	67641	100	135200	46670	-1.346
11	23491	400	41956	11203	-1.550
12	7359	0	12266	2621	-3.786
13	236639	15617	388839	114489	-1.328

Table 4: Descriptive statistics inflow data. All data are in MWh/week. ADF is the Augmented-Dickey-Fuller test statistic having a critical value of -2.87 at a 5% sign. level.

Producer	*Mean*	*Min*	*Max*	*Std. dev*	*ADF*
1	11638.63	0	63125.10	12375.56	-8.820
2	7312.65	0	50556.00	9151.31	-6.058
3	1743.28	0	6860.34	1437.45	-11.25
4	2709.79	0	12063.05	2318.80	-8.951
5	1872.45	0	24083.89	2193.93	-12.98
6	2967.86	0	22342.42	3250.55	-8.376
7	5575.83	0	43000.00	7542.10	-6.666
8	8413.89	0	77892.03	11601.80	-7.876
9	24149.50	0	118600.00	22266.42	-9.825
10	4795.54	0	32790.00	6077.11	-6.456
11	1577.18	0	12780.18	1785.31	-11.73
12	2784.34	0	36409.64	3762.68	-9.312
13	13779.56	0	209859.60	27271.23	-7.281

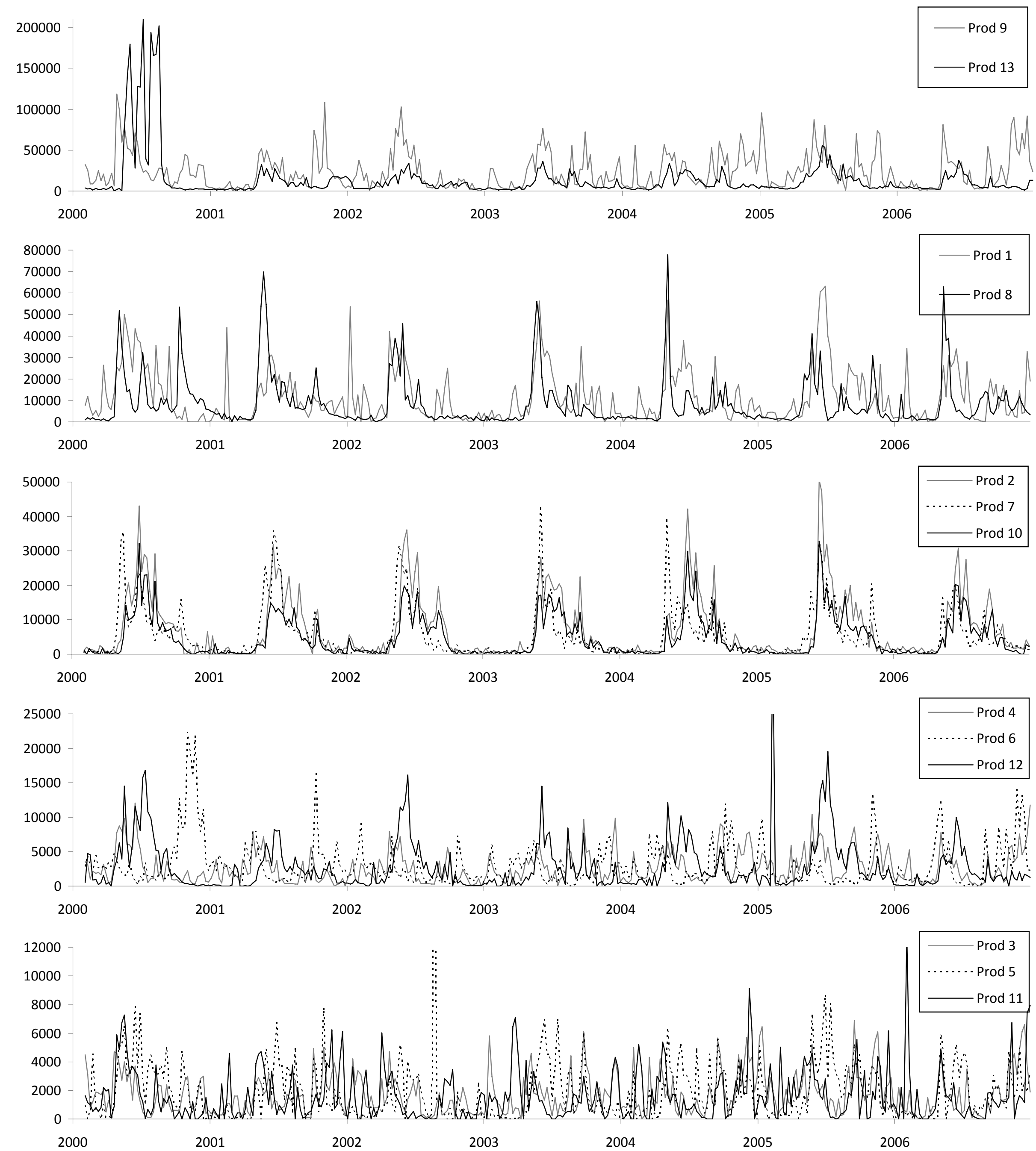

Figure 3.3: Inflow in MWh/week for all the producers during the sample period. Producers are sorted by decending mean annual production.

Figure 3.4 shows the development of the spot price in the sample period. As can be seen, during the selected time period there is no clear seasonal trend in the spot price. The winter 2002/2003 and the late summer of 2006 were dry and, therefore, had high price periods. In 2003 the electricity production from hydropower was only 106 TWh due to extremely low inflow [Ministry of Petroleum and Energy, 2006]. The low supply of power caused the very high prices.

Table 5: Descriptive statistics for spot prices, forward week, forward season and forward year prices. All prices are in Euro/MWh. ADF is the Augmented-Dickey-Fuller test statistic which has a critical value of -2.87 at a 5% sign. level.

	Mean	*Min*	*Max*	*Std. dev*	*ADF*
Spot Price	29.63	4.78	103.65	14.01	-2.928
Week futures	30.44	5.70	114.56	14.89	-3.446
Season swap	31.16	10.48	83.25	13.56	-2.890

3.6 Futures and Swap Price Data

