ECONOMIC STUDIES

DEPARTMENT OF ECONOMICS
SCHOOL OF ECONOMICS AND COMMERCIAL LAW
GÖTEBORG UNIVERSITY
151

THREE ESSAYS ON ELECTRICITY SPOT AND FINANCIAL DERIVATIVE PRICES AT THE NORDIC POWER EXCHANGE

Daniel Deng

ISBN 91-85169-10-2
ISBN 978-91-85169-10-8
ISSN 1651-4289 print
ISSN 1651-4297 online

THREE ESSAYS ON ELECTRICITY SPOT AND FINANCIAL DERIVATIVE PRICES AT THE NORDIC POWER EXCHANGE

Daniel Deng

Abstract

Essay I examines the market efficiency issues at the Nord Pool power exchange in the September 1995 – July 2002 period. A unique characteristic of this electricity exchange is the high hydropower proportion in the traded electricity; water in the hydro reservoir acting as hydropower inventory therefore plays an important role in the pricing of electricity. Inventory holding and the seasonality of both the supply and demand of hydropower generate inter- and intra-year autocorrelation in power prices. I present a theoretical discussion on why power price persistence invalidates the applicability of a market efficiency concept based on the random walk theory. To lend support for the theoretical argument, I conduct an empirical investigation consisting of various unit roots and cointegration methods to tackle the data problems/properties, and results show that weekly spot and futures prices are cointegrated. Philips-Loretan's nonlinear least square is applied in testing the restriction of the coefficient according to the market efficiency hypothesis. The Wald statistic shows that the cointegration vector being (1, -1) is not binding. Residual testing using a Ljung-Box Q-statistic confirms serial correlation. These findings are consistent with the theoretical prediction.

Essay II models electricity prices in the context of the Nord Pool power exchange which has a considerable proportion of hydropower supply. Since hydropower is storable in a producer perspective and the system price is a uniform price for all sources of electricity supply, the applicability of the rational expectation competitive commodity storage model to characterize the spot and futures/forward prices is validated. I further show the nonlinearity between futures/forward prices and water reservoir content as inventory. I perform a BDS test (a test for nonlinearity), Hsieh's third-order moment test (a test that discriminates between different types of nonlinearities) and a nonlinear causality test to portray the nonlinear relationship using short/long maturities contracts. Empirical evidence shows that futures/forward prices are nonlinearly connected with water reservoir content via variance changes, and that the detection of causality varies as maturities change from short to long. These findings provide strong support for the credibility of the arbitrage argument and in a certain case verify the existence of the non-arbitrage condition.

Essay III investigates convenience yield behavior at the Nord Pool power exchange given the considerable storable hydropower being traded. Several hypotheses are tested concerning the behavior and determinants of convenience yield from holding hydropower as inventory. The results reveal that 1) convenience yield has a negative relationship with hydro reservoir content as inventory, 2) convenience yield behavior can be statistically explained within a standard financial call option framework and the call option component can explain a large portion of variability in convenience yield, 3) convenience yield varies on both a yearly and a monthly basis, and 4) there is an asymmetry of volatility of convenience yield during high/low hydro inventory periods.

Keyword: Nord Pool, market efficiency, cointegration, rational expectation competitive storage model, BDS test, Hsieh's third order moment test, nonlinear causality, EGARCH, convenience yield, call option.

Daniel Deng, Center for Finance, Department of Economics, Göteborg University,
SE-40530 Göteborg, Sweden. Tel: +46-31-7734178
Email: Daniel.Deng@handels.gu.se

Acknowledgements

First and foremost, I would like to extend my deepest gratitude to my external and internal supervisors, Professor Carsten Tanggaard, Dr. Erik Hjalmarsson and Professor Lennart Hjalmarsson for their continuous support, encouragement, and guidance. Academically, I have benefitted from all of you in different ways when we face issues in a very unique commodity exchange. I also want to thank my opponent at the licentiate degree defence, Professor Hans Byström for his constructive comments on the papers.

I am especially grateful to Professor Clas Wihlborg who introduced me to the area of finance, and over the years has given me continuous support and encouragement.

I would also like to give special thanks to the administrative staff at the department for their support and assistance.

I thank my friends Erik Liden, Hong Wu and Jianhua Zhang for sharing their views on life and studies.

Finally, my thanks go to my family and relatives for their love and support.

Financial support from Jan Wallander and Tom Hedelius Foundation, Adlerbertska Foundation, SWEDCO AB and Norfa Foundation are gratefully acknowledged.

Göteborg, September 2005.

Daniel Deng

Table of Contents

Essay II: Modeling and investigating the relationship between electricity prices and water reservoir content at the Nord Pool power exchange.

Essay III: Convenience yield behavior at the Nord Pool power exchange.

1. *Introduction*

The three essays in this dissertation consider various financial aspects of the spot and futures/forward markets at the Nord Pool power exchange. Established in 1996, Nord Pool was the first multinational power exchange in the world specialized in trading electricity spot and derivative contracts. Although there have been a few papers generated on Nord Pool electricity pricing, very little attention has been given to the unique role of hydropower and the resulting implication for financial modeling of electricity prices. Therefore, this dissertation aims to explore the implication of hydropower inventory holding on electricity prices in several financial aspects, such as market efficiency testing, nonlinear causality between water reservoir content and futures/forward prices and the estimation of convenience yield and its behavior and determinants.

Since hydropower reservoirs can store future electricity as inventory, electricity can be regarded as storable in the hydropower producer perspective. Theoretically, this viewpoint allows me to approach the research issues by taking a route in the direction of storable commodities. Since the system price matching the electricity supply and demand conditions is a uniform price for all sources of electricity supply including hydropower, the system price is also the solution to the hydropower inventory holder or producer's profit maximization problem. [1] This validates the applicability of the rational expectation competitive storage model framework to the spot and futures/forward prices at Nord Pool.

This dissertation contains the following three essays:

I) Market efficiency at the Nord Pool power exchange.

II) Modeling and investigating the relationship between electricity prices and water reservoir content at the Nord Pool power exchange.

[1] Without loss of generality, we assume inventory holders are producers as well.

III) Convenience yield behavior at the Nord Pool power exchange.

The three essays can be read independently, and hence, as is customary, each essay contains an introduction that motivates the essay, reviews the literature and discusses the contribution to the research area. Rather than reviewing those here, I focus on the unique features of electricity prices that are emphasized in the essays and how the essays are connected.

In the dissertation the financial emphasis is on the storability of hydropower in a hydropower producer perspective, and how this enables a modeling of electricity prices by implementing modern financial inventory theory. Although Essay II contains an explicit rational expectation competitive storage model, the perspective of looking at hydropower inventory and its influence on pricing is undertaken throughout the dissertation. Essay I discusses theoretically why electricity prices show intra- and inter-year price autocorrelations given the influence of hydropower inventory and the seasonal dynamics of supply and demand and how the unique statistical properties of electricity price dynamics invalidate the market efficiency testing. The empirical part of Essay II investigates the nonlinear causal relationship between water reservoir content and futures/forward prices, gives further insight into the dynamic association between the two variables, and provides strong support for the credibility of the arbitrage argument via inventory holder's profit maximization and the existence of the non-arbitrage condition. A unique benefit of hydropower inventory is the convenience yield, or the benefit from the increased utility associated with availability in periods of scarce supplies. Convenience yield is not only an important factor contributing to the interpretation of the commodity spot-futures spread, but also has an effect on the pricing of commodity derivatives. By estimating convenience yield and investigating its behavior and determinants in Essay III, we gain an understanding on issues such as how convenience yield influences inventory holder behavior. What follows is an elaboration on some of the important theoretical issues and the applied estimation methods.

Electricity prices and the random walk theory

As hydropower is storable as inventory via water reservoirs, the hydropower inventory holding has some important implications. First, the availability of hydropower inventory in relation to demand influences both intra- and inter-year electricity prices. Hydro reservoir water content (level) reaches its peak value in September-December and its valley value in April-May. Electricity demand increases in the winter due to the heating demand. As electricity prices are determined by the law of supply and demand, the resulting electricity prices are usually low in June-July and high in January-February. This suggests that power prices typically have a seasonal component, implying intra-year autocorrelation. Although hydropower inventory supply is seasonal, the hydropower inventory carryover may be consumed not only within the year but also from year to year, suggesting inter-year autocorrelation in power prices. Second, factors that systematically influence commodity prices (such as seasonality in the dynamics of supply and demand, distributed lag effects, longer cycles, etc.) contribute to short-run price persistence (Tomek, 1994).

To illustrate how power price persistence invalidates the applicability of the random walk theory, I present a simple model to characterize the dynamics of commodity pricing:

$$CP_t = Y_t + e_t \,, \tag{1}$$

where CP is the commodity price, Y is the systematic component , e is the random component and t is the time measurement.

For an individual price series, *e.g.* spot price series alone, the notion of random walk implies that price changes are random, independent of each other and have identical normal distributions (*i.i.d.*). This can be expressed as follows:

$$S_t = S_{t-1} + e_t, \quad (2)$$

where S_t and S_{t-1} are spot prices at t and $t-1$ respectively, and e_t is assumed to be a random error with an ***i.i.d.*** distribution.

The trouble with directly generalizing the concept of random walk price dynamics from a security market to a commodity market lies in the fact that the systematic component may not be adequately modeled as lagged price alone, *i.e.* $Y_t \neq S_{t-1}$. As the systematic component for commodity prices, Y_t is composed of a mixture of factors representing seasonality, distributed lag effects, longer cycles, etc. These factors are likely to give rise to short-run persistence in price behavior. The intra- and inter-year power price persistence implies that the random walk hypothesis is not valid, *i.e.* $S_t - S_{t-1} \neq e_{St}$, and similarly, $F_{t-1} - F_{t-2} \neq e_{Ft}$, where F_{t-1} and F_{t-2} are futures prices at $t-1$ and $t-2$ respectively, and e_{St} and e_{Ft} are both random errors,[2] leaving a market efficiency evaluation questionable.

Essay I provides a detailed theoretical discussion on how price persistence specifically influences the empirical testing result based on the market efficiency testing procedures employed, *i.e.* why the cointegrating vector being (1, -1) is not binding and why the residuals from the Phillip-Loretan regression are autocorrelated. Efforts are also made to illustrate that appropriate econometric procedures should be selected to deal with electricity data properties such as endogeneity, serial correlation, etc.

An alternative discussion on the futures/forward price dynamics in connection with the random walk theory is provided in Mandelbrot (1971) who mentions how lagged effect

---

[2] Under special circumstances, price changes for commodity futures contracts might equal a random error that is not correlated (Tomek, 1994). The condition of a futures price process being a random walk process is stated in Mandelbrot (1971). In our case, if the length of maturity of futures prices is sufficient, the futures prices might become a random walk process as the significance of the lagged effect vanishes. However, for the one-week ahead futures price contract, price changes do not equal a random error with *i.i.d.* distribution.

influences the price dynamics of futures prices. He shows that for finite horizon anticipation and for every past innovation $N(s)$, one can only add the lagged effects up to time $t+f$, where t designates the present and f the depth of future. The total effect of the innovation $N(s)$ is considered equal to $N(s)\sum_{n=0}^{t+f-s} L(n)$, where $L(n)$ is called the lagged effect kernel. The resulting price $P_f(t)$ satisfies:

$$\Delta P_f(t) = \sum_{s=-\infty}^{t} N(s) \sum_{m=0}^{t+f-s} L(m) - \sum_{s=-\infty}^{t-1} N(s) \sum_{m=0}^{t-1+f-s} L(m) = N(t)\sum_{m=0}^{f} L(m) + \sum_{s=-\infty}^{t-1} N(s)L(t+f-s) . \quad (3)$$

Since $\lim_{n\to\infty} L(n) = 0$, it is easy to verify that as $f \to \infty$, $\Delta P_f(t) \to \Delta P(t)$ and $P_f(t) - P_f(0) \to P(t) - P(0)$ which expresses that a martingale process $P(t)$ (previously defined in his paper) can be considered identical to $P_\infty(t)$. But for finite f, $\Delta P_f(t)$ is a new moving average of the form: $\Delta P_f(t) = \sum_{s=-\infty}^{t} N(s) L_f(t+1-s)$. Define the function $L_f(n) = \sum_{m=0}^{f} L(m)$ for $n = 0$ and $L_f(n) = L(f+n)$ for $n \geq 1$. In the case that the lagged effect has a finite span f_0, $L(n)$ vanishes for lags n satisfying $n > f_0$, and we have $L_f(n) = L(f+n) = 0$ for all $n \geq 1$ and $f > f_0$. Hence as soon as $f > f_0$, $P_f(t)$ becomes identical to the martingale $P(t) = P_\infty(t)$. The depth of future f corresponds to the time span or length of maturity of the futures/forward contract in my paper. The lagged effect can be considered to be seasonality in an electricity pricing perspective. Essentially, Mandelbrot points out that futures/forward prices may become a random walk process as long as the depth of futures, *i.e.* the length of maturity, is sufficiently long for the lagged effect of seasonality to vanish. Because the empirical part of Essay II attempts to verify the existence of the non-arbitrage condition, it implements the linear/nonlinear Granger causality testing procedure. Theoretically, if the market is efficient, no arbitrage profit can be left in the market; hence it is not possible for futures/forward prices to be efficiently forecasted using water reservoir as inventory and we should not find causality in the Granger sense. This is possible when futures/forward prices are a random walk series. Based on Mandelbrot's discussion on futures/forward price dynamics, Essay II uses weekly futures prices as a benchmark series and includes a 1-month ahead futures contract, a 1-year ahead summer 0 seasonal forward, and 2-years ahead winter 1 and winter 2 seasonal forward contracts with longer maturities in order to compare the test results with the benchmark case. As maturity lengthens, the lagged effect function discussed in Mandelbrot's paper becomes strictly zero for large enough lags (***i.e.*** long enough maturity length), and the futures/forward prices may become a martingale price process. If the lagged effect on futures/forward prices becomes increasingly less influential, then we may expect a varying pattern of causality in terms of the length of maturity. Moreover, any case where no causality is detected between the futures and water reservoir content proves the validity of the non-arbitrage argument.

The rational expectation competitive storage model and convenience yield

Because hydropower is storable in a hydropower producer perspective and because the uniform system price is also the hydropower price and therefore the solution to the hydropower producer's profit maximization problem, the applicability of the rational expectation commodity storage model is validated. The hydropower producer's profit maximization problem can be expressed as:

$$\max_{S_t} E_t[\Pi_{t+1}] = \frac{E_t[P_{t+1}]\times(S_t)}{1+r} - P_t \times (S_t) - K_t(S_t)\,, \tag{4}$$

where S_t is the hydropower supply at Nord Pool at time t, r is assumed to be a constant risk-free rate and K_t is the cost of carry for the hydropower supply at time t. The cost of carry can be further decomposed to contain the following components:

$$K_t(S_t) = O_t(S_t) + M_t(S_t) - N_t(S_t)\,, \tag{5}$$

where O_t is the physical storage cost function, M_t is the risk premium function and N_t is the convenience yield function.

In the above formulation, we assume that the hydropower producer is risk neutral and that the producer profit equals the expected appreciation in price less the opportunity and carrying costs associated with storage. In addition, several supply and demand conditions must be fulfilled:

Condition 1: $Y_t + I_{t-1} = S_t$, (6)

where Y_t is the current production, I_{t-1} is the carryover inventory stocks from time t-1, and S_t is the total hydropower supply in the market.

Condition 1 expresses hydropower supply as the sum of carryover stocks and the current production.

Condition 2: $S_t = I_{t-1} - I_t + i_{t-1}$, (7)

where i_{t-1} is the inflow at time t-1.

Condition 2 implies that the hydropower supply at current time t can be expressed as the difference in water reservoir content between time t-1 and time t plus the inflow in between time t-1 and time t.

Condition 3: $S_t = D_t$. (8)

Condition 3 states that hydropower supply equals hydropower demand at time t.

Condition 4: $P_t = P(D_t)$, (9)

where $P(.)$ is the inverse demand function.

Condition 4 says that the spot price at time t is equal to the inverse demand function.

The first-order condition for the above maximization problem is as follows:

$$\frac{E_t[P_{t+1}]}{(1+r)} - P_t = K_t^{'}(S_t). \tag{10}$$

Equation (10) indicates that the spread between futures and spot prices reflects the marginal cost of carry for the hydropower generation. Note that Equation (10) is also valid for risk-averse inventory holders despite the initial assumption of risk neutrality.[3]

The prediction of the rational expectation competitive model is: whenever expected appreciation (*i.e.* futures-spot spread) exceeds the marginal cost of carry, the inventory holders will increase stock-holdings for profit motivation until the equilibrium is restored; on the other hand, whenever the marginal cost of carry exceeds the expected appreciation, inventory holders will decrease stockholdings until the equilibrium is restored. Hence, inventory holder's arbitrage through inventory management for profit maximization guarantees no arbitrage opportunities in equilibrium.

Since reservoir overflow is rare under normal conditions, we can assume the physical storage costs of water to be zero. The risk premium that the producer requests from the customer can also be assumed to be constant. In this way, it is the change in the convenience yield that induces the change in the total cost of carry. Miranda and Rui (1996)

[3] By using the certainty equivalent of a risky prospect to express the utility maximization problem for a risk averse hydropower producer, it can be shown that the solution is identical to the model assuming risk neutrality. See Just (1975).

use $a + b_1 \ln(I_t)$ to represent the marginal cost of carry with assumptions of physical storage costs being constant.[4] Following their spirit, Equation (10) can be re-expressed as follows:

$$\frac{E_t[P_{t+1}]}{(1+r)} - P_t = a + b_1 \ln(I_t). \qquad (11)$$

The above demonstration shows that there is a theoretical nonlinear relationship between the futures/forward prices and water reservoir content. However, the specific functional form of such a nonlinear relationship is analytically unavailable in general. To enrich our understanding of this relationship, an empirical investigation is in order. I carry out three tests in Essay II to further characterize the relationship between futures/forward prices and water reservoir content utilizing a BDS test, Hsieh's third order moment test and a linear/nonlinear Granger causality test. These tests are designed to be progressively linked and can provide empirical evidence on the plausibility of the non-arbitrage condition.

As discussed earlier, it is the change in convenience yield that induces the total cost of carry, and convenience yield is therefore a vital component driving the changing dynamics of the spot and futures/forward price spread. Essay III estimates convenience yields and investigates their behaviors and determinants.

2. Summary

Essay I examines the market efficiency issues at the Nord Pool power exchange in the September 1995 – July 2002 period. A unique characteristic of this electricity exchange is the high hydropower proportion in the traded electricity; water in the hydro reservoir acting as hydropower inventory therefore plays an important role in the pricing of electricity. Inventory holding and the seasonality of both the supply and demand of hydropower

[4] In that paper, risk neutrality is assumed.

generate intra- and inter-year autocorrelations in power prices. I present a theoretical discussion on why power price persistence invalidates the applicability of a market efficiency concept based on the random walk theory. To lend support for the theoretical argument, I conduct an empirical investigation consisting of various unit roots and cointegration methods to tackle the data problems/properties, and results show that weekly spot and futures prices are cointegrated. Philips-Loretan's nonlinear least square is applied in testing the restriction of the coefficient according to the market efficiency hypothesis. The Wald statistic shows that the cointegration vector being (1, -1) is not binding. Residual testing using a Ljung-Box Q-statistic confirms serial correlation. These findings are consistent with the theoretical prediction.

Essay II models electricity prices in the context of the Nord Pool power exchange which has a considerable proportion of hydropower supply. Since hydropower is storable in a producer's perspective and the system price is a uniform price for all sources of electricity supply, the applicability of the rational expectation competitive commodity storage model to characterize the spot and futures/forward prices is validated. I further show the nonlinearity between futures/forward prices and water reservoir content as inventory. I perform a BDS test (a test for nonlinearity), Hsieh's third-order moment test (a test that discriminates between different types of nonlinearities) and a nonlinear causality test to portray the nonlinear relationship using short/long maturities contracts. Empirical evidence shows that futures/forward prices are nonlinearly connected with water reservoir content via variance changes, and that the detection of causality varies as maturities change from short to long. These findings provide strong support for the credibility of the arbitrage argument and in a certain case verify the existence of the non-arbitrage condition.

Essay III investigates convenience yield behavior at the Nord Pool power exchange given the considerable storable hydropower being traded. Several hypotheses are tested concerning the behavior and determinants of convenience yield from holding hydropower as inventory. The results reveal that 1) convenience yield has a negative relationship with hydro reservoir content as inventory, 2) convenience yield behavior can be statistically explained within a standard financial call option framework and the call option component can explain a large portion of variability in convenience yield, 3) convenience yield varies on both a yearly and a monthly basis, and 4) there is an asymmetry of volatility of convenience yield during high/low hydro inventory periods.

References

Just, R. E. (1975). "Risk aversion under profit maximization", *American Journal of Agricultural Economics,* 57 : 347-352.

Mandelbrot, B. B. (1971). "When can price be arbitraged efficiently? A limit to the validity of the random walk and martingale models", *The Review of Economics and Statistics,* 53 : 225-236.

Miranda, M. J. and Rui, X. W. (1996). "An empirical reassessment of the commodity storage model", *Mimeo, Department of Agricultural Economics, Ohio State University.*

Tomek, W. G. (1994). "Dependence in commodity prices: A comment", *The Journal of Futures Markets,* 14 : 103-109.

Essay I

Market efficiency at the Nord Pool power exchange

Daniel Deng

Center for Finance
Department of Economics
School of Economics and Commercial Law
Göteborg University
P.O. Box 640
SE 405 30 Göteborg
Sweden

E-mail: Daniel.Deng@handels.gu.se

I want to thank Hans Byström, Erik Hjalmarsson, Lennart Hjalmarsson and Carsten Tanggaard for helpful comments. I also want to thank Kenneth Andreassen and Jan Foyn at the Nord Pool power exchange for providing the data used in this study.

Abstract

This paper examines the market efficiency issues at the Nord Pool power exchange in the September 1995 – July 2002 period. A unique characteristic of this electricity exchange is the high hydropower proportion in traded electricity; water in the hydro reservoir acting as hydropower inventory therefore plays an important role in the pricing of electricity. Inventory holding and the seasonality of both the supply and demand of hydropower generate inter- and intra-year autocorrelation in power prices. I present a theoretical discussion on why power price persistence invalidates the applicability of a market efficiency concept based on the random walk theory. To lend support for the theoretical argument, I conduct an empirical investigation consisting of various unit roots and cointegration methods to tackle the data problems/properties, and results show that weekly spot and futures prices are cointegrated. Philips-Loretan's nonlinear least square is applied in testing the restriction of the coefficient according to the market efficiency hypothesis. The Wald statistic shows that the cointegration vector being (1, -1) is not binding. Residual testing using a Ljung-Box Q-statistic confirms serial correlation. These findings are consistent with the theoretical prediction.

Keywords: cointegration, market efficiency, electricity spot and futures prices, endogeneity, serial correlation.

1. Introduction

As a result of the power market restructuring beginning in 1991, a national Norwegian power market has developed into a Nordic power exchange embracing all the Nordic countries. Sweden joined the market in 1996, and the bilateral trades between Norway and Sweden were expanded into multilateral trades among Nordic countries when Finland joined in June 1998, Western Denmark in 1999 and Eastern Denmark in 2000.

The exchange consists of spot and derivative markets. The spot market is called a day-ahead market in which power contracts are traded for next day physical delivery. The derivative markets are financial markets for price hedging and risk management; various contracts including futures, forwards, option contracts, and contracts for difference (a type of forward contract for electricity introduced in 2000) are traded with maturity varying from several days to 3-4 years.

A unique feature of this exchange is that around 50% of the traded electricity comes from hydropower. The hydro share of electricity production is almost 100% in Norway and around 50% and 20% in Sweden and Finland, respectively.[1] The hydropower generation depends largely on the use of water reservoir technology. This offers the producer the chance to withhold water as hydropower inventory. Although electricity is nonstorable when generated, withholding water may effectively store future "electricity". Storability of hydropower gives the hydropower producer the possibility to time the market for profit maximization. Specifically, if the power price is expected to go up, it is then profitable to withhold water for sale at a later higher price, and vice versa. Spot and derivative power contract trading in combination with inventory management enable arbitrage possibilities at Nord Pool.

The fact that the water acts as hydropower inventory has important implications. First, the availability of hydropower inventory in relation to demand influences both intra-

[1] These figures are calculated from the 2001 statistics on hydropower generation capacities (including hydropower that is not traded at Nord Pool) reported in "The Nordic power markets" published by Nord Pool. Other forms of electricity generation within Nordic countries include: nuclear power, thermal power, and renewable power including wind power. Note that not all generated electricity is traded at Nord Pool. For example, Nord Pool's market share in Norway in 2001 was around 45%.

and inter-year electricity prices. Hydro reservoir water content (level) reaches its peak value in September-December and its valley value in April-May. Electricity demand increases in the winter due to the heating demand. As electricity prices are determined by the law of supply and demand, the resulting electricity prices are usually low in June-July and high in January-February.[2] This suggests that power prices typically have a seasonal component, implying intra-year autocorrelation. Although hydropower inventory supply is seasonal, the hydropower inventory carryover may be consumed not only within the year but also from year to year, suggesting inter-year autocorrelation in power prices. Second, factors that systematically influence the commodity prices (such as seasonality in the dynamics of supply and demand, distributed lag effects, longer cycles, etc.) contribute to the short-run price persistence (Tomek, 1994).

This paper investigates market efficiency at the Nord Pool power exchange. On one hand, if a market is perfectly efficient, then prices should fully reflect all available information and adjust fully and instantaneously to new information (Fama, 1970). This suggests that the prices should follow a random walk process. On the other hand, we observe intra- and inter-year autocorrelations in electricity prices at Nord Pool. A simple conclusion from this evidence suggests a violation of the random walk hypothesis, implying that there are information components in past prices beyond a general trend that can be used to predict futures prices, i.e. market inefficiency. Is this a correct conclusion? Can we talk about market efficiency without discussing the reasons for price persistence? And essentially, can we generalize the market efficiency concept from a security market to a commodity market such as Nord Pool in a straightforward manner? To shed light on these questions, this paper discusses theoretically how impossible market efficiency can be achieved given power price persistence and provides empirical evidence supporting the theoretical argument.

The investigation is important and interesting for several reasons. First, although the efficient market hypothesis is an old concept dating back to the early works of Samuelson (1965) and Fama (1970), market efficiency on power markets or power exchange appears to be a fresh topic due to the recency of the power market

[2] The spot and futures prices used in this paper are system-wide prices without consideration of transmission congestion. Specific area prices may differ from these prices due to transmission constraints.

restructuring. Second, electricity as a commodity is very unique. It can not be conveniently stored when generated while hydropower can be stored via a hydropower reservoir, enabling possible arbitrage activity via inventory management. Moreover, inventory holding with seasonal dynamics of supply and demand of hydropower contributes to intra- and inter-year price autocorrelations. The autocorrelated power prices have important implications relevant for the analysis of market efficiency. Third, given the uniqueness of electricity as a commodity, how to empirically tackle the data's statistical problems posts a new challenge to researchers; the recognition of the statistical problems in the electricity data and the empirical methods employed in this paper may be conducive to empirical studies using similar data sources. Fourth, a good understanding of the movements of the spot and futures prices has significant implications for regulators and hedgers. For example, if a cointegration relationship exists between the spot and futures prices, then this relationship should be taken into consideration in the statistical modeling when forming an optimal hedge ratio (Ghosh, 1995; Ghosh and Clayton, 1996).

An influential paper that studies the spot and futures price relationship at Nord Pool is that of Gjolberg and Johnsen (2001). In their paper, they consider water in the hydro reservoirs as stocks for future electricity, and producers can use the future contract together with the reservoir storage function to arbitrage. They consider spot and futures price parity and use *monthly* spot and futures prices in their study. They find that the futures price has periodically been outside the theoretical arbitrage limits. In addition, the futures price and the basis have been biased and poor predictors of subsequent spot price levels and changes, respectively. Their general conclusion is that the market is inefficient or irrational. There are two problems with their test of market efficiency: (1) They do not consider the endogeneity and serial correlation problems that could be present in the data, which may bias their econometric result. (2) The assumption underlying the market efficiency. As seasonality in supply and demand of hydropower introduces intra- and inter-year price autocorrelations, applying market efficiency testing for Nord Pool based on the random walk hypothesis is inappropriate.

The perspective taken by Gjolberg and Johnsen (2001) is the spot and futures price parity.[3] Such a perspective rests heavily upon the assumption of perfect functionality of the cost of carry relationship between the spot and futures electricity prices, i.e. perfect arbitrage is assumed. Since power prices tend to be persistent in the form of high slowly decaying autocorrelation, arbitrage can not be perfect and the arbitraged price is not a martingale (Mandelbrot, 1971). This paper opts to test the efficient market hypothesis directly. Instead of ignoring the reason for price persistence, I explicitly point out factors generating price persistence and how these factors affect our appraisal of the market efficiency at Nord Pool.

This paper contributes to the literature on electricity exchange in several ways. First, I explicitly recognize and test to verify the statistical problems such as endogeneity and serial correlation in the electricity weekly data from Nord Pool. Failure to take these into account may lead to biased and inconsistent empirical results. Second, I employ special procedures for modeling and testing market efficiency that successfully deal with the data problems/properties, and to my knowledge, this paper is the first to empirically show that weekly spot and futures electricity prices are cointegrated.

The disposition of the paper is as follows. First, a brief discussion of the concepts surrounding market efficiency is presented. Second, a discussion of the data and the choice of unit root tests, cointegration tests and a market efficiency test is presented, and I report my empirical results. Finally, a summary and a conclusion end the paper.

2. Theoretical framework

The hypothesis of unbiasedness implies that the current commodity futures prices expiring in $t+1$ should equal the commodity spot price expected to prevail in $t+1$. This notion of unbiasedness is conceptually consistent with the notion of speculative efficiency in that the participants in the markets exploit all available information in

[3] Gjolberg and Johnsen (2001) approach the market efficiency issue mainly through testing spot and futures parity, but they also carry out a direct market efficiency test using a conventional OLS regression.

forming their expectations about the future spot price, or conversely, there are no systematic and unexploited profitable opportunities. This implies that the forecast error,

$$e_t = S_t - E_{t-1}(S_t), \tag{1}$$

where e_t is the forecast error, S_t is the spot price at time t, and $E_{t-1}(S_t)$ is the expected spot price at time t, conditional on the information available at t-1,

should not be autocorrelated.

The unbiasedness hypothesis assumes a zero transaction cost, risk neutrality and a zero interest rate. Under these assumptions, futures prices will be forced to equal the expected spot prices. That is,

$$F_{t-1} = E_{t-1}(S_t), \tag{2}$$

where F_{t-1} is the price at time t-1 of a one-week ahead futures contract for delivery at time t.

By combining Equations (1) and (2), we have

$$S_t - F_{t-1} = e_t\,. \tag{3}$$

This equation can be further expressed as,[4]

$$S_t = a + b\,F_{t-1} + e_t\,. \tag{4}$$

If a =0 and b =1, then futures price is an unbiased predictor of the spot price. Additionally, if the error terms are unpredictable from past information including their

[4] This specification corresponds to the test of weak form market efficiency.

own past values, ***i.e.*** they are not autocorrelated, then F_{t-1} is an efficient predictor of S_t and the market is said to be an efficient market.

The unbiasedness test is a joint test of market efficiency, and the risk premium is zero under the assumption of risk neutrality. This implies that failure to reject the null hypothesis of unbiasedness is an acceptance of market efficiency with no risk premium; rejecting the null hypothesis could be caused by either market inefficiency or the presence of a risk premium. The problem with the interpretation of the test result is that if the null is rejected, we do not know what specifically causes the rejection ─ market inefficiency or the existence of a non-zero risk premium. Further, it is arguable that the assumption of market participants being risk neutral might not be very appropriate because if risk-averse producers demand futures contracts to hedge their output, then the futures prices become biased towards expected spot prices due to the risk premium. Empirically, because there is evidence showing that a non-zero risk premium exists, many authors argue that the test of market efficiency should not depend on the absence of a risk premium (Beck, 1993; Park, 1985). Beck (1994) suggests that if we assume that market participants are risk-averse, then market efficiency can be tested, conditional on the assumed form of the risk premium being either constant or dependent on variables uncorrelated with past spot or futures prices.

In this paper, I assume that there is a non-zero constant[5] risk premium. This appears to be a reasonable assumption because the high concentration of ownership of production and reservoir capacity at Nord Pool induces an excess of long hedging demand, which requires that a risk premium be paid by the consumers to the producers. Further, a reservoir rent created by the high concentration of supply may be added as a part of the risk premium (Gjolberg and Johnsen, 2001).

[5] Existence of a time-varying risk premium can be investigated conditional on the assumption that the market is efficient. See Serletis and Scowcroft (1991).

With a non-zero constant risk premium assumption, Equation (4) is modified to the following:[6]

$$S_t = a + b F_{t-1} + m_t \, . \qquad (5)$$

In this formulation, if (1) b =1 and (2) the error term m_t is not autocorrelated,[7] then the market is said to be an efficient market.

An important econometric issue that deserves attention is that when nonstationary data are used, a simple OLS procedure becomes invalid, resulting in unreliable test statistics because the distribution is non-standard. One of the solutions to the problem is to rely on the cointegration methodology, which deals specifically with the nonstationarity of the data.

Under the assumption of a non-zero risk premium, the market is said to be an efficient market if all of the following criteria are satisfied:

1. Spot and futures prices are cointegrated;
2. The cointegration vector b = (1, -1);
3. Residuals from the cointegration estimation are free of autocorrelation.

The validity of using a cointegration method to test for market efficiency in the electricity context also depends on the possible cointegration relationship between the spot and futures prices. A traditional argument against cointegration of spot and futures prices for a nonstorable commodity (*e.g.* Covey and Bessler, 1995; Fortenbery and Zapata, 1993) asserts that, without storage, arbitrage may not work effectively and it

---

[6] First, Equation (2) is modified to include risk premium p_{t-1} (conditional on the information available at t-1): $F_{t-1} = E_{t-1}(S_t) - p_{t-1}$. Second, Equation (3) is then changed to: $S_t - F_{t-1} = e_t + p_{t-1}$ = m_t and transformed into Equation (5).

[7] When risk premium is assumed, it introduces a correlation between the regressor and the error term, inducing a potential simultaneity bias when spot and lagged futures prices are included in the regression. This requires us to be careful when choosing the testing procedure to deal with the *endogeneity* and *serial correlation* problems. The non-zero risk premium can enter into the intercept term a in Equation (5).

seems that there is no other economic force that links spot and futures prices together.[8] In this case, it seems that spot and futures prices are determined separately and they are not likely to be cointegrated series. However, a recent paper by Yang *et al.* (2001) shows ***empirically*** that cointegration may not need to depend on asset storability, and at the 5% significance level, cointegration is found between the spot and futures prices for all three nonstorable commodities in the study, ***i.e.*** hog, live cattle and feeder cattle.[9]

Electricity is nonstorable which means that, when it is generated, it must be consumed immediately and that there is no "electricity" inventory holding. This seems to suggest that we can not expect cointegration between the spot and futures electricity prices. On the other hand, future hydropower can be stored via a hydropower reservoir. Hydropower inventory management together with the aid of spot and derivative power contract trading enable the possibility of arbitrage. Therefore futures and spot prices can be connected via cost of carry modeling which gives rise to the possible cointegration between spot and futures prices.

To illustrate how power price persistence invalidates the applicability of the random walk theory in a test of market efficiency discussed in the introduction, I present a simple model to characterize the dynamics of commodity pricing:

$$CP_t = Y_t + e_t, \tag{6}$$

where CP is the commodity price, Y is the systematic component , e is the random component and t is the time measurement.

For an individual price series ***e.g.*** spot price series alone, the notion of random walk implies that price changes are random, independent of each other and have identical normal distributions (***i.i.d.***). This can be expressed as follows:

[8] For storable commodities, spot and futures prices are linked by the cost of carry model.
[9] As mentioned by Yang *et al.* (2001), the reason why earlier works do not find cointegration relationships between the spot and futures prices for nonstorable commodities may be because the nonstationarity of the dataset was ignored. Consequently, traditional OLS estimations may yield false results.

$$S_t = S_{t-1} + e_t, \tag{7}$$

where S_t and S_{t-1} are spot prices at t and $t-1$ respectively, e_t is assumed to be random error with an *i.i.d.* distribution.

The trouble with directly generalizing the concept of random walk price dynamics from a security market to a commodity market lies in the fact that the systematic component may not be adequately modeled as lagged price alone, *i.e.* $Y_t \neq S_{t-1}$. As the systematic component for commodity prices, Y_t is composed of a mixture of factors representing seasonality, distributed lag effects, longer cycles, etc. These factors are likely to give rise to short-run persistence in price behavior. The intra- and inter-year power price persistence discussed in the introduction implies that the random walk hypothesis is not valid, *i.e.* $S_t - S_{t-1} \neq e_{St}$, and similarly $F_{t-1} - F_{t-2} \neq e_{Ft}$, where F_{t-1} and F_{t-2} are futures prices at $t-1$ and $t-2$ respectively, and e_{St} and e_{Ft} are both random errors,[10] leaving a market efficiency evaluation questionable.

To see how price persistence specifically influences the empirical testing result, recall the unbiasedness hypothesis first. This hypothesis implies $S_t - F_{t-1} = e_t$. If $S_t - F_{t-1} = e_t$ holds, then $S_{t-1} - F_{t-2} = e_{t-1}$ also holds. Rearranging the two equations, the resulting equation $(S_t - S_{t-1}) - (F_{t-1} - F_{t-2}) = m_t$ should also be true (since e_t and e_{t-1} are both random errors, their summation m_t is also random). However, given our discussion above, price changes at Nord Pool are not random given the intra- and inter-year price autocorrelations. The non-random price changes imply $S_t - S_{t-1} \neq e_{St}$ and $F_{t-1} - F_{t-2} \neq e_{Ft}$ (since e_{St} and e_{Ft} are random errors, their summation m_t is also random.). This is the same as $(S_t - S_{t-1}) - (F_{t-1} - F_{t-2}) \neq m_t$. Moreover, this is equivalent to $S_t - F_{t-1} \neq e_t$. As

[10] Under special circumstances, price changes for commodity futures contracts might equal a random error that are not correlated. The condition of the futures price process being a random walk process is stated in Mandelbrot's (1971) paper. In our case, if the length of maturity of futures prices is sufficiently long, the futures prices might be a random walk process as the significance of the lagged effect vanishes. However, for the one-week ahead futures price contract, price changes do not equal a random error with an *i.i.d.* distribution.

$S_t \neq F_{t-1} + e_t$, the b coefficient in Equation (4) may not be 1 and therefore the restriction on $b = 1$ will not be binding. Because $(S_t - F_{t-1}) \neq e_t$ and $(S_{t-1} - F_{t-2}) \neq e_{t-1}, \ldots (S_{t-n} - F_{t-n-1}) \neq e_{t-n}$, the residual series in Equation (4) will also be autocorrelated.

To summarize, the impact of hydropower inventory holding and the seasonality in the supply and demand of hydropower on the overall electricity price dynamics implies intra- and inter-year price autocorrelations. Price autocorrelation suggests that price changes are not random, which invalidates the applicability of the random walk theory in a test of market efficiency in the context of Nord Pool.

To verify the theoretical discussion presented above, I proceed with the empirical investigation on Nord Pool market efficiency with the following testable hypothesis:

The Nord Pool markets are efficient under the assumption of a non-zero risk premium.

3. Data, econometric methodology and empirical results

3.1 Data

The data (spot and futures prices information and water reservoir content[11]) series are obtained from the Nord Pool FTP server. The weekly spot price series is calculated by averaging the daily spot prices for the week, while the weekly futures price series is constructed by taking the nearby futures prices.[12] Each series contains 356 data entries from September 5th, 1995 to July 26th, 2002. The sample's duration should be the longest available at the time the data was collected, as Nord Pool is the world's oldest electricity exchange.

[11] Water reservoir content figures are the sums of figures from Norway, Sweden (as of January 1st, 1996) and Finland (as of June 15th, 1998).
[12] The nearby futures prices are obtained through the futures contract closest to maturity. By doing so, the temporal span between the spot price for immediate delivery and the futures prices for later delivery is minimized. In our case, the Friday futures prices are usually chosen. If not available, the nearby futures price closest to the next week is used.