The financial market for electricity derivative instruments at Nord Pool has gone through considerable changes in our sample period. There has been a gradual introduction of new products and at the same time products have been phased out. In 2000 all the products were listed in Norwegian kroner (NOK) per MWh and the product list was based upon a seasonal division of the year. The new products introduced are based upon the calendar year and are listed in Euro/MWh. Hence, through the sample period so called seasonal and block products have been replaced with quarterly and monthly products, and the prevailing currency has changed.

Based on the fact that the producers in the sample have a quite short relative regulation, products with time to maturity less than a year were considered. Specifically we use two different derivative products: a weekly futures contract with delivery next week, and a seasonal swap with delivery next season. Because of the changes in the product list at Nord Pool the seasonal swap product had to be constructed. The seasonal swap product consists of the seasonal product with delivery next season until week 40 in 2005 and after this week it consists of the quarterly product with delivery next quarter. The weekly futures product have not changed during our time period.

Futures and swap products are traded continuously during a trading day, but for consistency with the other data items, "weekly" derivative prices are required. We select the Wednesday closing prices (least likely to be a non-trading day) to represent the weekly closing prices. To allow for the change in currency we use the historical annual average currency spot rate between NOK and EUR published by Norges Bank (the central bank of Norway).

3.7 Stationarity Test

A Dickey-Fuller test has been conducted for all the time series in Tables 2, 3, 4 and 5. This test is used for testing of the stationarity of time series, see e.g. Dickey and Fuller [1979]. With a 5% significance level the critical value is -2.87. The production and inflow series as well as the spot,