3.2 Descriptive data statistical analysis

Visual inspections of the plot (Figures (1)-(3)) reveal that spot (WS) and futures (WF) prices are seasonal with low values in the summer and high values in the winter. A significant seasonal regular cycle pattern is observed in the graph of the water reservoir content series (WR).

In Figure (4) (the combined graph of spot and futures price series) we see that the series seem to be almost exact copies of each other with relatively few different data points. This suggests that the two series are cointegrated and the spread is small. Figure (5) shows the spread between spot and futures prices, which appears to be highly autocorrelated.

Moreover, there seems to be a broken trend in the spot and futures prices plot. Up until the end of 2000, it seems clear that the low prices in the summer declined over the years and the high prices in the winter became lower. This is an indication of a slightly downward sloping linear trend in the series. This linear trend seems to have been broken at the end of 2000, during which time the electricity prices were comparatively higher than in the previous years. From an economic perspective, the multinational electricity exchange improves efficiency as a result of heightened competition, and results in lower electricity prices (this should be true under "normal weather conditions"). Although prices are subject to competition, the high degree of dependence on hydropower generation renders the prices highly sensitive to climatic conditions. The drought in 2000 can well explain the jump in prices.[13]

Basic statistics of the data series are presented in Figures (6)-(8) and Table (1). Several points need to be mentioned: First, since it is sensible to study conditional distribution, I use price series and water reservoir content series in first difference. The resulting distribution graphs show that all series are non-normally distributed, with Jarque-Bera

---

[13] 1996 was also a drought year, but since our data series starts in late 1995, the high prices appear to be the starting point. A more appropriate way of looking at the general trend of prices should refer to the earlier spot prices (futures contracts began being traded in October, 1995). The standard conclusion is that heightened competition brings down the prices at Nord Pool.

(1980) statistics highly significant. Both differenced price series are negatively skewed (long right-tailed distribution) and the resulting water reservoir content is positively skewed. The skewness observed in the differenced price series is quite usual for commodity prices. In an electricity context, when there is a sudden increase in demand relative to the stable available supply in the short-run, we can observe spikes[14] in the electricity prices. Spikes in prices imply that the probability distribution of prices is skewed. Second, all series show high, slowly decaying serial correlations over time.[15] Significant correlations of individual spot and futures price are observed even at lag 200. This is consistent with our expectation ─ inventory holding in combination with seasonality in both supply and demand of hydropower introduce both intra-year and inter-year price dependence, and the autocorrelation is very slowly decaying.

3.3 Non-stationarity / Stationarity test

To test whether the spot and futures price series are cointegrated, I first need to test the nonstationarity of the two series using a unit root test. Since seasonality is clearly present in the data, I should first adjust the data seasonally. If the data is not seasonally adjusted, then the joint null hypothesis of a unit autoregressive root and the seasonality is tested. When the joint null hypothesis is rejected with the unadjusted data, it is not clear whether the rejection is due to the absence of a unit root or to the seasonality or both.

Care should be taken when performing a seasonal adjustment. For example, the commonly used X-11 filter may result in substantially reduced power for Dickey-Fuller (DF) tests (Ghysels and Perron, 1993; Ghysels *et al*., 1994). In this paper, I use the seasonal dummy variable to adjust the original series and then apply the unit root test. This procedure does not have any major size distortions (Ghysels *et al*., 1994).

Of the numerous unit root tests, the augmented Dickey-Fuller (1979) unit root test (ADF) and the Phillips-Perron (1988) unit root tests (PP) are the most popular. Compared to

[14] It differs from mean reverting behavior, *i.e.* prices jump to high levels relative to the long run average of the series and then return to the prior level.
[15] I use level data here.

the standard DF test which rests on the assumption that the series is an AR(1) process, the ADF test assumes that the series follows an AR(p) process and constructs a parametric correction for higher order correlation. This seems to be the right choice for our high-order correlation sample series. Further, the test can also be modified to account for seasonal unit root. The alternative PP test is a nonparametric unit root test controlling for serial correlation. It estimates the standard DF test, and modification is made so that the serial correlation does not affect the asymptotic distribution of the test statistics. The PP test can here be regarded as a robustness test compared to the ADF test.

Because all series have positive values, I should include a constant in the unit root test. Also, since both price series appear to have trends, I should include a trend assumption in the unit root test. The problem is, we can never be sure about including appropriate deterministic regressors in our test, and too few or too many regressors may cause the failure of rejecting the unit root. Being aware of this, I follow the guideline suggested by Doldado *et al*. (1990) to test stepwise determination of the econometric specification. Note that the null hypothesis in each test is a unit root process, against the alternative hypothesis of a stationary process. The decision rule is: if the absolute value of the test statistics is smaller than the absolute value of the critical value, then do not reject the null; otherwise, reject it. This decision rule is applicable to all other unit root tests presented in this paper. The test results indicate that both price series are unit root processes (see Tables (2)-(5)).

The problem with the unit root tests is that they have little power to distinguish between a trend stationary and a difference stationary process. In finite samples, any trend stationary process can be arbitrarily well approximated by a unit root process and a unit root process can be arbitrarily well approximated by a trend stationary process. This implies that the ADF and the PP unit root tests, when testing a linear trend stationary process, are likely to accept the unit root hypothesis, *i.e.* they have no power against linear trend stationary processes. Prior data exploration suggests that there might be a downward sloping trend in the price series; if they are covariance stationary, they might be stationary around a deterministic trend. In this case, if I need to test the unit root hypothesis against the linear trend stationary process (note: in earlier ADF and PP tests, the alternative hypothesis is a stationary process), a trend term should be included in the auxiliary regressions in the ADF and PP case. The formulations of the ADF and PP tests with auxiliary regressions are as follows:

For ADF auxiliary regression:

$$\Delta y_t = \alpha_0 + \sum_{j=1}^{p-1} \alpha_j \Delta y_{t-1} + \alpha_p y_{t-1} + \alpha_{p+1} t + \nu_t, \ \ \nu_t \sim \textit{i.i.d.}\ N(0, \sigma^2); \tag{8}$$

For PP auxiliary regression:

$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 t + \nu_t, \ \ \nu_t \sim \textit{i.i.d.}\ N(0, \sigma^2), \tag{9}$$

where Δ is the difference operator, t is the time trend and ν_t is the residual term. The null hypothesis of a unit root with drift corresponds to the hypothesis $\alpha_p = \alpha_{p+1} = 0$.

Tables (6)-(9) show the auxiliary regression result of ADF and PP tests on the deseasonalized spot and futures prices, respectively. The results are obtained after 1500 simulations. The truncation lag p of the Newey-West (1987) estimator of the long run variance of Δy_t used by the PP test, and the ADF lag length p, have been chosen as follows: $p = [10n^{1/4}] = 43$ for $n = 356$. Nonstationarity of the deseasonalized price series is further verified.

One characteristic of the sample is that it is small in sample size, which may influence the performance of the unit root test. In the case of high order sample autocorrelation, the power of the Bierens nonparametric unit root test is reported to outperform the PP test. In view of this, I also conduct the Bierens (1993) high-order sample autocorrelation tests (HOAC) and the results in Tables (10)-(11) confirm our previous results. Note that the critical values of the Bierens test are not reported, but the conclusion based on the test statistics is reported. This also applies to later tests of Bierens.

Since we observe strong seasonality in the plots of the series, we should be concerned about the presence of seasonal unit roots. Before one sets out to conduct a seasonal unit root test, one should note that the first difference of a seasonal unit root process will not be stationary, while the seasonal difference of a unit root process may be stationary. Several cases can be considered here when using first difference to informally diagnose whether the series contains a seasonal unit root: (1) if the series contains a seasonal unit root and a unit root, then the first difference can not render stationarity of the differenced series because of the seasonal unit root part; (2) if the series contains only a seasonal unit root, then the first difference will not make the differenced series stationary (which only seasonal differencing can). Following the above discussion, I take the first difference of the original price series, and the resulting series are stationary. Further, the original price series plots do not seem to suggest that the series are seasonally cointegrated; they are simply a copy of each other. Based on the pretest, I then conclude the absence of the seasonal unit root. As neither of the price series is found to contain a seasonal unit root, seasonal cointegration is not an issue in our later test. [16]

While performing a unit root test, care should be taken when structural changes are suspected. When structural breaks take place, the various ADF and PP test statistics are biased towards the non-rejection of a unit root. As mentioned earlier, a downward trend appears to exist before the end of 2000 for spot and futures prices, while after that the trend seems to have been broken. I conduct the Perron's 1989 test for structural change under the null of a unit root with a structural break, against the alternative of trend stationarity with a structural break. The test results reported in Table (12) and Table (13) confirm that the price series are unit root processes.

With some difference in assumptions, both the KPSS (Kwiatkowski *et al.*, 1992) and the Bierens and Guo (1993) test use trend stationarity as the null hypothesis and have unit root as the alternative. There is practical significance in testing trend stationarity against

---

[16] A sophisticated formal method of testing a seasonal unit root is that of Hyllerberg *et al.* (1990), in which they did the tests on quarterly data. Beaulieu and Miron (1993) extend the methodology to test for the presence of monthly seasonal unit root. To my knowledge, critical values for the Hyllerberg (1990) seasonal unit root test on weekly data are currently not available.

the unit root hypothesis, rather than the other way around. According to Bierens and Guo (1993), the null hypothesis of a stationarity hypothesis can be a natural choice, particularly for cointegration testing; even if unit root is a natural null, it is reasonable to perform trend stationary tests as well. This is because the power of the unit root tests is often quite low and the size distortion can be substantial. Following this advice, all previous unit root tests are also repeated using KPSS and the Bierens and Guo (1993) type 5-6 tests. The previous results are all confirmed but are not reported here.

To summarize, I have used seasonally adjusted data to test for the presence of unit roots. In order to ensure that the tests have the right power and size, various unit root tests have been conducted and they confirm that the deseasonalized spot and futures price series are nonstationary. Independent causes for price changes such as a sudden increase in electricity demand, plant shutdown and plant maintenance may give rise to nonstationarity of the deseasonalized spot and futures price series.[17]

3.4 Cointegration test

Various methods that have been developed to test the cointegrating vectors can be classified into roughly three categories. (1) A residual based cointegration test examines the residuals from the long run equilibrium relationship. If the residuals have a unit root, then the variables can not be cointegrated of order (1,1). (2) The VAR methodology, which estimates a VAR in first difference and includes the lagged level of the variables in some periods. By using a multivariate generalization of the Dickey-Fuller test, one can check the vector for unit root and in an n equations system, n minus the number of the unit root equals the number of cointegration vectors. (3) The least square regression type of cointegration test.[18]

[17] Generally speaking, weekly electricity spot and futures prices may be alternatively considered as prices that consist of a mixture of both a random walk component and a mean reverting component. Because the influence of the factors generating a random walk component prevails, the resulting weekly electricity prices are nonstationary processes with seasonality. Fama and French (1988) give a discussion on this kind of price dynamic in the stock market.

[18] Other types of classifications are possible due to the variety of methods and the purpose/criteria of the classification. Here I focus on the most common methods, which are also relevant for my test. RB, JML NB and FMOLS (see abbreviation declaration later in this paper) fall into the above mentioned cointegration test categories, respectively.

Coporale and Pittis (1999), among others (Gonzalo, 1994; Hargreaves, 1994; etc.), have surveyed a number of methods to give some guidelines for applied research. The methods discussed in their paper include the following: the Johansen full-system maximum likelihood estimator (JML) as proposed by Johansen *et al.*, (1990) and Johansen (1991, 1995), the fully modified OLS estimator (FMOLS) introduced by Phillips and Hansen (1992), the augmented leads of regressors (AECM) developed by Stock and Watson (1993), the nonparametric Bierens cointegration test (NB) suggested by Bierens (1997), the standard error correction model (SECM), and the autoregressive distributed lag model (ADSL) due to Pesaran and Shin (1995). They argue (for the unidimensional cointegration space in a single equation framework) that the asymptotic efficiency of a number of estimators depends on the extent to which they correct for possible endogeneity and serial correlation of the regressors in the general case. Even in the case of multi-dimensional cointegration space, these estimates can achieve asymptotical equivalent estimates compared to that of full system methods, as long as no cross equation restrictions are imposed. Under weak exogeneity, FMOLS, AECM and JML are asymptotically equivalent. In small samples, the JML, FMOLS, NB and ARDL outperform others, sharing desirable small sample properties. FMOLS, NB and ARDL are also quite effective in coping with problems of endogeneity and serial correlation.

Because we test for unidimensional cointegration space, a single equation framework can be used. Under this framework, small sample property, endogeneity and serial correlation are the relevant factors to consider when choosing the appropriate testing method. It is obvious that the estimation might suffer from a small sample bias, and JML, FMOLS, NB and ADSL should therefore be considered. In order to determine serial correlation and endogeneity, simple tests have to be carried out since we do not have the knowledge *a priori*. To check for endogeneity, I conduct the Hausmans (1978) test. In our case, the residuals from regressing WF over WS are first preserved, and then I regress the preserved residuals and WF over WS again. If the residuals are significant in the second regression, endogeneity is confirmed. Table (14) shows that the endogeneity problem exists. Here serial correlation refers to residual correlation. I conduct the Q-test on the residuals that were previously preserved from Hausmans test (first regression), and it shows a high degree of correlation in the residuals. The tests listed above suggest that I should use NB, FMOLS and ADSL. Overall, following the discussion above, I decide to use NB and FMOLS[19] to test for cointegration. A test not mentioned in the Coporale and Pittis (1999) article is the residual based cointegration test (RB) found in Phillips and Ouliaris (1991). This test has an obvious advantage of being simple and intuitive to carry out.

In the following sections, I first discuss the basic mechanisms of each test, their pros and cons, and finally I report the test results.

3.4.1 Bierens nonparametric cointegration test

The Bierens cointegration test is nonparametric in that it obtains a consistent cointegration testing that does not require specification of the data generating process (except for some mild regularity conditions) or estimation of nuisance parameters. The critical values are case independent.

However, Bierens' test also has its shortcomings. The nonparametric tests are not invariant for scales and it is suggested that caution should be taken when conducting this test: if not all components in the vector process are in logs, log transformation should be performed before the test.

The nonparametric cointegration test results are shown in Table (15), confirming that spot and futures prices are indeed cointegrated with a cointegration vector being (1, -0.9849384).

[19] Since JML is not capable of dealing with serial correlation and endogeneity adequately, it is not selected to formally test a cointegration relationship here. In fact, I apply this method to a cointegration test with level data. A seasonal dummy is modeled within the JML framework and an optimal lag-length detected by AIC, SBC, FPE and LR criteria suggest that a lag length should be within 1-2. I obtain a cointegration vector estimation of (1, -0.98). However, the residuals are autocorrelated, which is caused by the high slow decaying autocorrelation in prices rather than by a misspecification which is commonly suspected. Results are not reported here.

3.4.2 Phillips-Ouliaris residual based cointegration test

In addition to the Bierens test, the Phillips-Ouliaris cointegration test is also performed. It tests the null hypothesis of cointegration by testing the null that there is a unit root in the residuals against the alternative that the root is less than unity. If the null of a unit root is rejected, then the null of cointegration is rejected. This test does not require the residual series to be white noise.

Table (16) reports the residual based cointegration test results. The corresponding test statistic of Phillips and Ouliaris is PZ=348.1119. The decision rule is: reject the null hypothesis of no cointegration if the computed value is greater than the appropriate critical value. The critical value for one cointegrating vector under the assumption of a constant and a linear trend is –28.3218 (Phillips and Ouliaris, 1990, Appendix B, Table1b). I therefore conclude that the spot and futures prices are cointegrated. The cointegration relationship is estimated to be (1, -0.99575).

3.4.3 Phillips-Hansen fully modified ordinary least square test of cointegration

A merit of the FMOLS methodology is that it uses a plug-in bandwidth to remove endogeneity and serial correlation in the cointegration residuals, thereby reducing any bias of the kernel estimation.[20] The test produces three different test statistics: meanF, supF and Lc. Each statistic is designed for a particular purpose. If we suspect that there is a shift in regime, we should use supF. If we want to test whether or not the specified model is a suitable model to capture a stable cointegration relationship, meanF is the choice. In addition, if we consider the likelihood of the parameter variation to be relatively constant throughout sample, we should use Lc. Since visual inspection does not indicate a significant regime shift or an instability of the cointegration relationship (no significant deviation from the two price series), it is reasonable to assume that the parameter variation is relatively constant throughout the sample period. Based on this

[20] For a moderate sample size, the covariance matrices can be estimated using both a kernel function and a plug-in bandwidth parameter on the prewhitened (prewhitening is done for the purpose of reducing bias from the kernel estimation) cointegration residual. The kernel is a weight function that yields positive semi-definite estimates. The use of a plug-in bandwidth parameter can dramatically improve the mean squared error of semi-parametric estimates of the cointegration relationships.

intuition, Lc statistic is the appropriate test statistic for cointegration.[21] The Lc statistic and the cointegration estimation are shown in Table (17). The Lc statistic is an F statistic, in our case equal to 1.24219, and the critical value is 3.67 at the 1% significance level. Since 1.24219 is less than the critical value, I do not reject the null of cointegration. The resulting estimation of the cointegration relationship between the spot and futures is (1, -0.9852).

In summary, I have based my choice of cointegration methods on the specifics of the dataset and have chosen the nonparametric Bierens cointegration test, the residual based cointegration test and the semi-parametric FMOLS test in order to test for cointegration between spot and futures prices. All three test results confirm the existence of a single cointegration relationship.

3.5 Market efficiency testing using the Phillips-Loretan (1991) procedure

As mentioned earlier, market efficiency conditions request not only that the spot and futures prices are cointegrated, but also that the cointegrating vector is (1, -1) and that the residuals are free of autocorrelation. In this section, I use the Wald statistic to test the restriction that the cointegration vector is (1, -1). I also use the Q-statistic to test for residual autocorrelation. To test the market efficiency hypothesis, I use the Phillips and Loretan (1991) nonlinear estimation procedure.[22] This method is designed to correct for both serial correlation in the errors and endogeneity of the regressors in the cointegrating regression that involves I(1) regressors. Test statistics resulting from this

---

[21] One can examine the stability of the estimated cointegration vector by conducting sub-sample yearly cointegration tests. This appears to be interesting, because the infancy of Nord Pool can lead to parameter instability. By carrying out the yearly cointegration tests, one can plot the cointegrating parameters to visually inspect the stability characteristics. However, the author decides not to do so because the yearly subsample contains only 52 observations (53 observations for the hydrological year 1999-2000). If I were to perform the tests, they would not provide robust results due to possible small sample bias (though FMOLS is robust for a sample number as small as 50). Comparatively speaking, the Lc test statistic provides a better choice in testing parameter stability with a much larger sample base. Moreover, based on the visual inspection of the combined plots of both price series, they are quite a copy of each other, showing no significant deviations. This suggests that the cointegrating parameters should be stable.

[22] An alternative method proposed by Barnhart *et al.* (1999) is to test the equivalence of the data generation process of the spot and futures prices. This test can be designed to avoid endogeneity and serial correlation problems. Because the Phillips-Loretan estimation results are sufficient to explain the problem we are facing in testing market efficiency at Nordpool, the Barnhart *et al.* (1999) procedure is not used here.

procedure have standard asymptotic distributions, which allow for the testing of restrictions on coefficients for market efficiency. I use the Ljung-Box (1978) Q-statistic to detect whether or not the errors from the Phillips-Loretan equation are autocorrelated. The Q-statistic is obtained when the Q-test is applied to the residuals constructed from Equation (1), with a and b being replaced by the Phillips-Loretan estimate.

The Phillips-Loretan equation is specified as follows:

$$S_t = a + b\,F_{t-1} + \sum\nolimits_{i=1}^{n} d_i (S_{t-i} - a - b\,F_{t-i-1}) + \sum\nolimits_{j=-L}^{L} g_j \Delta F_{t-j} + e_t \ . \qquad (10)$$

This procedure is asymptotically equivalent to FMOLS, and in a small-scale cointegrated system, simulation results show that this procedure, together with FMOLS, is substantially better than OLS.