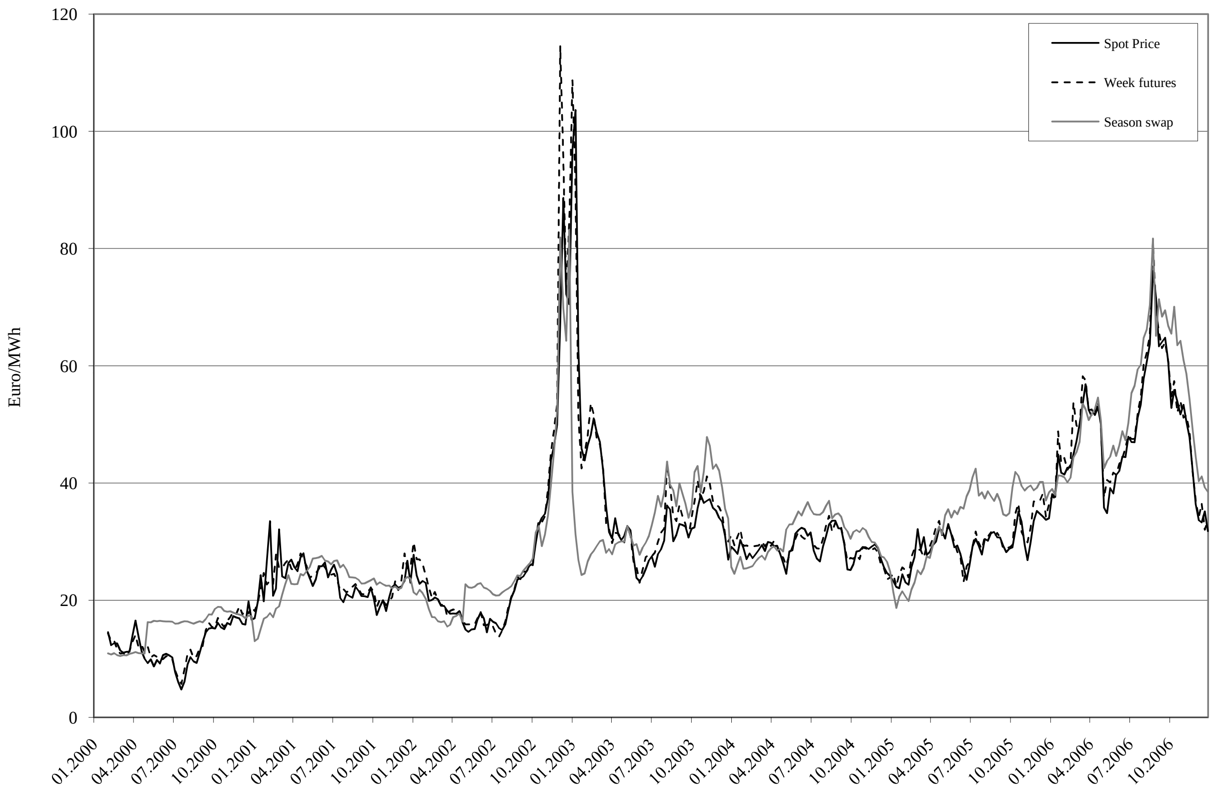

Figure 3.4: Spot and selected futures/swap price development between February 2000 and December 2006. Source: Nord Pool.

the week futures and season price series are all stationary but the reservoir time series is not. As explained in the next section, the best regression models do not use the reservoir level and, thus, all our main variables are stationary. Some of our models use differentiated time series. The first difference of the time series are all stationary with a 5% significance level.

4 Empirical Analysis

We model hydropower production by using linear regression models. The explanatory variables include inflow, spot price, swap price, spot relative to swap, lagged production, size dummies and filling/drawdown season dummies.

All the regression models are reported in the appendix. It is not obvious whether the production is best described as a function of absolute or relative difference between spot and swap prices, so both alternatives are considered. Two models used for testing the relationships:

$$p_{i,t} = \alpha + \beta_1 D_{cap,i} + \beta_2 w_{i,t} + \beta_3 D_s w_{i,t} + \beta_4 S_t/A_t + \beta_5 p_{i,t-1} + \epsilon_{i,t} \tag{4.1}$$

$$p_{i,t} = \alpha + \beta_1 D_{cap} + \beta_2 w_{i,t} + \beta_3 D_s w_{i,t} + \beta_4 S_t + \beta_5 F_t + \beta_6 p_{i,t-1} + \eta_{i,t} \tag{4.2}$$

Here $p_{i,t}$ is production in the production of plant i at week t, $D_{cap,i}$ is a size dummy variable which equals one if the annual generation of plant i is larger than 380 GWh/year and otherwise the dummy variable is zero, $w_{i,t}$ is the inflow of plant i at week t, D_s is a filling season dummy variable which equals one for weeks 18–39, S_t is spot price at week t, A_t is an average of the week ahead futures price and the shortest maturity seasonal swap price at week t, F_t is the shortest maturity seasonal swap price at week t, and $\epsilon_{i,t}$ and $\eta_{i,t}$ are i.i.d. error terms that have zero mean and variance σ^2.