Results in Table (18) show that the slope coefficient is 0.971744806, which is similar to the results obtained from previous cointegration tests. The c_2-statistic is 1.88E+10, suggesting that $b = 1$ is not binding. The Q-statistic on the regression residuals confirms autocorrelation. These empirical findings are consistent with the theoretical discussion presented in Section 2.

The empirical findings lend support to the argument that it is not appropriate to directly generalize the concept of market efficiency from a security market to a commodity market such as Nord Pool.

4. Summary and Conclusion

The Nord Pool power exchange is characterized by having hydropower predominance in the traded electricity, and water withheld in the reservoirs acts as a future hydropower inventory holding. These unique characteristics have important impacts on the electricity price dynamics. Hydropower inventory holding enables possible arbitrage between spot and derivative markets via hydropower inventory management and power contract trading. Hydropower inventory and the seasonality of supply and demand of hydropower, together with other factors, generate intra- and inter-year autocorrelations of power prices. Power price dynamics characterized as high, slowly decaying autocorrelation undermines the applicability of the market efficiency concept based on the theory of random walk.

The objective of this study was many-sided. First, I investigated the possible cointegration relationship between the spot and futures prices. Although electricity *per se* is non-storable, hydropower is considered storable via hydro reservoir in a producer perspective. This suggests that futures and spot prices are connected via a cost of carry relationship and it is possible that spot and futures prices are cointegrated. Taking into account the endogeneity, serial correlation and the small sample size that were all present in the dataset, I chose various cointegration technologies that are capable of dealing with these problems. Second, acknowledging the impact of hydropower inventory and seasonality of supply and demand of hydropower in generating intra- and inter-year autocorrelated power prices, I cast doubt on market efficiency testing for Nord Pool. I present a theoretical discussion on why it is impossible for market efficiency to be achieved in the presence of price persistence at Nord Pool. The purpose of conducting market efficiency tests was to provide empirical evidence consistent with the theoretical discussion. Empirically, I also showed the importance of choosing the correct econometric specification that adequately copes with the unique data problems and therefore renders correct test results.

Results showed that the spot and futures electricity prices were cointegrated, satisfying the first necessary condition for market efficiency. The Wald test suggested that the restriction of the cointegrating vector being (1,-1) is not binding. Finally, the Q-statistic indicated that the residuals were autocorrelated. These findings are consistent with the prediction in the theoretical discussion.

In conclusion, a market efficiency concept is not directly applicable to Nord Pool given the power price persistence generated by hydropower inventory holding and seasonality of supply and demand of hydropower, etc. The conclusion reached in this paper is in sharp contrast to that of Gjolberg and Johnsen (2001), who conclude that Nord Pool power exchange is inefficient without considering the applicability of a market efficiency concept.

The empirical findings in this study have important implications for the electricity market regulators and hedgers. First, the findings in this study present an argument that regulators should take the influence of hydropower inventory into consideration when appraising market efficiency. This perspective of analysis is also relevant to any other electricity exchange in the world that has a considerable hydropower proportion in the traded electricity, ***e.g.*** the Swiss power exchange and/or the New Zealand power exchange. Second, the findings suggest that the hedgers at Nord Pool should incorporate a weekly spot and futures prices cointegration relationship into their weekly hedging decisions. The significance of this consideration is that if a cointegration relationship is mistakenly ignored from the statistical model, then hedge ratios may be underestimated and as such may deteriorate hedging performance (Ghosh, 1993).

References

Barnhart, S. W., McNown, R., and Wallace, M. S. (1999). "Non-informative tests of the unbiased forward exchange rate", *Journal of Financial and Quantitative Analysis*, 34, 2 : 265-291.

Beaulieu, J. J. and Miron, J. A.(1993). "Seasonal unit roots in aggregate U.S. data", *Journal of Econometrics*, 55, issue 1-2 : 305-28

Beck, S. E. (1993). "Tests of the intertemporal hedging model", *Journal of Futures Markets* 13 : 223-236.

Beck, S. E. (1994). "Cointegration and market efficiency in commodity futures markets", *Applied Economics*, 26 : 249-257.

Bierens, H. J. (1997). "Nonparametric cointegration analysis", *Journal of Econometrics*, 77, 2 : 379-404.

Bierens, H. J. and Guo, S. (1993). "Testing stationarity and trend stationarity against the unit root hypothesis", *Econometric Reviews*, 12, 1 : 1-32.

Bierens, H. J. (1993). "Higher-order sample autocorrelations and the unit root hypothesis", *Journal of Econometrics*, 57 : 137-160.

Caporale, G. M. and Pittis, N. (1999). "Efficient estimation of cointegrating vectors and testing for causality in vector autoregressions", *Journal of Economic Surveys*, 13 : 1-35.

Covey, T., and Bessler, D. A. (1995). "Asset storability and the information content of intertemporal prices ", *Journal of Empirical Finance*, 2: 103-115.

Dickey, D. A., and Fuller, W. A. (1979). "Distribution of Estimators for Autoregressive Time Series with a Unit Root," *Journal of the American Statistical Association*, 84 : 427-431.

Doldado, J., Jenkinson, T. and Sosvilla-Rivero, S. (1990). "Cointegration and unit roots", *Journal of Economic Surveys*, 4 : 249-273.

Fama, E. F. (1970). "Efficient capital markets: a review of theory and empirical work", *Journal of Business*, 25 : 383-417.

Fama, E. F. and French, K. R. (1988). "Permanent and temporary components of stock prices", *Journal of Political Economy*, 96 : 246-273.

Fortenbery, T. R. and Zapata, H. O. (1993). "An examination of cointegration relationships between futures and local grain markets", *Journal of Futures Markets*, 13 : 921-932.

Ghosh, A. (1993). "Hedging with stock index futures: estimation and forecasting with error correction model", *Journal of Futures Markets*, Vol. 13, 7 : 743-752

Ghosh, A. (1995). "The hedging effectiveness of ECU futures contracts. Forecasting evidence from an error correction model", *Financial Review*, 30 : 567-581.

Ghosh, A. and Clayton, R. (1996). "Hedging with international stock index futures. An intertemporal error correction model", *Journal of Financial Research*, 19 : 477-491.

Ghysels, E., Lee H. S. and Noh, J. (1994). "Testing for unit roots in seasonal time series: some theoretical extensions and a Monte Carlo investigation", *Journal of Economics*, 62 : 415-442.

Ghysels, E. and Perron P. (1993). "The effect of seasonal adjustment filters on tests for a unit root", *Journal of Econometrics*, 55 : 57-98.

Gjolberg, O. and Johnsen, T. (2001). "Electricity futures: inventories and price relationships at Nord Pool", *Working paper, Department of Economics and Social Sciences, Agricultural University of Norway.*

Gonzalo, J. (1994). "Five alternative methods of estimating long-run equilibrium relationships", *Journal of Econometrics*, 60 : 203-233.

Hargreaves, C. P. (1994). "A review of methods of estimating cointegrating relationships", In C. P. Hargreaves (ed.), "*Nonstationary Time Series Analysis and Cointegration*", 87-132, Oxford: Oxford University Press.

Hausman, J. A. (1978). "Specification tests in econometrics," *Econometrica*, 46: 1251-1272.

Hylleberg, S., Engle, R. F., Granger, C. W . J., and Yoo, B. S. (1990). "Seasonal integration and cointegration ", *Journal of Econometrics*, 48 : 373-384.

Jarque, C. and Bera, A. K.(1980)."An efficient large-sample test for normality of observations and regression residuals", *Manuscript, Department of Statistics, Australian National University*.

Johansen, S. and Juselius, K. (1990). "Maximum likelihood estimation and inferences on cointegration—with applications to the demand for money," *Oxford Bulletin of Economics and Statistics*, 52:169–210.

Johansen, S. (1991). "Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models," *Econometrica*, 59 : 1551–1580.

Johansen, S. (1995). "*Likelihood-based inference in cointegrated vector autoregressive models*", Oxford: Oxford University Press.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., and Shin, Y. (1992). "Testing the null hypothesis of stationarity against the alternative of a unit root: how sure are we that economic time series have a unit root?", *Journal of Econometrics*, 54 : 159-178.

Ljung, G. and Box, G. (1979). "On a measure of lack of fit in time series models", *Biometrika*, 66 : 265-270.

MacKinnon, J. G. (1991). “Critical values for cointegration tests”, Chapter 13 in R. F. Engle and C. W. J. Granger (ed.), “*Long-run economic relationships: reading in cointegration*”, Oxford University Press.

Mandelbrot, B. B. (1971). “When can price be arbitraged efficiently? A limit to the validity of the random walk and martingale models”, *The Review of Economics and Statistics*, 53 : 225-236.

Newey, W. and West K. (1987). “A simple positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix”, *Econometrica*, 55 : 703–708.

Nord Pool ASA (2001) . “The Nordic Power Market”.

Park, H (1985). “Reexamination of normal backwardation hypothesis in futures markets”, *Journal of Futures Markets*, 5 : 505-515.

Pesaran, M. H. and Shin, Y. (1995). “An autoregressive distributed lag modelling approach”, *Working paper No.9514, Department of Applied Economics, University of Cambridge*.

Phillips, P. C. B. (1995). “Fully modified least squares and vector autoregression”, *Econometrica*, 63 : 1023-1078.

Phillips, P. C. B. and Hansen, B. E. (1990). “Statistical inference in instrumental variables with 1(1) processes”, *Review of Economic Studies*, 57 : 99-125.

Phillips, P. C. B., and Loretan, M. (1991). “Estimating long-run economic equilibria”, *Review of Economic Studies*, 58 : 407-436.

Phillips, P. C. B., and Ouliaris, S. (1990). “Asymptotic properties of residual based tests for cointegration”, *Econometrica*, 58 : 165-193.

Phillips, P., and Perron, P. (1988). “Testing for a unit root in time series regression”, *Biometrika*, 75 : 335-346.

Samuelson, P.A. (1965). “Proof that properly anticipated prices fluctuate randomly”, *Industrial Management Review*, 6 : 41-50.

Serletis A. and Scowcroft, D. (1991). “Informational efficiency of commodity futures prices”, *Applied Financial Economics* 1 : 185-192.

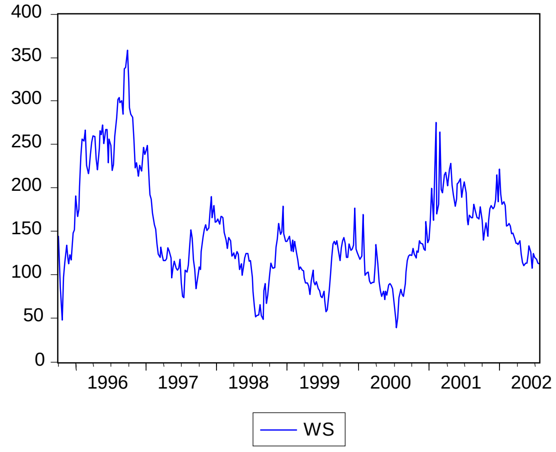
Stock, J.H. and Watson, M. W. (1993). “A simple estimator of cointegrating vectors in higher order integrated systems”, *Econometrica*, 61 : 713-820.

Tomek, W. G. (1994). “Dependence in commodity prices: A comment”, *The Journal of Futures Markets*, 14 : 103-109.

Yang, J., Bessler D. A. and Leatham D. J. (2001). “Asset storability and price discovery in commodity futures markets: A new look”, *The Journal of Futures Markets*, 21 : 279-300.

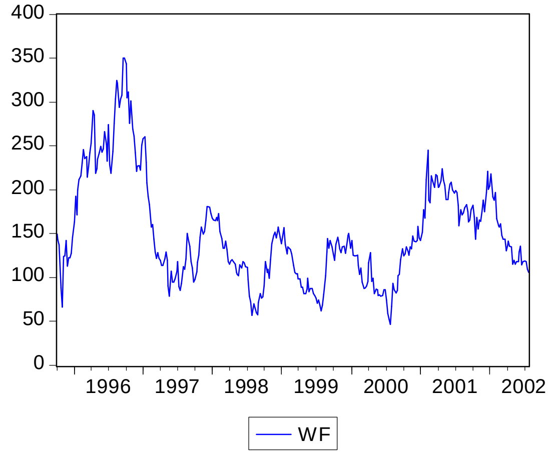
Appendix: Statistics and empirical results

Figure 1 Weekly spot prices



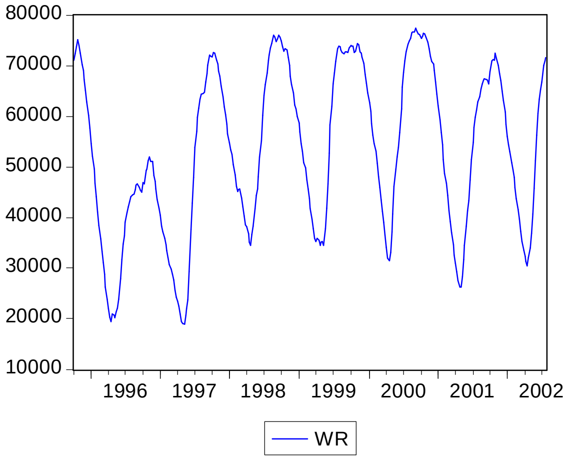
Notes: This figure shows weekly spot prices from September 5th, 1995 to July 26th, 2002. The unit of measurement on the Y-axis is Norwegian Kroner.

Figure 2 Weekly futures prices



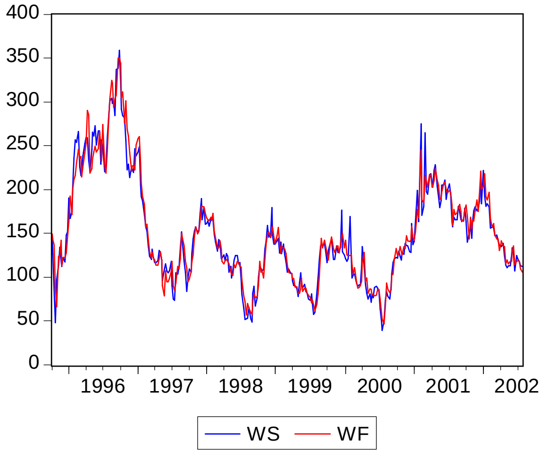
Notes: This figure shows weekly futures prices from September 5th, 1995 to July 26th, 2002. The unit of measurement on the Y-axis is Norwegian Kroner.

Figure 3 Weekly water reservoir content



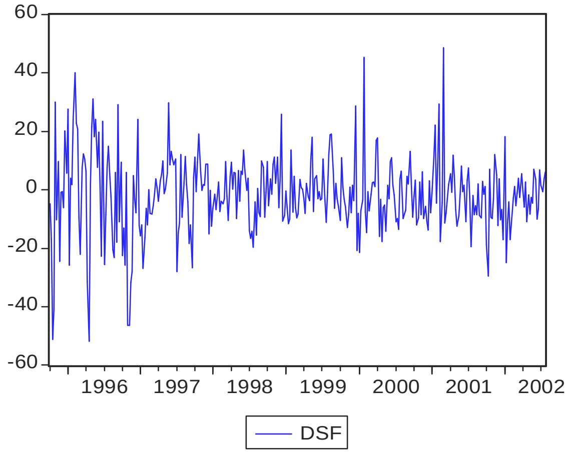
Notes: This figure shows weekly water reservoir content from September 5th, 1995 to July 26th, 2002. The unit of measurement on the Y-axis is GWh.

Figure 4 Weekly spot and futures prices combined graph



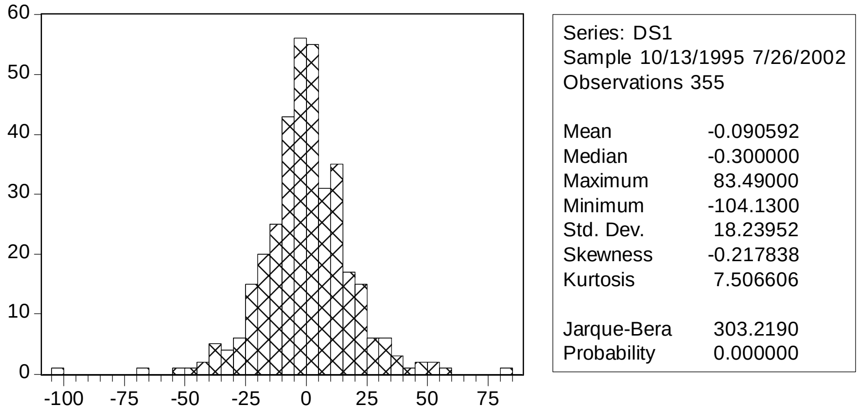
Notes: This figure shows weekly spot and futures prices in a combined graph from September 5th, 1995 to July 26th, 2002. The unit of measurement on the Y-axis is Norwegian Kroner.

Figure 5 Price difference (spread) between weekly spot and futures prices



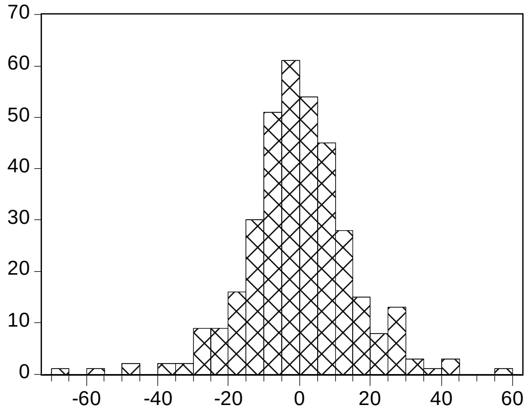
Notes: This figure shows price differences between weekly spot and futures prices from September 5th, 1995 to July 26th, 2002. The unit of measurement on the Y-axis is Norwegian Kroner.

Figure 6 Conditional distribution of weekly spot prices (in first difference) and basic statistics



Notes: This figure provides the conditional distribution of weekly spot prices in first difference from September 5th, 1995 to July 26th, 2002 and the corresponding basic statistics. DS1 denotes weekly spot prices in first difference.

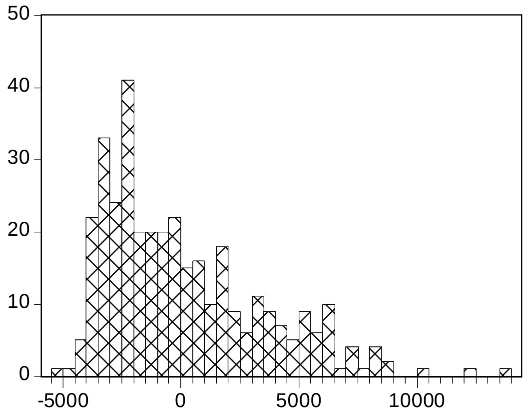
Figure 7 Conditional distribution of weekly futures prices (in first difference) and basic statistics



Series: DF1	
Sample 10/13/1995 7/26/2002	
Observations 355	
Mean	-0.121155
Median	-0.400000
Maximum	57.33000
Minimum	-66.27000
Std. Dev.	14.98682
Skewness	-0.184517
Kurtosis	5.199316
Jarque-Bera	73.56159
Probability	0.000000

Notes: This figure provides the conditional distribution of weekly futures prices in first difference from September 5th, 1995 to July 26th, 2002 and the corresponding basic statistics. DF1 denotes weekly futures prices in first difference.

Figure 8 Conditional distribution of weekly water reservoir content (in first difference) and basic statistics



Series: DWR1	
Sample 10/13/1995 7/26/2002	
Observations 355	
Mean	90.13843
Median	-783.2500
Maximum	13660.54
Minimum	-5027.019
Std. Dev.	3338.078
Skewness	1.009081
Kurtosis	3.626828
Jarque-Bera	66.05799
Probability	0.000000

Notes: This figure provides the conditional distribution of weekly water reservoir content in first difference from September 5th, 1995 to July 26th, 2002 and the corresponding basic statistics. DWR1 denotes weekly water reservoir content in first difference.

Table 1 Unconditional cross-correlation between spot and futures prices

	WS	WF
WS	1.000000	0.975011
WF	0.975011	1.000000

Notes: This table shows the unconditional cross-correlation between spot and futures prices from September 5th, 1995 to July 26th, 2002.

Table 2 ADF test on deseasonalized weekly spot prices with an intercept and a trend assumption

ADF Test Statistic	-2.471028	1% Critical Value*	-3.9880
		5% Critical Value	-3.4243
		10% Critical Value	-3.1349
*MacKinnon critical values for rejection of hypothesis of a unit root.			

Notes: This table reports the estimation result from an ADF test on deseasonalized weekly spot prices from September 5th, 1995 to July 26th, 2002 with an intercept and a trend assumption. The critical values are from Mackinnon (1991).

Table 3 PP test on deseasonalized weekly spot prices with an intercept and a trend assumption

PP Test Statistic	-2.547496	1% Critical Value*	-3.9877
		5% Critical Value	-3.4241
		10% Critical Value	-3.1348
*MacKinnon critical values for rejection of hypothesis of a unit root.			

Notes: This table reports the estimation result from a PP test on deseasonalized weekly spot prices from September 5th, 1995 to July 26th, 2002 with an intercept and a trend assumption. The critical values are from Mackinnon (1991).

Table 4 ADF test on deseasonalized weekly futures prices with an intercept and a trend assumption

ADF Test Statistic	-2.371467	1% Critical Value*	-3.9880
		5% Critical Value	-3.4243
		10% Critical Value	-3.1349
*MacKinnon critical values for rejection of hypothesis of a unit root.			

Notes: This table reports the estimation result from an ADF test on deseasonalized weekly futures prices from September 5th, 1995 to July 26th, 2002 with an intercept and a trend assumption. The critical values are from Mackinnon (1991).

Table 5 PP test on deseasonalized weekly futures prices with an intercept and a trend assumption

PP Test Statistic	-2.213354	1% Critical Value*	-3.9877
		5% Critical Value	-3.4241
		10% Critical Value	-3.1348
*MacKinnon critical values for rejection of hypothesis of a unit root.			

Notes: This table reports the estimation result from a PP test on deseasonalized weekly futures prices from September 5th, 1995 to July 26th, 2002 with an intercept and a trend assumption. The critical values are from Mackinnon (1991).

Table 6 ADF auxiliary regression for deseasonalized weekly spot prices

Actual test statistic = -2.5881

p-value based on 1500 simulations: 0.1093
Conclusion: H0 is not rejected at the 10% significance level

Notes: This table reports the estimation result from an ADF auxiliary regression for deseasonalized weekly spot prices from September 5th, 1995 to July 26th, 2002. The test statistics are obtained after 1500 rounds of simulation. The p-value denotes the marginal level of significance in testing the unit root.

Table 7 PP auxiliary regression for deseasonalized weekly spot prices

Actual test statistic = -16.9730

p-value based on 1500 simulations: 0.2460
Conclusion: H0 is not rejected at the 10% significance level

Notes: This table reports the estimation result from a PP auxiliary regression for deseasonalized weekly spot prices from September 5th, 1995 to July 26th, 2002. The test statistics are obtained after 1500 rounds of simulation. The p-value denotes the marginal level of significance in testing the unit root.

Table 8 ADF auxiliary regression for deseasonalized weekly futures prices

Actual test statistic = -2.4144

p-value based on 1500 simulations: 0.2213
Conclusion: H0 is not rejected at the 10% significance level

Notes: This table reports the estimation result from an ADF auxiliary regression for deseasonalized weekly futures prices from September 5th, 1995 to July 26th, 2002. The test statistics are obtained after 1500 rounds of simulation. The p-value denotes the marginal level of significance in testing the unit root.

Table 9 PP auxiliary regression for deseasonalized weekly futures prices

Actual test statistic = -12.5705

p-value based on 1500 simulations: 0.3307
Conclusion: H0 is not rejected at the 10% significance level

Notes: This table reports the estimation result from a PP auxiliary regression for deseasonalized weekly futures prices from September 5th, 1995 to July 26th, 2002. The test statistics are obtained after 1500 rounds of simulation. The p-value denotes the marginal level of significance in testing the unit root.

Table 10 Bierens high order sample autocorrelation tests on deseasonalized weekly spot prices

Actual test statistic = -11.6146 (HOAC(1,1))
Actual test statistic = -11.5194 (HOAC(2,2))

p-value based on 1500 simulations:
HOAC(1,1):0.2080
Conclusion: H0 is not rejected at the 10% significance level

Notes: This table reports the estimation result from Bierens' high order sample autocorrelation tests on deseasonalized weekly spot prices from September 5th, 1995 to July 26th, 2002. The test statistics are obtained after 1500 rounds of simulation. The p-value denotes the marginal level of significance in testing the unit root. HOAC denotes high order sample autocorrelation.

Table 11 Bierens high order sample autocorrelation tests on deseasonalized weekly futures prices

Actual test statistic = -7.8902 (HOAC(1,1))
Actual test statistic = -7.9472 (HOAC(2,2))

p-value based on 1500 simulations:
HOAC(1,1):0.2940
Conclusion: H0 is not rejected at the 10% significance level

Notes: This table reports the estimation result from Bierens' high order sample autocorrelation tests on deseasonalized weekly futures prices from September 5th, 1995 to July 26th, 2002. The test statistics are obtained after 1500 rounds of simulation. The p-value denotes the marginal level of significance in testing the unit root. HOAC denotes high order sample autocorrelation.

Table 12 Perron (1989) unit root test for structural breaks of deseasonalized weekly spot prices

Perron test for a unit root for DWS100 with 14 lags:	-3.704
At level 0.05 and for lambda 0.6	
The tabulated critical value:	-4.24
Coefficient and t-statistic on the CONSTANT:	
17.44213 3.441	
Coefficient and t-statistic on the DMU:	
-16.17802 -1.211	
Coefficient and t-statistic on the TREND:	
-0.07256 -2.968	
Coefficient and t-statistic on the DT:	
0.09850 1.870	
Coefficient and t-statistic on the DTB:	
0.81030 0.048	

Notes: This table reports the estimation result from a Perron (1989) unit root test for structural breaks of deseasonalized weekly spot prices from September 5th, 1995 to July 26th, 2002. The assumed structural break time point is the final week of the year 2000. DWS100 denotes deseasonalized weekly spot prices.

Table 13 Perron (1989) unit root test for structural breaks of deseasonalized weekly futures prices

Perron test for a unit root for DWF100 with 14 lags:		-3.463
At level 0.05 and for lambda 0.6		
The tabulated critical value:		-4.24
Coefficient and t-statistic on the CONSTANT:		
12.28810	3.331	
Coefficient and t-statistic on the DMU:		
-9.48851	-0.905	
Coefficient and t-statistic on the TREND:		
-0.05260	-2.877	
Coefficient and t-statistic on the DT:		
0.06410	1.573	
Coefficient and t-statistic on the DTB:		
-2.64306	-0.201	

Notes: This table reports the estimation result from a Perron (1989) unit root test for structural breaks of deseasonalized weekly futures prices from September 5th, 1995 to July 26th, 2002. The assumed structural break time point is the final week of the year 2000. DWF100 denotes deseasonalized weekly futures prices.

Table 14 Hausman's test for endogeneity

Dependent Variable: WS

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.693269	2.36E-14	1.14E+14	0.0000
WF	0.971742	1.46E-16	6.67E+15	0.0000
RESID01	1.000000	6.58E-16	1.52E+15	0.0000
R-squared	1.000000	Mean dependent var	149.0267	
Adjusted R-squared	1.000000	S.D. dependent var	59.66743	
S.E. of regression	1.64E-13	Sum squared resid	9.53E-24	
F-statistic	2.34E+31	Durbin-Watson stat	0.049804	
Prob(F-statistic)	0.000000			

Notes: This table reports the estimation result from Hausman's test for endogeneity. It shows the second regression result that includes the residual from the first regression (regressing WF over WS) as a regressor.

Table 15 Bierens nonparametric cointegration test

```
R is the number of cointegrating vectors:
Tests of H0: R = 0 against H1: R = 1:
m = 2 Test stat. = 0.00000        20% Crit.reg.: (0,0.017) -> Reject H0
m = 2 Test stat. = 0.00000        10% Crit.reg.: (0,0.005) -> Reject H0
m = 3 Test stat. = 0.00000         5% Crit.reg.: (0,0.017) -> Reject H0
Tests of H0: R = 1 against H1: R = 2:
m = 2 Test stat. = 18.13458       20% Crit.reg.: (0,0.241) -> Accept H0
m = 2 Test stat. = 18.13458       10% Crit.reg.: (0,0.111) -> Accept H0
m = 2 Test stat. = 18.13458        5% Crit.reg.: (0,0.054) -> Accept H0

Estimation result for m = 2
R          ghat(R)          Eigenvalue
0    16.46838147E+009
1    23.26969861E-009    18.13458054E+000
2    96.44117521E-002    33.48432642E-013
Estimation result: R = 1

Conclusion: R = 1

Calculation of the cointegrating vector:
Generalized Eigenvectors of A w.r.t.(A+c[A^-1]/n^2)^-1 for m = 4 and c = 1
 0.9849384  1.0000000
 1.0000000 -0.9849384
Note.: The last Eigenvector spans the space of cointegrating vectors

The space of cointegrating vectors is spanned by the following
standardized vector:
  1.0000000 -> LN[WS]
 -0.9849384 -> LN[WF]
```

Notes: This table reports the estimation result from Bierens' nonparametric cointegration test using natural logged weekly spot and futures prices from September 5th, 1995 to July 26th, 2002.

Table 16 Philips-Ouliaris residual based cointegration test

```
Multivariate trace statistic - Phillips and Ouliaris (1990)
Series:  WS
         WF
Includes constant and a linear trend

   Window size =  0   PZ = 353.6372
   Window size =  1   PZ = 348.1119
   Window size =  2   PZ = 361.0407
   Window size =  3   PZ = 367.9156
   Window size =  4   PZ = 367.8476

Orthogonal least squares estimation:

Smallest eigenvalue:   31684.13004

 Label   Var   Coefficient   normalizing to WS
********  ***  *************  ***************************
WS        1      0.70861         1.00000
WF        2     -0.70560        -0.99575
```

Notes: This table reports the estimation result from the Philips-Ouliaris residual based cointegration test using the weekly spot and futures prices from September 5th, 1995 to July 26th, 2002. The corresponding test statistic is PZ= 348.1119 (window size=1).

Table 17 Fully modified OLS cointegration test

```
 FMOLS RESULTS

 Fully modified coefficient ( Student t- statistics )

 Dependent variable: WS
 Regressors:
WF
     0.9852      ( 69.8582 )
Constant
     0.6814      (  0.2981 )

The L_c statistics equals       1.24219
```

Notes: This table reports the estimation result from a fully modified OLS cointegration test using the weekly spot and futures prices from September 5th, 1995 to July 26th, 2002. The test statistic is an Lc statistic.

Table 18 Phillips-Loretan nonlinear least square estimates of cointegration equations for test of market efficiency

Spot prices (S_t)	a	b	c_2-statistic $H_0: b=1$	Q-statistic Lag 200
Nord Pool	2.692817 (80802.41)	0.971744806 (4718313.)	1.88E+10 (0.00000)	0.457

Notes:
The first line indicates the estimates from the Phillips-Loretan equation:

$$S_t = a + b\,F_{t-1} + \sum_{i=1}^{n} d_i (S_{t-i} - a - b\,F_{t-i-1}) + \sum_{j=-L}^{L} g_j \Delta F_{t-j} + e_t \ .$$

The t-statistics are in parentheses with critical value 1.96 (5%) and 2.576 (1%), respectively.
The Q statistic is calculated based on the residual obtained as $e_t = S_t - a - b\,F_{t-1}$. Here a and b are the estimates from the Phillips-Loretan equation.

The Wald statistic has the null hypothesis that the restriction is binding; the alternative hypothesis is that the restriction is not binding. The restriction is tested using b =1 as a restriction and I obtain a corresponding c_2 statistic. The probability that the null is binding is reported in parentheses.

Essay II

Modeling and investigating the relationship between electricity prices and water reservoir content at the Nord Pool power exchange

Daniel Deng

Center for Finance
Department of Economics
School of Economics and Commercial Law
Gothenburg University
P.O.Box 640, SE-40530, Gothenburg
Sweden

E-mail: Daniel.Deng@handels.gu.se

I want to thank Erik Hjalmarsson, Lennart Hjalmarson and Carsten Tanggaard for helpful comments. I also want to thank Kenneth Andreassen and Jan Foyn at the Nord Pool power exchange for providing the data used in this study.

Abstract

This paper models electricity prices in the context of the Nord Pool power exchange which has a considerable proportion of hydropower supply. Since hydropower is storable in a producer's perspective and the system price is a uniform price for all sources of electricity supply, the applicability of the rational expectation competitive commodity storage model to characterize the spot and futures/forward prices is validated. I further show the nonlinearity between futures/forward prices and water reservoir content as inventory. I perform a BDS test (a test for nonlinearity), Hsieh's third-order moment test (a test that discriminates between different types of nonlinearities) and a nonlinear causality test to portray the nonlinear relationship using short/long maturities contracts. Empirical evidence shows that futures/forward prices are nonlinearly connected with water reservoir content via variance changes, and that the detection of causality varies as maturities change from short to long. These findings provide strong support for the credibility of the arbitrage argument and in a certain case verify the existence of the non-arbitrage condition.

Keywords: Nord Pool, hydropower, inventory, rational expectation competitive storage model, nonlinearity, BDS, Hsieh's third-order moment, nonlinear causality.

1. Introduction

Electricity as a commodity is very unique. When generated, it generally can not be conveniently stored and must be consumed instantaneously;[1] therefore it is considered to be nonstorable in a consumer perspective. However, if we take a producer's perspective and look at the different technologies of electricity production, then this view can be altered. In Scandinavia, electricity is produced by hydropower, nuclear-power, thermal-power and wind-power. The hydropower generation relies on the use of water reservoir technology. The fact that the hydropower related water reservoir content (or level) is quoted in GWh rather than in cubic meters points to the notion that the quantity of the water reservoir content that is being withheld equals the amount of hydropower that is being stored. That is to say hydropower is storable in a producer's perspective. A pivotal question confronting the hydropower producer is how to manage hydropower inventory in order to maximize the operating profit. Because the proportion of hydropower traded at Nord Pool is considerably high (nearly 50%) and the system price matching the electricity supply and demand conditions is a *uniform* price for all sources of electricity generation, the system price is also the solution to the hydropower producer's profit maximization problem. This means that the electricity spot and futures/forward prices at Nord Pool should be governed by the cost of carry, a cost function that may consist of a physical cost of storage plus a possible financial risk premium minus a convenience yield. In this paper, I implement the rational expectation commodity storage model framework to characterize the relationship between electricity spot and futures/forward prices. The theoretical framework adopted in the paper distinguishes itself from most of the theoretical electricity-pricing models developed for Nord Pool, such as Lucia and Schwartz (2000), Keokebakker and Ollmar (2001) and Fleten and Lemming (2001). These papers tend to focus on technologies such as term structure and bottom-up models to depict the futures/forward price dynamics, assuming electricity to be non-storable in a consumer perspective. Their perspective may serve a general theoretical modeling purpose for electricity trading with or without hydropower supply. In sharp contrast, this paper takes a hydropower producer perspective and looks at how prices should behave under a non-arbitrage

[1] Electricity may be stored in charged batteries. However, doing so is expensive and impractical.

condition based on the commodity storage model. The choice of the theoretical model is not trivial just for Nord Pool. The theoretical viewpoint can be applied to other power exchanges with considerable hydropower proportions in traded electricity, such as the Swiss power exchange and the New Zealand power exchange, offering a new angle to electricity price modeling.

Since inventory is a pivotal factor influencing prices in the commodity storage model framework, it is necessary to characterize the relationship between futures/forward prices and water reservoir content as inventory given the storability of hydropower. Based on the storage model framework, I theoretically show that the relationship between futures/forward prices and water reservoir content as inventory should be nonlinear. Because a specific functional form depicting the nonlinearity is not analytically available, empirical investigations are conducted to enrich our understanding about this relationship.

I carry out three tests to realize the following three primary objectives. The first is the BDS test, used to detect if there is nonlinear dependence in both of the univariate series. If the series are nonlinearly dependent, then the second test, Hsieh's third-order moment test, further investigates if the nonlinear dependence can be characterized by either additive or multiplicative dependence, or by both. Given evidence of nonlinearities in the first two tests, the third test applies the modified Baek and Brook approach to uncover if there is any nonlinear causality between the two series. This test is closely linked to the non-arbitrage argument and is able to provide evidence on its plausibility. If the market is efficient, no arbitrage profit can be left in the market. Hence it is not possible for futures/forward prices to be efficiently forecasted using the water reservoir as inventory, so we should not find causality in a Granger sense. This is evident regarding the credibility of the argument for a hydropower producer's arbitrage and the existence of the non-arbitrage condition. On the other hand, if one can better forecast current and future futures/forward prices by knowing past water reservoir content, we may detect causality from water reservoir content to futures/forward prices. This may suggest that either the cost of carry relationship is violated or the argument for the existence of arbitrage is simply invalid, given that most of the papers on Nord Pool view electricity as purely nonstorable. An in-depth analysis of the empirical results may offer a definite judgement of the plausibility of the model.

A typical statistical property of electricity price is seasonality. Seasonality implies that seasonal supply and demand conditions together with other factors such as inventory holding, etc. result in price changes being dependent or autocorrelated. The lagged effect of seasonality on each price change innovation may be followed to some finite horizon beyond which it can be neglected. For example, a shortage of water reservoir content due to a one year drought may result in electricity prices that are high for a while, but not forever. Mandelbrot (1971, p232)[2] discusses the influence of the lagged effect on price changes. He shows that if the lagged effects have a finite time span, the resulting future price becomes a martingale price process; if the lagged effects continue indefinitely, the price will not be a martingale. Based on his finding, I use weekly futures prices as a benchmark series and include a 1-month ahead futures contract, a 1-year ahead summer 0 seasonal forward contract, and a 2-years ahead winter 1 and

---

[2] Mandelbrot (1971, p232) shows that for a finite horizon anticipation and for every past innovation $N(s)$, one can only add the lagged effects up to time $t+f$, where t designates the present and f the depth of the future. The total effect of the innovation $N(s)$ is considered equal to $N(s)\sum_{n=0}^{t+f-s} L(n)$, where $L(n)$ is called the lagged effect kernel. The resulting price $P_f(t)$ satisfies:

$$\Delta P_f(t) = \sum_{s=-\infty}^{t} N(s)\sum_{m=0}^{t+f-s} L(m) - \sum_{s=-\infty}^{t-1} N(s)\sum_{m=0}^{t-1+f-s} L(m) = N(t)\sum_{m=0}^{f} L(m) + \sum_{s=-\infty}^{t-1} N(s)L(t+f-s).$$

Since $\lim_{n\to\infty} L(n)=0$, it is easy to verify that as $f\to\infty$, $\Delta P_f(t)\to\Delta P(t)$ and $P_f(t)-P_f(0)\to P(t)-P(0)$ which expresses that a martingale process $P(t)$ (defined earlier in his paper) can be considered identical to $P_\infty(t)$. But for finite f, $\Delta P_f(t)$ is a new moving average of the form: $\Delta P_f(t)=\sum_{s=-\infty}^{t} N(s)L_f(t+1-s)$. Define the function $L_f(n)=\sum_{m=0}^{f} L(m)$ for $n=0$ and $L_f(n)=L(f+n)$ for $n\geq 1$. In the case that the lagged effect has a finite span f_0, $L(n)$ vanishes for lags n satisfying $n>f_0$, and we have $L_f(n)=L(f+n)=0$ for all $n\geq 1$ and $f>f_0$. Hence as soon as $f>f_0$, $P_f(t)$ becomes identical to the martingale $P(t)=P_\infty(t)$. The depth of future f corresponds to the time span or length of maturity of the futures/forward contract in my paper. As every random walk without drift is a martingale and the converse is also true in the Gaussian universe (Mandelbrot, 1971), I use the words interchangeably in this paper.

winter 2 seasonal forward contracts with longer maturities in order to compare the test results with the benchmark case. As maturity lengthens, the lagged effect function discussed in Mandelbrot's paper becomes strictly zero for large enough lags (maturity length as time span), and the futures/forward prices may become a martingale price process. If the lagged effect on futures/forward prices becomes increasingly less influential, then we may expect a varying pattern of causality in terms of the length of maturity. Moreover, any case where no causality is detected between futures prices and water reservoir content proves the validity of the non-arbitrage argument.