The two models' R^2 values, parameter values, and p-values are in Table 6. Naturally, electricity production is an increasing function of inflow, although less so in the filling season. Production also rises in the size of the plant, spot price minus/divided by the swap prices, and the lagged production. Lagged production captures (unobserved) variables such as persistent weather patterns and/or internal factors such as breakdown or maintenance. Thus, the results regarding the relationship between spot prices, swap prices, and production are as expected. Further, Table 6 indicates that the financial market through the swap and futures prices provide information that is applicable in the production scheduling. High current spot prices relative to the future prices is an indication to reduce inventory level, and high prices for future delivery (swap prices) relative to the current delivery means water should be saved.

Table 6: Estimated parameters of the regression models.

	Eq. (4.1)		Eq. (4.2)	
	Coeff.	p-val.	Coeff.	p-val.
Constant	-1045	0.002	389.9	0.002
Size, D_{cap}	913.3	0.000	926.4	0.000
Inflow, w	0.0694	0.000	0.0692	0.000
Filling season inflow, $D_s w$	-0.0546	0.001	-0.0561	0.001
Spot price, S			23.57	0.000
Season swap, F			-27.62	0.000
Spot relative to future prices, S/A	1361.9	0.000		
Lagged production, p_{t-1}	0.8670	0.000	0.8670	0.000
In-sample R^2	87.37%		87.37%	
Out-of-sample R^2	88.56%		88.55%	

The out-of-sample R^2 values indicate that the models are able to capture production well. With the linear regression model we are able to explain more than 88% of the variation in the production. This number must be considered in the light of the amount of resources that are put into the production scheduling, typically involving preparing and analyzing data and after that running a stochastic dynamic programming model. Thus, even though the electricity scheduling is solved by using complicated estimation and optimization techniques our linear models explains the realized production remarkably well. Therefore, this regression model can simplify the practical production planning considerably.

Figure 4.1 illustrates the out-of-sample test by using model (4.1) and the actual production of all the power plants. The model indeed fits the actual production well in the out-of-sample. In the out-of-sample study the cash-flows of the true production plans are on average 1.755% higher than our model's cash flows.