This paper contributes to the literature on electricity exchange in several important ways. First, by taking a hydropower producer perspective and recognizing the storability of hydropower, I adopt the rational expectation competitive storage model framework to bridge futures/forward-spot spreads and water reservoir content as inventory. Based on this, I theoretically show the nonlinearity between the water reservoir content and futures/forward prices. Second, this paper employs several empirical tests to further portray the nonlinear relationship between the two series. By using various maturity contract prices in the estimation, this study provides empirical support for the theoretical argument on a hydropower producer's arbitrage and shows that the non-arbitrage condition can be maintained. Third, both the theoretical framework and the empirical findings have important implications for power exchange related research and for practitioners such as hedgers, speculators, and other power market participants.

The rest of the paper is organized as follows. In Section 2, I present a brief description of the Nord Pool power exchange. In Section 3, I set up the theoretical framework concerning the spread of the futures-spot prices and water reservoir content as inventory. Based on this model, I also show that the relationship between futures/forward prices and water reservoir content should be characterized as nonlinear, and design three testable hypotheses concerning the nonlinearities. Section 4 discusses the data and their statistical properties. Section 5 presents three tests characterizing empirically the relationship between the series concerned. Finally, Section 6 provides a summary and a conclusion.

2. The Nord Pool power exchange

The Nord Pool power exchange is a multinational power exchange embracing all the Nordic countries. As a result of the power market restructuring, it has since 1991 developed from being a national Norwegian power market into an exchange consisting of both spot and derivative markets. The spot market trades power contracts for next day physical delivery, and the derivative markets are established for price hedging and risk management purposes.

The futures and forward contracts are traded in blocks. Within a year there are three seasonal blocks: winter 1, winter 2, and summer 0. A contract is available for trading three years before the start of delivery to the beginning of the previous season. Then the contract splits into 3-6 blocks with a delivery period of four weeks. These blocks are available for trading again until the start of the previous block, and then split into four weekly contracts that are traded until the day before delivery. One of the differences between futures and forward in trading convention is that forward contracts do not split into smaller blocks but are traded until the beginning of the delivery period.

The fact that around 50% of the traded power comes from hydropower and that the system price is also the hydropower price suggests that electricity prices may be modeled under the framework of the rational expectation competitive storage model, utilizing the arbitrage argument. In the following section, I present and accommodate the commodity storage models to the scenario of the hydropower inventory situation at Nord Pool.

3. Theoretical framework

3.1 The nonlinear relationship between futures/forward prices and inventory.

There are two strands of the rational expectation competitive storage model in the literature, differing in the specification of the storage cost function.

Deaton and Laroque (1992) design the constant decay commodity storage model. They base their argument on the competitive or speculative storage theory developed by Samuelson (1971) and Williams and Wright (1991).

The model specification is as follows:

$$\frac{1-g}{1+r}E[P_{t+1}]-P_t=0\text{, when } I_t>0\text{;}$$
$$\frac{1-g}{1+r}E[P_{t+1}]-P_t<0\text{, when } I_t=0\text{,} \tag{1}$$

where P_t is the commodity price at time t, $E[P_{t+1}]$ is the conditional expectation of price P_t at time t, g is the shrinkage coefficient, r is the risk-free interest rate, and I_t is the carryover inventory stocks at time t.

Equations (1) are the non-arbitrage condition, asserting that storage costs arise exclusively from stock spoilage or decay at a fixed rate g . Under this formulation, one unit of commodity stored in the current period will yield (1-g) units in the following period. Under this constant decay assumption, the supply of storage function is decreasing in the stock level.

$$Y_t+I_{t-1}=S_t\text{,} \tag{2}$$

where Y_t is the new production, I_{t-1} is the carryover inventory stocks from time t-1, and S_t is the total supply in the market.

Total supply in the market is equal to the carryover inventory at t-1 plus the new production or harvest at t.

$$S_t=D_t+I_t\text{,} \tag{3}$$

where D_t is the current demand at time t.

The total market supply is equal to the current demand and carryover inventory at t.

$$P_t = P(D_t), \tag{4}$$

where $P(.)$ is the inverse demand function.

The spot price at time t is equal to the inverse demand function.

The second version of the storage model can be found in Miranda and Glauber (1993) and in Miranda and Rui (1996). These models specify a storage cost function based on the classical supply of storage theory (see Working 1949, Brennan 1958 and Telser 1958), and incorporate the storage under backwardation. A market is said to be in backwardation when the spot price exceeds the futures price, or when the nearby futures price exceeds the distant futures price.

This version of the storage model is presented as follows:

$$\frac{1}{1+r}E[P_{t+1}] - P_t = K_t^{'}(S_t), \tag{5}$$

where $K_t^{'}(.)$ is the marginal cost of carry at time t.

Equation (5) specifies the non-arbitrage condition, saying that the spread between the futures and spot prices equals the marginal cost of carry. As a classical supply of storage model, inventory stocks never fall to zero and thus the link between the current and futures price is never completely served.

Other conditions are the same as in Equations (2)-(4) in the first version and are not repeated here.

The merit of the second version is that it does not permit stock-outs by allowing storage under backwardation. In this way, prices of successive periods are interconnected. This feature is not allowed in the first version of the model. That is, assuming constant decay, high prices induce a stock-out, ***i.e.*** a depletion of all stocks. Further, unlike the second version, the first version imposes the non-arbitrage condition when the price spread is above the storage costs. The problem with the first model's non-arbitrage condition is that it fails to capture the coincidence of negative spot-futures price spreads and positive stock levels, which is commonly observed in the commodity markets. In contrast, the second model specification admits the negative inter-temporal price spreads with positive stocks.

There are no clear-cut criteria on which version of the model one should choose. A practical guideline is to choose the model in accordance with the stylized facts. Here I consider the second commodity storage model version based on the constant supply storage theory to be a more decent choice. This is because the shrinkage assumption in the first version may not be appropriate for reservoir water holding, and it is highly unlikely that reservoir content will be depleted at a high price.

There are some variants concerning the forms of the cost of carry. A direct extension following the classical supply of storage literature assumes that the cost of carry may consist of a marginal physical cost of storage plus a possible financial risk premium minus the convenience yield of inventory stocks (Brennan, 1958). The cost of carry may be expressed as:[3]

$$K_t(S_t) = O_t(S_t) + M_t(S_t) - N_t(S_t), \tag{6}$$

where O_t is the physical storage cost function, M_t is the risk premium function, and N_t is the convenience yield function.

[3] The resulting marginal cost of carry in time t may be expressed as:
$K_t^{'}(S_t) = O_t^{'}(S_t) + M_t^{'}(S_t) - N_t^{'}(S_t)$.

The physical cost of storage consists of expenditure on rent for storage space, interest and handling charges. The physical cost of water storage is zero if the reservoir is not full; if overflow occurs (this is seldom the case[4]), the cost equals the value of the lost electricity generation from the "wasted" (out-flowed) water.

If a risk-averse inventory holder is assumed, a risk premium term should be added. The risk premium should be an increasing function of stocks or a constant. Since there is a high concentration of ownership of production and reservoir capacity at Nord Pool, it induces an excess of long hedging demand, which requires that a risk premium should be paid by consumers to producers.

Convenience yield is defined as the benefit from owning the physical commodity that is not obtained by holding a futures contract, such as the ability to profit from unexpected orders or the ability to keep an operation running. Convenience yield reflects the expectations of the market concerning the future availability of the commodity, and is a decreasing function of the stocks being held. Consider water reservoir content as futures electricity inventory stocks ─ the greater the shortage of available water reservoir content, the larger the convenience yield and vice versa. If we assume a high enough level of reservoir content, then the marginal convenience yield is zero. On the other hand, the marginal convenience yield may exceed the marginal expenditure on physical storage and the risk premium when stocks are relatively small; hence the futures price will be below the spot price.

The prediction of the second version of the commodity storage model is: whenever expected appreciation (*i.e.* future-spot spread) exceeds the marginal cost of carry, the inventory holder[5] will increase stock holdings until the equilibrium is restored; on the other hand, whenever the marginal cost of carry exceeds the expected appreciation, inventory holders will decrease stockholdings until the equilibrium is restored. Hence an inventory holder's arbitrage through inventory management for profit maximization guarantees no arbitrage opportunities in equilibrium.

[4] The sample water reservoir content data indicate that reservoir content has been well below 90% of the total reservoir capacity during the sample periods.
[5] Without loss of generality, we assume that inventory holders are producers as well.

As argued in the introduction, the uniform system price is also the hydropower price and therefore the solution to the hydropower producer's profit maximization problem. The hydropower producer's profit maximization problem can be expressed as:

$$\max_{S_t} E_t[\Pi_{t+1}] = \frac{E_t[P_{t+1}]\times(S_t)}{1+r} - P_t \times (S_t) - K_t(S_t)\,, \tag{7}$$

where S_t is the hydropower supply at Nord Pool at time t, r is assumed to be a constant risk-free rate, and K_t is the total carrying cost for the hydropower supply at time t.

In the above formulation, we assume that the hydropower producer is risk-neutral and that the producer profit equals the expected appreciation in price less the opportunity and carrying costs associated with storage.

Other conditions are modified accordingly to accommodate the situation at Nord Pool:

Condition 2 as in Equation (2) is modified as:

$$S_t = I_{t-1} - I_t + i_{t-1}\,,^{6} \tag{8}$$

where i_{t-1} is the inflow at time t-1.

The hydropower supply at current time t can be expressed as the difference in water reservoir content between time t-1 and time t plus the inflow between time t-1 and time t.

[6] The derivation utilizes the fact that $I_t = I_{t-1} + i_{t-1} - S_t$, or that the carryover water reservoir content at time t equals the carryover water reservoir content from t-1 plus the inflow occurring between t-1 and t minus the new hydropower production at time t.

Condition 3 as in Equation (3) is changed to:

$$S_t = D_t \,. \tag{9}$$

This condition states that hydropower supply equals hydropower demand at time t.

Condition 4 as in Equation (4) remains the same.

The first-order condition for the above maximization problem is as follows:

$$\frac{E_t[P_{t+1}]}{(1+r)} - P_t = K_t^{'}(S_t) \,. \tag{10}$$

Equation (10) indicates that the spread between the futures and spot prices reflects the marginal cost of carry for the hydropower generation. Note that Equation (10) is also valid for a risk-averse inventory holder despite the initial assumption of risk neutrality.[7]

Since reservoir overflow is rare under normal conditions, we can assume the physical storage costs of water to be zero. The risk premium that the producer requests from the customer can also be assumed to be constant. In this way, it is the change in the convenience yield that induces the change in the total cost of carry. Miranda and Rui (1996) use $a + b_1 \ln(I_t)$ to represent the marginal cost of carry assuming the physical storage costs to be constant.[8] Following their spirit, Equation (10) can be re-expressed as follows:

$$\frac{E_t[P_{t+1}]}{(1+r)} - P_t = a + b_1 \ln(I_t) \,. \tag{11}$$

---

[7] Using the certainty equivalent of a risky prospect to express the utility maximization problem for a risk-averse hydropower producer, it can be shown that the solution is identical to the model assuming risk neutrality. See Just (1975).
[8] In that paper, risk neutrality is assumed.

3.2 The nonlinear relationship between futures prices and water reservoir content — a demonstration

Having derived the future-spot spread and water reservoir content relationship for Nord Pool, I show that the futures/forward prices have a nonlinear relationship with water reservoir content as follows:

$$P_t = f(S_t) = f[I_{t-1} - I_t + i_{t-1}]. \tag{12}$$

The spot price P_t is a function of the hydropower supply S_t that can be represented by the difference in the water reservoir content at t and t-1 plus the inflow between time t-1 and time t.

The equilibrium price function $f(.)$ is characterized by a nonlinear functional equation, which stipulates that for every realizable supply S,

$$P_t = f(S_t), \tag{13}$$

where I_t solves,

$$\frac{E_t[P_{t+1}]}{(1+r)} - P_t = a + b_1 \ln(I_t). \tag{14}$$

3.3 Setting up testable hypotheses

The above demonstration shows that there is a theoretical nonlinear relationship between the futures/forward prices and water reservoir content. However, the specific functional form of such a nonlinear relationship is analytically unavailable in general. To further enrich our understanding of this relationship, an empirical investigation is in order. The first task of the empirical design is to detect and verify any presence of nonlinearity between futures/forward prices and water reservoir content.

Econometrically, the basic idea behind various nonlinearity tests is the assumption that residuals of a properly specified linear model should be independent under the null hypothesis of linearity. Any violation of independence in the residuals is indicative of the inadequacy of the linear model, including the linear assumption. Therefore, a symptom of nonlinear dependence is an indication of nonlinearity. The testing of nonlinearity is the basic building block of further in-depth empirical investigation on the nonlinear structure between futures/forward prices and water reservoir content. Based on this consideration, I set up the following testable hypotheses:

1) There is nonlinear dependence between P_t and S_t in Equation (14).

If both futures/forward prices and water reservoir content series are generated by nonlinear processes, then nonlinear dependence might exist between the two variables. Prices for financial and commodity markets are generally regarded as nonlinear (Savit 1988, Hsieh 1991), and market microstructure, nonlinear transaction cost functions and the role of noise traders may be attributed to the price nonlinearity. Hurst (1951, 1956) studies the time series property of the water reservoir content and concludes that it is of a nonlinear nature. The nonlinearity may influence both the mean and the variance of a process.

2) P_t and S_t are connected either via mean change or via variance change, or via both.

This hypothesis characterizes the manner of association between P_t and S_t as mean and/or variance changes. The finding will further serve as an argument for designing the appropriate testing procedure in the subsequent empirical investigation.

3) There is either a uni-directional or a bi-directional causal relationship between P_t and S_t.

First, let us define Granger causality. We say that if a variable X_t can be predicted more efficiently if the information in the Y_t process is taken into account in addition to all other information available, then Y_t is Granger-causal for X_t. Econometrically, suppose that Ω_t is the information set containing all available information up to and including period t. Let $X_t(h \mid \Omega_t)$ be the optimal h-step forecast of the process X_t that minimizes the MSE at t, given the information contained in Ω_t. The corresponding forecast MSE is denoted $M_x(h \mid \Omega_t)$. The process Y_t is said to cause X_t in Granger's sense if $M_x(h \mid \Omega_t) < M_x(h \mid \Omega_t \setminus \{Y_s \mid s < t\})$ for at least one $h = 1,2\ldots$, where $\Omega_t \setminus \{Y_s \mid s < t\}$ is the information set that contains all available relevant information except for the information in the past and present of the Y_t process.

The motivation for conducting the causality tests is to further delineate the nonlinear relationship and to provide evidence on the plausibility of the non-arbitrage condition in Equation (10). Since the commodity storage model predicts that hydropower producers adjust their hydro-inventory according to the expected appreciation (futures/forward-spot spread) in relation to the marginal cost of storage for profit maximization, we might expect uni-directional causality running from futures/forward prices to water reservoir content. However, we must also acknowledge a fundamental difference between electricity markets and other commodity markets: supply and demand in electricity markets must be in equilibrium all the time, and thus power producers are compelled to provide additional power supply to meet sudden and unexpected increases in demand, resulting in volatile electricity prices. The relatively high proportion of hydropower production in Scandinavia provides flexibility in electricity production. Hence, in case of a sudden demand increase, the resulting supply gap due to capacity constraints is smoothed to some extent and consequently prices are not so volatile compared to those in regions where hydropower accounts for smaller proportions. However, the smoothing effects should not be exaggerated since price spikes are still observed in the short-term. It can therefore be argued that the smoothing effect offered by hydropower may work better in the long run than in the short run.[9] The supply-side capacity constraint in meeting sudden increases in electricity demand pushes up prices in the short run and hence causality from water reservoir content to futures/forward prices is possible, particularly for the short maturity contracts.

Moreover, Hiemstra and Jones (1994) indicate that their modified Baek and Brock approach may detect spurious nonlinear causality due to volatility persistence associated with latent information flow. If water reservoir content and futures/forward prices each serves as a proxy of latent information flow in the counterpart's variance, then inference of nonlinear causality associated with volatility persistence is invalid. Since hydropower producers want to maximize profits, changes in hydropower inventory reflect the production scheduling to sell at the best possible prices in the short and long run. The hydropower supply changes result in renewed futures/forward prices, therefore water reservoir content can serve as a proxy for information flow in the stochastic process generating futures/forward price variance. In this case, the volatility persistence associated with nonlinear dependence in the futures/forward prices can account for the nonlinear Granger causality from water reservoir to futures/forward prices. On the other hand, since futures/forward prices incorporate all available information on all aspects of the market, the hydropower producers may react to this information. Therefore futures/forward prices may also well act as a proxy for information flow in the stochastic process generating water reservoir content variance. Consequently, the volatility persistence associated with the nonlinear dependence in the water reservoir content can explain the nonlinear Granger causality from futures/forward prices to water reservoir content. Such a concern is particularly reasonable if testing of the second hypothesis shows that futures/forward prices and water reservoir content are nonlinearly associated via variance changes.

4. Data and the statistical properties of the variables

[9] The discussion about the standard deviations for the short and long maturity contracts in the summary statistics in Section 4 supports this view.

The data series (futures/forward prices information and water reservoir content) are obtained from Nord Pool covering the period between October 29, 1997[10] and September 25, 2002. Because causality tests can be sensitive to non-stationarities associated with structural breaks (Hiemstra and Jones, 1994), and because extreme drought pushed electricity prices sky high from October of 2002 and onwards giving rise to structural breaks in all futures/forward series, data series after October of 2002 are discarded to avoid disruptions.[11]

Since water reservoir content is available to the Nord Pool traders at 13:00 every Wednesday, the futures/forward price series (weekly, 1-month ahead futures contracts and 1-year ahead seasonal summer 0 and 2-years ahead winter 1 and winter 2 forward contracts[12]) are constructed by taking every Wednesday's closing futures/forward prices.[13]

Since non-stationary[14] series may render spurious causality test results, it is necessary to transform the series into stationary ones. An important concern here is the existence of non-arbitrage conditions between futures/forward-spot spread and water reservoir content. If only the non-stationary price series are transformed into stationary ones

---

[10] Weekly water reservoir content and weekly and 1-month ahead futures prices are available since 1995 or even earlier, but forward prices are only available since October 1997. Therefore I choose the data time interval for which all types of contracts and water reservoir information in this study are available.

[11] An alternative perspective is to split the data set into sub-samples and to test if structural breaks do have an effect on causality testing. The problem is if I were to divide the sample using October 2002 as a dividing time line, the sub-sample of the recent period could have been too small, and small sample bias in estimation may be a serious concern.

[12] In the first two weeks of the year 2000, 2-years ahead winter 1 and winter 2 forward contracts were not traded. The corresponding water reservoir content series are properly adjusted when running regression with these two forward contract series.

[13] Ideally, every Wednesday's 13:00 hour's futures/forward prices should be used. However, these prices are not available to the author since only futures/forward daily closing prices are recorded.

[14] To investigate the non-stationarity of the sample series, I first seasonally adjust the data, and then conduct augmented Dickey-Fuller, Philips-Perron and their auxiliary variants, Bierens high-order sample autocorrelation, Perron 1989 test, KPSS, and Bierens and Guo type 5-6 tests to detect whether the seasonally adjusted series concerned is non-stationary or not. For a detailed description and justification of the choice of the procedures, please refer to Deng (2003). The unit root test results, not reported here but available from the author upon request, indicate that the null hypothesis of a unit root is not rejected for each of the price series but is rejected for the water reservoir content series. Note that since seasonality implies autocorrelation which may influence the causality testing, appropriate ARMA filters are applied to the series in the later testing. A seasonal adjustment approach is necessary for the unit root testing since without seasonal adjustment, we are testing the joint null hypothesis of a unit autoregressive root and the seasonality. In the case of a rejection of the joint null hypothesis, we do not know if the rejection of the null hypothesis is due to seasonality, to unit root or to both.

while I keep the stationary water reservoir content unchanged, this leads to spurious causality results.[15] In this situation, it is necessary to adopt a uniform transformation method so that the inherent futures/forward and water reservoir content relationship is not damaged. I obtain the returns[16] for both futures/forward and water reservoir content by taking the natural logarithm of the returns of both futures prices and water reservoir content series times 100. For example, the weekly futures prices and water reservoir content return series are obtained through transformation of the forms $100\times(P_{w,t}/P_{w,t-1})$ and $100\times(WC_{w,t}/WC_{w,t-1})$, respectively. I denote weekly and 1-month ahead futures, 1-year ahead seasonal summer 0 and 2-years ahead seasonal winter 1 and winter 2 returns series as $F_{w,t}, F_{m,t}, F_{s,t}, F_{v1,t}, F_{v2,t}$, respectively, while weekly water reservoir content return is denoted $W_{w,t}$. Consequently, linear/nonlinear causality between futures/forward and water reservoir content returns implies linear/nonlinear causal relationships between futures/forward prices and water reservoir content.

Table (1) gives the summary statistics of the futures/forward and water reservoir content returns. None of the returns is normally distributed, suggested by the Jarque-Bera (1980) statistic and evidenced by the positive skewness and excess kurtosis in all return series. Non-normality, skewness and excess kurtosis will influence the choice of the empirical method used in the paper and will be discussed in a later section. Moreover, the standard deviation generally decreases as contract maturity increases. For example, the standard deviation for 2-years ahead winter 2 contract returns is just 25% of that of the weekly futures contract returns, which supports the previously discussed view that water reservoir content may smooth the supply gap more effectively in the long run than the in short run.

[15] The sign of the correlation between the transformed price series (returns) and original water reservoir content series is different from that of the original series. Since causality testing may be sensitive to the correlation, inappropriate transformation of the water reservoir content series here may lead to spurious results.

[16] Strictly speaking, it is not appropriate to use the term “return” for the water reservoir content.

5. Methodologies and empirical results

5.1 Methodology for detecting nonlinear dependence and empirical results

Several nonlinearity tests have been proposed in the literature. These can be classified into parametric and nonparametric testing procedures. An advantage of the nonparametric nonlinearity test statistics is the flexibility in capturing the dependence structure in the data without relying on the specific parametric family. This paper therefore opts to adopt nonparametric nonlinearity procedures. Of the three major nonparametric approaches, the Bispectral test (as in Hinich 1982, Hinich and Patterson 1985) typically requires a large sample size to obtain decent power against nonlinearity. Therefore, due to the small sample in this paper, the test is not selected. Hsieh (1989) performs a Monte Carlo study and shows that the BDS test statistic has a good finite sample property. We can therefore trust the BDS test result based on our small sample base. Before formally conducting the BDS test, I perform a preliminary nonlinearity test based on the Q-statistic of the squared data suggested by McLeod and Li (1983). This test is based on the Ljung-Box Q-statistic for the squared data and is useful in detecting conditional heteroskedasticity. The test results of the McLeod-Li Q-statistic (not reported here but available from the author upon request) indicate that return series of both futures/forward and water reservoir content exhibit conditional heteroskedasticity, indicative of a nonlinear structure in each of the examined univariate time series.[17]

The formal nonlinearity test implements the BDS statistic suggested in Brock, Deckert and Scheinkman (1987). This test statistic distinguishes between data that are *i.i.d.* distributed and data that contain deterministic or stochastic dependence. It utilizes the idea of a correlation integral, which is defined as the probability that any two points are within a certain length, e, apart in phase space. If the observations of the series are virtually *i.i.d.* distributed, then for any pair of points, the probability of the distance between these points being less than or equal to e will be constant. The correlation integrals are calculated according to the following equation:

[17] Conditional heteroskedasticity is a form of nonlinearity.

$$C(m,e,N) = I[(t,s):\| W_t^m - W_s^m \| < e] / N^2, \tag{15}$$

where $W_t^m = (w(t),...w(t-m+1))$, $\|.\|$ is the $L\infty$ norm on R^m, and $I[.]$ denotes the number of elements. As $N \to \infty$, subject to only modest regularity conditions, $C(m,e,N)$ has a limit $C(m,e)$ such that if $\{w(t)\}$ is *i.i.d.*, then it follows that

$$C(m,e) = C(1,e)^m. \tag{16}$$

Consequently, the BDS test statistic is defined as:

$$B(m,e,N) = \sqrt{\frac{T}{Var_m(e,T)}} \times [C(m,e,N) - C(1,e,N)^m], \tag{17}$$

which converges in distribution to $N(0,1)$ as $N \to \infty$.

It is worth noting that the BDS test rejects *i.i.d.* for the linear stochastic process as well as for the nonlinear process. Since the purpose of conducting a BDS test is to detect any nonlinear dependence, I first apply an appropriate ARMA filter to pre-whiten the data series' autocorrelation. I use the Schwartz Bayesian Criterion (SBC) to determine the suitable filter models. The filters for $W_{w,t}, F_{w,t}, F_{m,t}, F_{s,t}, F_{v1,t}, F_{v2,t}$ are ARMA(1,1), ARMA (1,2), ARMA(1,2), ARMA(1,1), ARMA(2,2), ARMA(1,1), respectively. These filters are found adequate in purging the raw return series.

The filtered return innovations are then used in the BDS test. Following Brock *et al.* (1991) and Hsieh (1991), the value of e used[18] in this study equals 0.5s, s, 1.5s and 2s. The value of s represents the standard deviation of the filtered data.

Moreover, if the BDS test for the filtered return innovation rejects the *i.i.d.*, it can be subject to non-stationarity associated with structural breaks (Hsieh 1991), a nonlinear

[18] A large value for e will retain all pairs and the value of the correlation integral will equal unity, while a small value will lead to no retention of any pair, and will result in a value of zero for the correlation integral. The choice on what value to choose for e is therefore delicate.

stochastic process or a nonlinear deterministic system (chaos). Since the selection of the data interval has discarded the period that may have structural breaks and since the returns series are all stationary, we can safely rule out the non-stationarity in connection with structural breaks. As a result, the rejection of ***i.i.d.*** can be associated with either a nonlinear stochastic or a deterministic process. Unfortunately, the nonlinear process that is either stochastic or chaos can not be distinguished further by the BDS test itself; further testing using other methods is needed. For this paper, it is sufficient to show that the rejection of the ***i.i.d*** is an indication that the underlying process is indeed nonlinear.

Table (2) reports the results of the BDS test applied to the residual innovation series from the respective ARMA filter. Except for the two BDS test statistics for 1-month ahead futures return innovation being significant at the 10% level, all other test statistics for all return innovations are significant at the 1% level. We can reject the null hypothesis of ***i.i.d*** behavior in all the residual series.

5.2 Methodology for discriminating between different types of nonlinearities and empirical results

An additional test that I employ to characterize the nonlinear relationship between futures/forward prices and water reservoir content is Hsieh's third-order moment test. Hsieh (1989) defines two types of nonlinearities in a series: additive dependence and multiplicative dependence.

We define the innovation series u_t from a filtered data series x_t. Additive dependence is defined as:

$$u_t = v_t + f(x_{t-1},...,x_{t-k,}u_{t-1},...,u_{t-k}) , \tag{18}$$

while multiplicative dependence is defined as:

$$u_t = v_t f(x_{t-1},...,x_{t-k},u_{t-1},...,u_{t-k}), \tag{19}$$

where v_t is an *i.i.d* random variable with a zero mean and independent of past x_t 's and u_t 's, and $f()$ is an arbitrary nonlinear function of $x_{t-1},...,x_{t-k,}$ and $u_{t-1},...,u_{t-k}$, for some finite k.

Additive dependence posits that the nonlinearity enters only through the mean of the stochastic process while the multiplicative dependence posits that nonlinearity is channeled through the variance of the process. Hsieh (1989) points out that statistic processes like the nonlinear moving average, the threshold autoregression and the bilinear model are examples of additive dependence, while multiplicative dependence essentially includes a statistical process of the general form of conditional heteroskedasticicility. ARCH-M is a hybrid since nonlinearity influences both the mean and the variance.

Both additive and multiplicative nonlinearity imply that u_t^2 is correlated with its own lags. However, a distinction between the two types of nonlinearity does exist.

Multiplicative dependence suggests that

$$E[u_t \mid x_{t-1},...,x_{t-k,}u_{t-1},...,u_{t-k}] = 0, \tag{20}$$

while additive dependence suggests that

$$E[u_t \mid x_{t-1},...,x_{t-k,}u_{t-1},...,u_{t-k}] \neq 0. \tag{21}$$

Hsieh (1989) supposes that $f()$ is at least twice continuously differentiable, approximates it by a second-order Taylor series expansion around zero, and obtains terms such as $u_{t-i}u_{t-j}, x_{t-i}u_{t-j}$, and $x_{t-i}x_{t-j}$.

The third-order moment test makes use of the fact that multiplicative dependence implies that u_t is not correlated with terms like $u_{t-i}u_{t-j}, x_{t-i}u_{t-j}$, and $x_{t-i}x_{t-j}$, whereas the additive dependence implies that u_t is usually correlated with at least some of these terms.

Further, Hsieh (1989) defines $r_{uuu}(i, j) = E(u_t u_{t-i} u_{t-j}) / r_u^3$. The test has multiplicative nonlinearity as the null hypothesis, which implies $r_{uuu}(i, j)$ =0 for all $i, j > 0$, against the alternative hypothesis of additive nonlinearity that $r_{uuu}(i, j) \neq 0$. To estimate $r_{uuu}(i, j)$, we calculate:

$$r_{uuu}(i, j) = \left[\frac{1}{T}\sum u_t u_{t-i} u_{t-j}\right] \Big/ \left[\frac{1}{T}\sum u_t^2\right]^{1.5}, \qquad (22)$$

where u_t is the individual filtered return innovation series for $W_{w,t}, F_{w,t}, F_{m,t}, F_{s,t}, F_{v1,t}, F_{v2,t}$ that is obtained after purging the raw return series in the BDS test.

$r_{uuu}(i, j)$ is asymptotically normally distributed with mean zero and variance $w(i, j) / s_u^6$, which can be consistently estimated by $[(1/T)\sum u_t^2 u_{t-i}^2 u_{t-j}^2]/[(1/T)\sum u_t^2]^3$. The test is designed to reject only in the presence of additive nonlinearity; not multiplicative nonlinearity.

Table (3) presents the results of Hsieh's third-order moment test statistics for i, j =1,2,3,4,5. Since none of the test statistics is statistically significant at any reasonable levels, we can not reject the null hypothesis of multiplicative dependence. This suggests that nonlinearity between the futures/forward prices and water reservoir contents are only connected via variance changes in each process.

5.3 Methodology for linear Granger causality and empirical results

There are several alternative linear tests for bivariate Granger causality. Here I choose to follow the procedure in Fleming *et al.* (1996) to investigate bi-directional linear causality between $W_{w,t}$ and futures/forward prices. The estimation is based on the following multivariate regression:

$$R_{f,t} = q + \sum_{K=-i}^{k>0} q_k R_{w,t-k} + x_t \,, \qquad (23)$$

where $R_{f,t}$ is the returns in futures/forward prices and $R_{w,t}$ is the returns in water reservoir content.

In this regression, if $\sum_{i=1}^{k} q_{-k} = 0$, then Equation (23) suggests that the past water reservoir content has no influence over the futures/forward prices in the long run, meaning that water reservoir content does not linearly Granger cause futures/forward prices. In a similar fashion, if $\sum_{i=1}^{k} q_k = 0$, then Equation (23) implies that the past futures/forward prices do not linearly Granger cause water reservoir content. On the other hand, if for some k, $q_k \neq 0$, then Equation (23) suggests that futures/forward prices linearly Granger cause water reservoir content in the short run. To obtain test statistics for the null hypothesis that the q coefficients are individually zero, I estimate the covariance matrix using the generalized method of moments[19] (GMM) by Hansen (1982). To check the statistical significance of whether the aggregate linear causalities (*i.e.* $\sum_{i=1}^{k} q_{\pm k} = 0$) exist in the long run, I calculate the test statistics of the null hypothesis that the lead/lag coefficients $q_{\pm k}$ are jointly zero using an x^2 test. [20]

Caution needs to be observed when either of the futures/forward or water reservoir content return series shows evidence of any significant autocorrelation. In this situation, the linear causality testing on Equation (23) using the raw return series is likely to lead

[19] A strong reason for choosing the GMM estimator lies in the fact that our data series are not normally distributed and that GMM is considered to be a robust estimator in that it does not require information on the exact distribution of the disturbances. By choosing the weighting matrix in the criterion function appropriately, GMM can be made robust to heteroskedasticity and/or autocorrelation of an unknown form.

[20] The x^2 statistic is a Wald test statistic.

to spurious results regarding the direction of the causal effect. Both the price and the water reservoir content series demonstrate significant autocorrelations. For the price series, the autocorrelation could have been induced by seasonality of the supply and demand dynamics,[21] but hydropower inventory holding, cycles etc. can also give rise to it. Seasonality mainly accounts for the autocorrelation in the water reservoir content series as it largely depends on the climatic condition on the supply side and the changes in heating needs in different time periods of the year on the demand side.

A solution to this problem is to use the Autoregressive Moving Average (ARMA) specification advocated by Stoll and Whaley (1990) in order to preliminarily filter the series. The resulting innovation series after the appropriate filtering can then replace the unfiltered counterpart in the multivariate regression in Equation (23).

$$IR_{f,t} = q + \sum_{K=-i}^{k>0} q_k IR_{w,t-k} + x_t \, , \tag{24}$$

where $IR_{f,t}$ and $IR_{w,t-k}$ are the relevant return innovation series.

Since the ARMA filters for causality testing are the same as those used for filtering linear dependence in the BDS test, I use the same residual innovation series from linear filtering to replace the unfiltered counterpart in the estimation of Equation (24).[22]

The lag length determination for each of the regressions is based on the cross-correlation pattern between the futures/forward returns and water reservoir content returns. The lag length is also determined with reference to the AIC and the Ljung-Box test on the residuals.

---

[21] It is difficult to compare directly how serial autocorrelations differ among different price processes of different maturities.

[22] Note that linear filtering in the BDS test is compulsory if the aim of the test is to detect nonlinear dependence, while it is not a necessary step in causality testing if the data series does not demonstrate significant autocorrelations. This is why seasonality induced significant slow-decaying autocorrelation is an important issue here and is discussed in detail.

Tables (4)-(8) present the linear causality test results. The results displayed in Table (4) show evidence of unidirectional linear causality in the long run from water reservoir content to weekly futures prices. The Wald statistic that tests the exclusion of the water reservoir content series from the weekly futures returns is significant at the 1% level, while the Wald statistic testing the aggregate long run causality from weekly futures prices to weekly water reservoir content is not significant. Interestingly, all other regressions using longer maturity futures/forward return innovation series show no sign of a significant uni-directional or bi-directional linear causal relationship. The results are consistent with Mandelbrot's argument that lagged effect on price changes may become increasingly smaller until strictly zero if the time span for the contract maturity becomes long enough. Since it is possible that long enough maturity contracts may be free of a lagged effect, the linear causality testing approach only detects causality in short maturity contracts such as the weekly futures contract. Causality runs from water reservoir content to weekly futures contract, implying an imperfection of hydropower production in smoothing temporary supply gaps created by sudden increases in demand.

5.4 Methodology for nonlinear Granger causality testing and empirical results

Linear causality testing can be regarded as the initial step towards testing of a nonlinear Granger causal relationship between futures/forward and water reservoir content returns. Due to the restrictive linear assumption, the linear causality tests have low power in detecting certain kinds of nonlinear causal relationships. Baek and Brock (1992) propose a nonparametric test to detect nonlinear causal relations which has since been modified by Hiemstra and Jones (1994). The test is able to uncover nonlinear causal relations that conventional linear causality testing can not. Further, it employs the correlation integral, which is an estimator of spatial probabilities across time.

Consider the two time series of electricity futures/forward returns $\{F_t\}$ and water reservoir content $\{W_t\}$, which are assumed to be two strictly stationary, weekly dependent scalar time series. Let the m-length lead vector of W_t be denoted W_t^m, and the Lw- length and Lf -length lag vectors of W_t and F_t be denoted W_{t-Lw}^{Lw} and F_{t-Lf}^{Lf}, respectively, where:

$$W_{t-Lw}^{Lw} = (W_{t-Lw}, W_{t-Lw+1}, ..., W_{t-l}), Lw = 1, 2..., t = Lw+1, Lw+2 \ldots,$$
$$F_{t-Lf}^{Lf} = (W_{t-Lf}, W_{t-Lf+1}, ..., W_{t-l}), Lf = 1, 2..., t = Lf+1, Lf+2 \ldots$$

For $m \geq 1$, $Lw \geq 1, Lf \geq 1$ and e>0, F does not strictly Granger cause W if

$$\begin{aligned} &\Pr(\| W_t^m - W_s^m \| < e \, \| \, \| W_{t-Lw}^{Lw} - W_{s-Lw}^{Lw} \| \, e, \| F_{t-Lf}^{Lf} - F_{s-Lf}^{Lf} \| < e) \\ &= \Pr(\| W_t^m - W_s^m \| < e \, \| \, \| W_{t-Lw}^{Lw} - W_{s-Lw}^{Lw} \| \, e), \end{aligned} \tag{25}$$

where Pr(.) denotes probability and ||.|| denotes the maximum norm.

The probability on the left hand side of Equation (25) is the conditional probability that any two arbitrary m-length lead vectors of $\{W_t\}$ are within a distance, e, of each other, given that the corresponding Lw-length lag vectors of $\{W_t\}$ and Lf -length lag vectors of $\{F_t\}$ are within a distance, e, of each other. The probability on the right-hand side of Equation (25) is the conditional probability that two arbitrary m-length lead vectors of $\{W_t\}$ are within a distance, e, of each other, assuming that their corresponding Lw-length lag vectors are within a distance, e, of each other.

The nonparametric test statistic of Baek and Brock (1992), modified by Hiemstra and Jones (1994), can be obtained by the following steps:

First, the conditional probabilities in terms of the corresponding ratios of joint probabilities in Equation (25) are expressed as:

$$\frac{C_1(m+Lw, Lf, e)}{C_2(Lw, Lf, e)} = \frac{C_3(m+Lw, e)}{C_4(Lw, e)}, \tag{26}$$

where the $C_1(m+Lw,Lf,e)$, $C_2(Lw,Lf,e)$, $C_3(m+Lw,e)$ and $C_4(Lw,e)$ are the correlation-integral estimators of the joint probabilities.

Second, if $\{F_t\}$ does not nonlinearly Granger cause $\{W_t\}$, under this null hypothesis, for all m, Lw and Lf ≥ 1 and for all $e>0$ and the mixing distribution assumptions in Denker and Keller (1983), then

$$\sqrt{n}\left[\frac{C_1(m+Lw,Lf,e,n)}{C_2(Lw,Lf,e,n)}-\frac{C_3(m+Lw,d,n)}{C_4(Lw,d,n)}\right]\overset{asy}{:} N(0,s^{2}(m,Lw,Lf,e)). \qquad (27)$$

The nonlinear Granger causality test represented by Equation (27) is applied to the VAR[23] residuals of the linear causality test. Because the linear predictive power is removed by the linear causality procedure, Baek and Brock (1992) argue that any remaining incremental predictive power of one residual series for another can be considered to be a nonlinear predictive power.

The appropriate values for the lead length, m, the lag lengths, Lw and Lf, and the scale parameter, e, have to be chosen in order to carry out the Baek and Brock test. However, there is no guideline for choosing optimal values for lag lengths and the scale parameter. Therefore, I rely on the Monte Carlo results in Hiemstra and Jones (1993) by setting the lead length at m = 1, the respective common lag lengths are the same as those used in the linear testing, *i.e.* $Lw = Lf$, and a common scale parameter of e = 1.5 s, where s = 1 denotes the standard deviation of the standardized time series. [24]

The empirical results of the nonlinear Granger-causality tests are reported in Tables (9)-(13), where CS and TVAL denote the difference between the two conditional probabilities in Equation (26) and the standardized test statistic in Equation (27). The

---

[23] For a precise linear causality estimation, we should use GMM here. But for removing linear predictive power, VAR is suitable.

[24] There is no material difference in the results if we use a common scale parameter of $e=1.0s$ or $e=0.5s$

test statistic CS has a $N(0,1)$ distribution under the null hypothesis of nonlinear Granger causality.

These results suggest that there are strong bi-directional nonlinear causal relations between all futures/forward prices and water reservoir content. The standardized test statistics, significant at the 1% or 5% levels, can be found in every part of the tables reporting the nonlinear causality test.