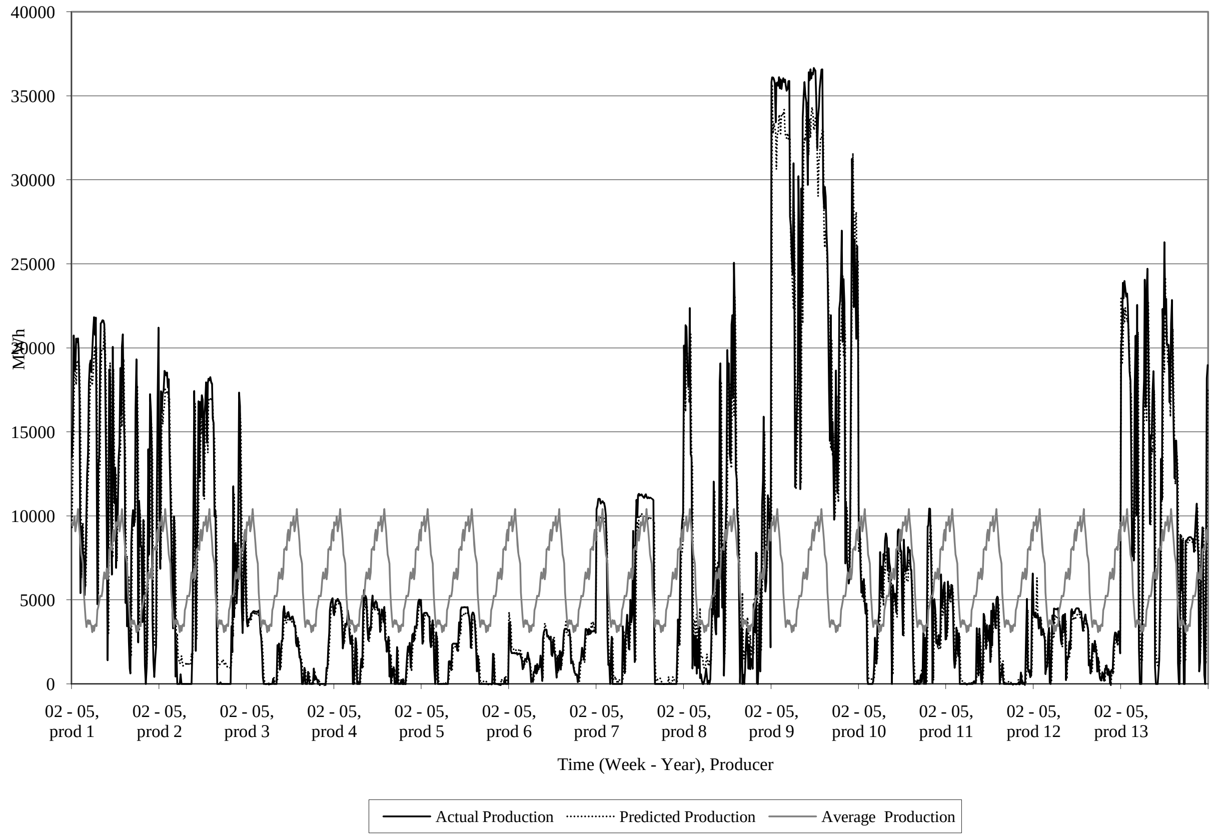

Figure 4.1: Realized production, average production and predicted production using model (4.1) for the out-of-sample period. The model predicts production well out-of-sample.

In the appendix we report on other regressions, where the dependent variable is production in a week relative to capacity, and (deviation from average) reservoir level. These models give lower R^2 values. In addition we tried using next week's inflow as an independent variable, since inflow to a certain extent can be predicted up to a week ahead. However, the R^2 did not increase.

4.1 Tests for Extreme Cases

In addition to the modeling of the general hydropower production, we also test how the power plants behave in specific situations, such as high (or low) reservoir levels, price levels, and price and inflow volatility. This is done by adding dummy variables one by one to the best models (4.1) and (4.2) and analyzing the change in the out-of-sample R^2 values.

There are six hypotheses formulated in these additional tests:

1. *If the reservoir level is higher than usual then the production is also higher.* Scheduling engineers try to steer reservoir levels toward a "comfort zone" which here is taken to lie around the average reservoir level. Also supporting this hypothesis is producers' eagerness to comply with concession requirements that specify that the reservoirs need to be within a certain range during specific periods of the year.

2. *If the reservoir level is more than 90% or less than 10% of the maximum level then the market prices affect the production less.* This hypothesis has the same explanation as above. Furthermore, we simply expect inflow and other non-price factors to determine production in these extreme cases.

3. *If the reservoir level is more than 90% of the maximum level then the production depends more on the inflow.* If the reservoir is nearly full then additional inflow needs to be produced, otherwise the risk of spilling becomes unacceptably high.

4. *If the spot price is within the highest 5% of the realized prices then the production is higher than usually.* This hypothesis assumes that producers are able to profit from high-price market situations.

5. *If the spot price volatility is within the highest 5% of the realized volatilities then the production is lower than usually.* Volatile prices increase the real option value of the water reservoir. Hence the marginal water value increases with the increased volatility since the probability of higher future prices rises, which in turn leads to lower production. Here we calculate volatility based on previous 20 days.

6. *If the forward price volatility is within the highest 5% of the realized volatilities then the production is lower than usually.* As in 5 above, the volatile raises the value of waiting and, therefore, production falls. As above, the volatility equals 20 day historical volatility.

Table 7 summarizes the results. For testing hypothesis 1 we add a dummy variable to (4.1) where the dummy is one if the reservoir level is higher than the historical average for that week, and zero

Table 7: Results of the extreme cases. The sign indicates which effect the dummy has on production. p-val is the in-sample p-value. R^2_{OS} is the out-of-sample R^2 with the dummy variable.

	Dummy variable definition	Model	Sign	p-val	R^2_{OS}
1	Positive deviation from average reservoir level	(4.1)	+	0.00	89.76%
2	Reservoir level outside [10%, 90%]	(4.2)	-	0.002	89.70%
3	Reservoir level more than 90%	(4.2)	+	0.045	89.76%
4	Spot price is within the highest 5% prices	(4.2)	-	0.021	89.66%
5	Spot volatility[3] is within the highest 5% volatilities	(4.2)	-	0.006	90%
6	Seasonal swap price volatility[a] is within the highest 5% volatilities	(4.2)	-	0.852	90%

otherwise. The coefficient turns out to be positive and is significant in explaining the production level, i.e., supports the hypothesis 1. With hypotheses 2–6 we use dummies appended to (4.2). Table 7 indicates that hypotheses 2, 3, and 5 are supported by the data, while hypothesis 4 and 6 are not. Note that with hypothesis 2 we have negative sign because then the spot and swap prices affect less the production (as indicated in the hypothesis). The result for hypothesis 4 is interesting because it has an opposite sign than expected by the hypothesis, i.e., the data indicates that the extreme high prices are accompanied by *low* production, not high. The reason for this is the fact that the highest prices coincide with very low reservoir levels, which explains the low production. Low reservoir levels drive production down more than high prices drive it up. Thus, the producers are not able to utilize the high market prices.

4.2 Production Changes

Although weekly production and explanatory variables are found to be stationary (see Section 3.7), swap prices are inherently nonstationary. We perform a regression model for production changes by using the changes of the factors in the previous section as explanatory variables. The aim is to confirm that the spot price relative to the swap prices are significant in explaining the electricity production.

After confirming that the dummies used in the original regression (4.1) were not significant, the following regression gives the best out-of-sample R^2:

$$\Delta p_{i,t} = \alpha + \beta_1 \cdot \Delta w_{i,t} + \beta_2 \cdot \Delta\left(S_t/A_t\right) + \epsilon_{i,t} \tag{4.3}$$

where Δ indicates the first difference. Results are given in Table 8 and they indicate that changes in the relative prices are indeed important in explaining the changes in the production. Note that the R^2 values are much lower than in Table 6 because in (4.3) we model differences. These R^2 might seem low, but are consistent with the best empirical work in financial time series (see, e.g. Table 3 in Campbell and Thompson [2008]. The results indicate that changes in relative prices are indeed very important in explaining the changes in production. Note that the R^2 values are much lower than in Table 6 because in (4.3) we model differences.

Table 8: Regression results for first difference variables.

	Eq. (4.3)	
	Coeff.	p-val.
Constant	6.05	0.09
Inflow, Δw	0.03	4.21
Spot relative to swap price, $\Delta\left(S_t/A_t\right)$	5152.68	8.06
In-sample R^2	3.30%	
Out-of-sample R^2_{OS}	2.27%	

4.3 Shortcomings

In panel data analysis it is important to have enough individuals for the regression results to be valid [Yaffee, 2003]. Thirteen producers is somewhat low and, therefore, increasing the sample size could improve our analysis. The regression analysis could also improve if the producers in the sample were more alike. This could be achieved by imposing even stricter criteria in the selection of the producers. However, this would decrease the sample size even more.

There are some shortcomings with the data set which may have influenced the analysis. For instance, there is no information about maintenances. Maintenance data would clearly help in the modeling of the production. Further, since scheduling is done by using inflow forecasts, these forecasts would also help. In these forecasts at least snow reservoir data is used and, thus, even this information could improve the model. Similarly, the drivers of the demand process could increase our model fit. These drivers include at least temperature and, in general, weather. However, introducing more independent variables may explain the scheduling decision better, albeit at the risk of over-fitting. In our analysis, we use the aggregate information from the forward and spot prices as well as producer specific inflow data that we expect to capture, at least partly, the above discussed factors.

Time dependent restriction due to esthetic or environmental reasons are important in the scheduling of generation [Yeh, 1985]. Unfortunately, data regarding other restriction than maximum and minimum production capacities and reservoir levels were not available.

The time span considered include very different market situations. In 2000 the hydropower production in Norway was at a historical high level with a production of 142 TWh, while in 2003 the electricity production from hydropower was only 106 TWh due to extremely low inflow [Ministry of Petroleum and Energy, 2006]. The low supply of power caused very high prices in the same period. These peculiar circumstances are unfavorable for the analysis because we might draw inference based on data affected by very special incidents.

5 Conclusion

Our analysis is based on a unique data set from thirteen independent Norwegian hydropower producers and from Norwegian electricity financial market. Our findings show that hydropower production depends on inflow, spot- and swap prices, seasonal variation, and lagged production.

In the hydropower industry, it is common to construct price forecasts based on bottom-up analysis. Therefore, our most interesting result is that electricity forward prices affect the production scheduling. That is, forward prices explain a significant part of the realized variations in the production and, therefore, the information from the electricity financial markets can be used in the scheduling instead of conducting price forecasts from the prevailing bottom-up models.

The empirical analysis shed light also on how the producers act in different situations. Most of these results indicate that hydropower scheduling is performed as expected. However, a little surprisingly we found that producers are not able to utilize high spot prices and that the forward volatility does not affect the production. On the other hand, high prices and low inventory levels happen usually at the same time and, therefore, production is low at these events. Further, the producers might ignore the forward price volatility because, according to our results, they do follow spot price volatility. So, it is only the level of forward prices that matters in the production, not their volatility.

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Additional Regressions and Diagnostics

A Additional Regressions

Tables 9, 10 and 11 show the estimated coefficients and the corresponding p-values of respectively the production, relative production and deviation from expected reservoir models presented. The two last rows shows the in-sample R^2 and the out-of-sample R^2_{OS}, respectively.

B Regression Diagnostics

B.1 Correlation Between Variables

A high correlation in absolute value between variables indicates collinearity, i.e. a linear relationship among the variables. The result of collinearity among independent variables in a regression

Table 9: Production regressions where trying different independent variables. The coefficients and the corresponding p-values (in parentheses) are reported.

Variables					Regressions				
Constant	-419.1	58.49	550.8	-1045	-337.4	389.9	-808.5	-221.9	413.7
	(0.218)	(0.741)	(0.000)	(0.002)	(0.044)	(0.002)	(0.005)	(0.122)	(0.002)
Season dummy D_s	-224.6	-238.4	-253.3						
	(0.036)	(0.019)	(0.016)						
D_{cap}	1072	1073	1079	913.3	915.6	926.4	950.4	952.2	964.6
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dev from avg inflow	0.025	0.025	0.024						
	(0.000)	(0.000)	(0.000)						
Inflow (w_t)				0.069	0.070	0.069			
				(0.000)	(0.000)	(0.000)			
D_s * Inflow				-0.055	-0.055	-0.056			
				(0.001)	(0.001)	(0.001)			
Led Inflow (w_{t+1})							0.045	0.046	0.045
							(0.000)	(0.000)	(0.000)
D_s * Led Inflow							-0.037	-0.037	-0.038
							(0.000)	(0.000)	(0.000)
Spot price			15.32			23.57			20.37
			(0.006)			(0.000)			(0.000)
Season swap			-18.75			-27.62			-24.88
			(0.014)			(0.000)			(0.001)
Spot relative to forward price	890.3			1362			1130		
	(0.004)			(0.000)			(0.000)		
(Spot relative to forward price)^2		405.8			635.8			528.0	
		(0.003)			(0.000)			(0.000)	
Production lagged	0.881	0.881	0.880	0.867	0.867	0.867	0.875	0.875	0.875
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
In-sample R^2	0.872	0.872	0.872	0.874	0.874	0.874	0.872	0.872	0.872
Out-of-sample R^2_{OS}	0.883	0.883	0.883	0.886	0.885	0.885	0.882	0.882	0.882

Table 10: Regressions where the dependent variable is relative production, i.e. production divided by capacity. The coefficients and the corresponding p-values (in parentheses) are reported.

Variables					Regressions				
Constant	0.056	0.083	0.119	-0.040	0.010	0.062	-0.022	0.022	0.072
	(0.004)	(0.000)	(0.000)	(0.035)	(0.365)	(0.000)	(0.162)	(0.009)	(0.000)
Season dummy D_s	-0.046	-0.047	-0.048						
	(0.000)	(0.000)	(0.000)						
Dev from avg inflow	0.834	0.829	0.809						
	(0.000)	(0.000)	(0.000)						
Inflow (w_t)				2.008	2.019	2.004			
				(0.000)	(0.000)	(0.000)			
D_s * Inflow				-1.746	-1.782	-1.815			
				(0.000)	(0.000)	(0.000)			
Led Inflow (w_{t+1})							0.989	0.996	0.977
							(0.011)	(0.01)	(0.013)
D_s * Led Inflow							-0.944	-0.973	-0.998
							(0.014)	(0.011)	(0.010)
Spot price			0.001			0.002			0.001
			(0.000)			(0.000)			(0.000)
Season swap			-0.001			-0.002			-0.002
			(0.000)			(0.000)			(0.000)
Spot relative to forward price	0.051			0.095			0.083		
	(0.002)			(0.000)			(0.000)		
(Spot relative to forward price)^2		0.023			0.044			0.038	
		(0.001)			(0.000)			(0.000)	
Production lagged	0.810	0.810	0.808	0.840	0.840	0.839	0.846	0.846	0.844
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
In-sample R^2	0.751	0.751	0.751	0.749	0.749	0.749	0.744	0.744	0.745
Out-of-sample R^2_{OS}	0.689	0.689	0.688	0.691	0.691	0.692	0.681	0.681	0.681

Table 11: Regressions where the dependent variable is deviation from seasonal average reservoir. Note that since the reservoir level time series are tested to be nonstationary, these regressions are performed with all variables differenced. The coefficients and the corresponding p-values are reported. When the reservoir deviation goes up, it means production is being held back. For most regressions there are variables with wrong sign of the estimated coefficient, or coefficients are insignificant. For the two exceptions, the out-of-sample R^2_{OS} has been calculated.

Variables	Regressions								
Season dummy D_s	75.48	77.18	105.6						
	(0.185)	(0.178)	(0.096)						
Dev from avg inflow	0.377	0.377	0.375						
	(0.087)	(0.087)	(0.088)						
Inflow (w_t)				0.587	0.587	0.584			
				(0.000)	(0.000)	(0.000)			
D_s * Inflow				-0.335	-0.336	-0.334			
				(0.008)	(0.008)	(0.008)			
Led Inflow (w_{t+1})							-0.271	-0.271	-0.274
							(0.000)	(0.000)	(0.000)
D_s * Led Inflow							0.160	0.159	0.162
							(0.085)	(0.088)	(0.084)
Spot relative to swap price	-5120			-4367			-5700		
	(0.004)			(0.005)			(0.007)		
(Spot relative to swap price)^2		-2229			-1931			-2469	
		(0.002)			(0.003)			(0.006)	
Spot price			-132.0			-116.7			-173.6
			(0.003)			(0.005)			(0.012)
Season swap			-39.67			-35.81			-72.27
			(0.067)			(0.045)			(0.013)
Lagged dep var	0.577	0.577	0.572	0.576	0.576	0.572	0.402	0.402	0.397
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
In-sample R^2	0.422	0.422	0.423	0.445	0.445	0.446	0.246	0.246	0.252
R^2_{OS}				0.534	0.534				

model is biased estimators. To avoid collinearity a rule of thumb, is to not include two variables with at correlation coefficient higher than 0.8 or 0.9 in absolute value in the same regression model. In Table 12 the correlation matrix for the stationary variables is presented. The highest correlation is found between the prices. Particularly the correlation between S and FW and (S_t/A_t) and $(S_t/A_t)^2$ with a correlation coefficient of respectively 0.9755 and 0.9847 are very high.

B.2 Testing for Heteroskedasticity: White's Test

White's test for heteroskedasticity is conducted for the two models used in the hypotheses testings; model (4.1) and (4.2). For model (4.1) the square of the residuals were regressed against 18 variables, while for model (4.2) 25 non-redundant squares and cross-products of the original dependent variables were used. The results of the White's tests are summarized in Table 13 and since the observed χ^2 value for both models are higher than the critical χ^2 values the null hypothesis of homoskedasticity is rejected.

Hence, our assumption of heteroskedastic regression errors is verified. It is therefore reasonable to say that our choice of GMM as regression estimator seems proper.

Table 12: Correlation coefficient between all stationary variables. Production and inflow are denoted with p and w, respectively. Spot, season swap and week futures are denoted S, FS and FW. The variables will be discussed thoroughly later. The problematic high correlation between S and FS and (S_t/A_t) and $(S_t/A_t)^2$ should be noted.

	p	w	w_{t+1}	$w-E[w]$	S	FW	FS	(S_t/A_t)	$(S_t/A_t)^2$
p	1								
w	0.3133	1							
w_{t+1}	0.2900	0.7559	1						
$w-E[w]$	0.1139	0.7029	0.4017	1					
S	-0.0196	-0.1444	-0.1273	-0.1266	1				
FW	-0.0194	-0.1412	-0.1297	-0.1205	0.9755	1			
FS	-0.1033	-0.0440	-0.0421	-0.0976	0.8368	0.8568	1		
(S_t/A_t)	0.1509	-0.2417	-0.2063	-0.1163	0.3429	0.2340	-0.1258	1	
$(S_t/A_t)^2$	0.1452	-0.2183	-0.1848	-0.0957	0.3402	0.2277	-0.1460	0.9847	1

Table 13: Results of the White's test conducted for model (4.1) and (4.2). In the right column $\chi^2_{0.05}$ presents the critical value of acceptance of the test.

	R^2 *auxiliary regression*	χ^2_{obs}	$\chi^2_{0.05}$
Model (4.1)	0.1698	565.12	28.869
Model (4.2)	0.1811	602.76	37.652