5.5 Methodology for adjusting volatility persistence and the empirical results for both linear and nonlinear causality testing

In Section 3.3 it is argued that the nonlinear causality detected by the modified Baek and Brock test can be attributed to water reservoir content/futures/forward prices being a proxy for the flow of new information to the market. This information flow is a latent common factor that may influence both the water reservoir content and futures/forward prices. The empirical findings of Hsieh's third-order moment test verify that futures/forward prices and water reservoir content are nonlinearly connected via variance changes. In light of this, the evidence of bi-directional nonlinear Granger causality could be merely due to simple volatility effects associated with information flow, rendering nonlinear causality results spurious.

To control for volatility persistence, I apply EGARCH proposed by Nelson (1991) to the raw returns of both futures/forward and water reservoir content. At the same time, since the estimation involves raw returns containing significant autocorrelation, I account for this in the mean equation of the EGARCH by using the same respective ARMA filters discussed earlier. After the ARMA(p,q)-EGARCH filtering, I can apply the modified Baek and Brock test to the new EGARCH-filtered standardized residuals. The EGARCH model takes the following form:

$$IR_{f,t} = q + \sum_{K=-i}^{k>0} q_k IR_{w,t-k} + x_t \qquad x_t \sim N(0, h_t^2)$$

$$\log(h_t^2) = g_0 + g_1 \log(h_{t-1}^2) + h_1 \,|\, x_{t-1} / h_{t-1} \,|\, + h_2 (x_{t-1} / h_{t-1}) \,, \qquad (28)$$

where $IR_{f,t}$ and $IR_{w,t-k}$ are the relevant return innovation series for the futures/forward prices and water reservoir content, $\log(h_{t-1}^2)$ in the variance equation is chosen to capture the persistence of variance over time and the $|x_{t-1}/h_{t-1}|$ and (x_{t-1}/h_{t-1}) are terms designed to model the asymmetric volatility in returns.

The specification of EGARCH implies that negative surprises affect the conditional variance differently than positive ones, which can also account for the significant conditional skewness in both futures/forward and water reservoir content series.

I determine the appropriate lag truncation lengths for the EGARCH effects based on the AIC. The model specification is further checked by three tests on the standardized residuals: correlogram-Q-statistics checking for any remaining serial correlation in the mean equation, correlogram-squared-residuals testing for any remaining ARCH in the variance equation and checking for the specification of the variance equation, and ARCH-LM detecting for any remaining nonlinear dependence in the standardized estimated residuals.

The standardized EGARCH filtered residuals are used in a linear Granger causality test based on Equation (24). There is no material difference between the results with and without EGARCH filtering. The results are reported in Tables (14)-(16).

The results for the nonlinear Granger causality tests using standardized EGARCH filtered residuals constitute a sharp contrast to the results obtained without controlling for volatility persistence, and are reported in Tables (17)-(21). First, the TVAL test statistics are substantially smaller in both magnitude and statistical significance compared to the results obtained without controlling for volatility persistence. This substantial difference in statistical significance between the two tests implies that the nonlinear causality detected by the modified Baek and Brook approach can be largely attributed to the simple volatility effects. This explanation is consistent with the findings of Hsieh's third-order moment test confirming that the futures/forward prices and water reservoir content series are nonlinearly connected via variance. Second, after controlling for volatility persistence, the earlier result of the bi-directional nonlinear causalities disappears; I find uni-directional causality only in some but not all regressions. Furthermore, the direction of causality differs among different maturities. For the weekly futures contract, there is still a strong nonlinear causality running from water reservoir content returns to weekly futures returns, which is the same result as found in the linear causality testing. This is consistent with the fact that hydropower inventory can not smooth out sudden supply gaps very effectively or completely, leaving price spikes in the short run. However, this inability seems to be mitigated in the long run, since I can not find the same causality in the long maturity contract regressions. On the other hand, for monthly futures, 1-year ahead summer 0, and 2-years ahead winter 1 contracts, there is a uni-directional causality running from futures/forward prices to water reservoir content. This suggests that these prices, which contain all information about the market, influence the hydropower production through the optimizing of scheduling and allocation of hydro-inventory resources in order to maximize profit. This indicates that the hydropower producer reacts to changes in the expected future price movement in order to maximize profits. As contract maturities vary from 1-month to 2-years, the number of significant TVALs decreases arithmetically, revealing that the influence of the lagged effect on price changes becomes increasingly less significant. The resulting price increasingly resembles a random walk process, consistent with Mandelbrot's (1971) argument. However, the modified Baek and Brook approach does not find strong evidence of either a uni-directional or a bi-directional causal relationship between the 2-years ahead winter 2 forward contract and weekly water reservoir content. This indicates that the price is a random walk process, providing strong evidence in support of the existence of the non-arbitrage condition set forth in this paper.

Combining all the empirical evidence, we can rule out the possibility that the argument for the hydropower producer's arbitrage is purely imaginary. Among the different maturity contracts, for the longest maturity contract, *i.e.* the 2-years ahead winter 2 contract, the non-arbitrage condition is maintained while in terms of shorter maturity contracts, this condition may be violated.

6. Summary and conclusion

This paper considers hydropower storability in a producer perspective and in an environment of power exchange where hydropower predominates. Because the system price is also the hydropower price, I model electricity price by solving the hydropower producer's profit maximization problem. I further show the nonlinear relationship between futures/forward prices and water reservoir content as inventory. I perform three empirical tests to further characterize this relationship that generally does not possess a specific functional form. In particular, I choose the nonlinear causality test to verify the non-arbitrage condition. This evidence provides support for the argument of hydropower producers being active arbitrageurs, and in a certain case verifies the existence of the non-arbitrage condition.

I apply a BDS test, Hsieh's third-order moment test and linear/nonlinear causality tests to a data set consisting of weekly, 1-month ahead futures and 1-year ahead seasonal summer 0, and 2-years ahead seasonal winter 1 and winter 2 forward prices, plus weekly water reservoir contents from the Nord Pool power exchange for the October 29th , 1997 to September 25th , 2002 period. The BDS test results confirm that there is a nonlinear dependence between the futures/forward prices and water reservoir content, and Hsieh's third-order moment test results suggest that such nonlinear dependence enters only via variance changes. Consequently, both return series are adjusted for volatility effects in the linear and nonlinear Granger causality testing. A sharp contrast in the results is observed before and after controlling for volatility persistence in nonlinear causality. The strong bi-directional causal relationship without EGARCH filtering for volatility detected by the modified Baek and Brook approach is due to the volatility effects. After volatility filtering, only uni-directional causality is detected between short/medium term futures/forward contracts and water reservoir content. There is no sign of a causal relationship between the longest forward contract and water reservoir content. This finding suggests that arbitrage does exist at the Nord Pool power exchange, and as maturity lengthens, the influence of the lagged effect on price changes becomes increasingly less significant and hence the futures/forward price processes increasingly resemble random walk. Neither uni-directional nor bi-directional causality is found between the 2-years ahead winter 2 contract and water reservoir content series, indicating that the non-arbitrage condition can be maintained. Moreover, the empirical results further our understanding of the nonlinear relationship between futures/forward prices and water reservoir content.

The theoretical framework may prove to be very useful for future theoretical and empirical research on power exchanges with considerable hydropower supply. The model suggests that the hydropower producer plays the role of an active arbitrageur through hydropower inventory management for profit maximization. Optimal hydropower production may prove to be an important subject for researchers in the power research area.

The empirical findings of this study also have practical values for the traders and other futures/forward market participants. Since linear and nonlinear uni-directional causality from weekly water reservoir content to weekly futures prices implies that knowledge of current water reservoir content improves the ability to forecast weekly futures prices, it can help to construct more accurate hedge ratios and to improve speculative activities on weekly futures, because the success of speculators and hedgers alike hinges on the accurate forecasting of futures prices.

References

Baek, E., and Brock, W. (1992). “A general test for nonlinear Granger causality: bivariate model”, *Working Paper, Iowa State University and University of Wisconsin, Madison.*

Brennan, M. J. (1958). “The supply of storage”, *American Economic Review*, 48 : 50-72.

Brock, W. (1991). “Causality, chaos, explanation and prediction in economics and finance” in “*Beyond belief: randomness, prediction and explanation in science*”, 230-279, Casti, J., and Karlquist, A. (eds.)- Boca Raton, FL: CRC Press.

Brock, W., Dechert, W., and Scheinkman, J. (1987). “A test for independence based on the correlation dimension”, *Working Paper, University of Wisconsin, Madison*.

Deaton, A. and Laroque G. (1992). “On the behaviour of commodity prices”, *Review of Economic Studies*, 59 : 1-23.

Deng, D. (2003) “Market efficiency at the Nord Pool power exchange”, *Working Paper, Center for Finance, Department of Economics, Gothenburg University, Sweden*.

Denker, M. and Keller, G. (1983). “On U-Statistics and Von Mises statistics for weakly dependent processes”, *Zetschrift fur Wahrscheinlichkeistheorie und Verwandte Gebiete*, 64: 505-522.

Fleming, J., Ostdiek, B., and Whaley, R. (1996). “Trading costs and the relative rates of price discovery in stock, futures and options markets”, *The Journal of Futures Markets*, 16: 353-387.

Fleten S. E. and Lemming J. (2001). “Constructing forward price curves in electricity markets”, *Working Paper, Risoe National Laboratory, Denmark.*

Hansen, L. P. (1982). “Large sample properties of generalized method of moment estimators”, *Econometrica*, 50 : 1029-1051.

Hiemstra, C., and Jones, J. D. (1992). “Detection and description of linear and nonlinear dependence in daily Dow Jones stock returns and NYSE trading volume”, *Working Paper, University of Strathclyde and Securities and Exchange Commission.*

Hiemstra, C., and Jones, J. D. (1993). “Monte Carlo results for a modified version of the Baek and Brock nonlinear Granger causality test”, *Working Paper, University of Strathclyde and Securities and Exchange Commission*.

Hiemstra, C., and Jones, J. D. (1994). “Testing for linear and non-linear Granger causality in the stock price-volume relation”, *Journal of Finance,* 49 : 1639-1664.

Hinich, M. J. (1982). “Testing for Gaussianity and linearity of a stationary time series”, *Journal of Time Series Analysis,* 3 : 169-76.

Hinich, M. J., and Patterson, D. M. (1985). “Evidence of nonlinearity in daily stock returns”, *Journal of Business and Economic Statistics*, 3 : 69-77.

Hsieh, D. A. (1989). “Testing for nonlinear dependence in daily foreign exchange rates”, *The Journal of Business*, 62 : 339-368.

Hsieh, D. A. (1991). “Chaos and nonlinear dynamics: application to financial markets”, *The Journal of Finance*, 46 : 1839-1877.

Hurst, H. E. (1951). “Long-term storage capacity of reservoirs”, *Transactions of the American Society of Civil Engineers*, 116 : 770-808.

Hurst, H. E. (1956). “Methods of using long-term storage in reservoirs”, *Proceedings of the Institution of Civil Engineers*, part 1, 519-577.

Jarque, C. and Bera, A. K.(1980).“An efficient large-sample test for normality of observations and regression residuals”, *Manuscript, Department of Statistics, Australian National University*.

Just, R. E. (1975). “Risk aversion under profit maximization”, *American Journal of Agricultural Economics*, 57 : 347-352.

Koekebakker, S., and Ollmar, F. (2001). “Forward curve dynamics in the Nordic electricity market”, *Working paper, Norwegian School of Economics and Business Administration*.

Lucia, J. J. and Schwartz, E. S. (2000). “Electricity prices and power derivatives: evidence from the Nordic power exchange”, *Working Paper 16-00, The Anderson Graduate School of Management, UCLA.*

Mandelbrot, B. B. (1971). “When can price be arbitraged efficiently? A limit to the validity of the random walk and martingale models”, *The Review of Economics and Statistics*, 53: 225-236.

McLeod, A. J., and Li, W. K. (1983). “Diagnostic checking ARMA time series models using squared-residual autocorrelations”, *Journal of Time Series Analysis,* 4 : 269-273.

Miranda, M. J. and Glauber, J. W. (1993). “Estimation of dynamic nonlinear rational expectation models of primary commodity markets with private and government stockholding”, *Review of Economic and Statistics,* 75(2) : 463-470.

Miranda, M. J. and Rui, X. W. (1996). “An empirical reassessment of the commodity storage model”, *Mimeo, Department of Agricultural Economics, Ohio State University.*

Nelson, D. B. (1991). “Conditional heteroskedasticity in asset returns: a new approach”, *Econometrica*, 59 : 347-370.

Samuelson, P. A. (1971), “Stochastic speculative price”, *Proceedings of the National Academy of Science*, 68 : 335-337.

Savit, R. (1988). “When random is not random: an introduction to chaos in market prices”, *Journal of Futures Markets,* 8 : 271-290.

Stoll, H. R., and Whaley, R. E. (1990). “The dynamics of stock index and stock index futures returns”, *Journal of Financial and Quantitative Analysis,* 25 : 441-468.

Telser, L. G. (1958). “Futures trading and the storage of cotton and wheat”, *Journal of Political Economy*, 66 : 233-255.

Williams, B. D. and Wright, J. C. (1991). “*Storage and commodity markets*”, Cambridge, Cambridge University Press.

Working, H. (1949). “Theory of the price of storage”, *American Economic Review*, 39 : 1254-1262.

Appendix: Statistics and empirical results

Table 1 Summary statistics for futures/forward of various maturities and water reservoir content returns

	$W_{w,t}$	$F_{w,t}$	$F_{m,t}$	$F_{s,t}$	$F_{v1,t}$	$F_{v2,t}$
Mean	0.004528	0.099178	0.069628	0.001749	-0.016407	-0.037926
Median	-0.928381	-0.198567	0.000000	-0.038096	-0.060969	0.000000
Maximum	14.35321	35.93740	24.51225	10.10594	11.50332	12.58995
Minimum	-7.690693	-22.00619	-16.90245	-7.274341	-7.847162	-7.620046
Std. Dev.	5.000948	8.355084	5.938712	2.235741	1.659701	1.685969
Skewness	0.936408	0.640960	0.481574	0.650436	0.846389	1.145214
Kurtosis	3.275401	4.924736	4.342436	5.999146	14.08312	16.77480
Jarque-Bera	38.22172	57.04459	29.11775	113.9962	1330.335	2063.656
Prob.	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

Notes: This table reports the summary statistics for futures/forward of various maturities and water reservoir content returns from October 29th, 1997 to September 25th, 2002.

Table 2 BDS test statistics for the filtered futures/forward and water reservoir returns

e/s	m	$IW_{w,t}$	$IF_{w,t}$	$IF_{m,t}$	$IF_{s,t}$	$IF_{v1,t}$	$IF_{v2,t}$
0.5	2	6.149079	4.968378	2.446625	4.305578	4.257363	3.806495
0.5	3	7. 098818	5.424037	2.352462	5.632142	6.593671	5.705012
0.5	4	6.917820	4.153548	2.511081	6.693232	7.852463	7. 629335
0.5	5	6. 444484	4.735568	1.706944	6. 799040	8.901231	9. 030413
0.5	6	6.291379	5. 237353	1.723496	6. 645699	9.880379	12.20179
1.0	2	6.850073	4.509423	2.598693	2.849129	3.894336	4.205630
1.0	3	7.583150	4. 972171	2. 429924	4. 106166	5.195910	4.900469
1.0	4	7. 767041	4.393890	2. 662475	5.142139	6.011643	5.689951
1.0	5	7. 766936	3.939745	2.589644	5.696843	6.613609	5.979647
1.0	6	7. 748922	3. 810158	2.766011	6.722685	7. 514552	7. 174038
1.5	2	6.978545	3.766323	2.522890	2.193077	5.035551	4.017352
1.5	3	7. 673542	4.224356	2.528914	2. 774634	6.032400	4.529204
1.5	4	8. 047794	3.866314	2.900645	3.277254	6. 485288	5.055653
1.5	5	8.047863	3.759726	3.000046	3.578664	6.693636	4.999650
1.5	6	7. 942940	3.398111	3.067148	4.146106	6. 980642	5.577340
2.0	2	5.851112	3.157290	2.356639	1.982119	5.018062	3.539757
2.0	3	6.496209	3.573967	2. 972048	2.170018	5.906257	4. 119451
2.0	4	6.730197	3.511023	3.296942	2.635022	6.116481	4. 215298
2.0	5	6.651737	3.561680	3.309017	2.730127	6. 128410	4.100017
2.0	6	6.498289	3.250940	3.466399	3.099962	6.107746	4.255120

Notes: This table reports the BDS test statistics for ARMA-filtered futures/forward and water reservoir content returns from October 29th, 1997 to September 25th, 2002. The BDS statistic has a limiting standard normal distribution. The null hypothesis is that the process is i.i.d.
The critical value for the 10%, 5% and 1% significance levels are 1.645, 1.96, 2.575, respectively.

Table 3 Hsieh's third-order moment test statistics for filtered futures/forward and water reservoir content returns

Lag i	j	$IW_{w,t}$	$IF_{w,t}$	$IF_{m,t}$	$IF_{s,t}$	$IF_{v1,t}$	$IF_{v2,t}$
1	1	0.3853	0. 23972	0. 08287	-0. 0854	0.19635	0. 28681
2	1	0.07755	- 0. 0407	-0.12949	0.12365	0.01169	-0. 0278
2	2	0.16587	0. 10695	0.02874	-0. 0376	0. 20425	0.11911
3	1	-0. 35998	- 0.03909	-0.03097	- 0.14455	-0.03648	0.04842
3	2	0.10119	0. 01225	-0.11662	0.00312	-0.24163	-0.18988
3	3	0. 29226	0. 15616	-0.02506	0. 06532	-0.06317	0. 00342
4	1	-0. 01227	-0. 10297	0.08859	-0.16424	0.061	-0.00737
4	2	-0. 06733	-0.018	0.08061	0.08049	-0.0324	-0.12
4	3	0. 02781	0. 21098	- 0.06481	-0. 0613	-0.04505	-0.05335
4	4	-0. 23476	0. 07566	-0.04088	0. 21434	0. 02252	0. 13974
5	1	-0. 03644	-0.13404	- 0.07373	-0.11985	0. 08204	0. 06894
5	2	-0. 01682	-0. 0568	-0.00797	-0.10282	-0.10893	-0.09225
5	3	-0. 06496	-0. 00124	0.05564	-0.09689	-0.19204	-0.10389
5	4	-0. 13068	0.07873	-0. 03957	0. 02909	0. 06427	-0.04843
5	5	0. 08107	0. 07426	-0. 0462	0.0151	-0. 09275	-0.25785

Notes: This table reports Hsieh's third-order moment test statistics for filtered futures/forward and water reservoir content returns from October 29^{th}, 1997 to September 25^{th}, 2002. The null hypothesis is that the process is multiplicative dependent.
The critical values for the 10%, 5% and 1% significance levels are 1.645, 1.96, 2.575, respectively.

Table 4 Test results for linear Granger causality between weekly futures and water reservoir content filtered returns (After ARMA filtering for linearity but before GARCH filtering for volatility persistence)

Dependent variable: Weekly futures return Independent variable: Weekly water reservoir content return

Coefficient estimations for independent variable:

q_{-20}=0.602275 (2.763585)	q_{+20}=0.557009 (2.280481)	q_{-9}=-0.436962 (–1.392487)	q_{+9}=-0.407380 (–1.930881)
q_{-19}=0.225391 (1.010402)	q_{+19}=0.0396490 (0.154503)	q_{-8}=-0.411383 (–1.665708)	q_{+8}=-0.203863 (–1.100756)
q_{-18}=-0.35817 (–1.55460)	q_{+18}=-0.726384 (-3.525556)	q_{-7}=0.176910 (0.921906)	q_{+7}=0.263085 (1.807909)
q_{-17}=0.32222 (1.509818)	q_{+17}=0.066678 (0.302032)	q_{-6}=0.158576 (0.606420)	q_{+6}=-0.099851 (–0.561008)
q_{-16}=0.07848 (0.295793)	q_{+16}=0.148594 (0.748538)	q_{-5}=0.362333 (1.788432)	q_{+5}=-0.492043 (–2.494820)
q_{-15}=0.35003 (1.629903)	q_{+15}=-0.020360 (–0.083504)	q_{-4}=-0.423982 (–2.227477)	q_{+4}=0.395091 (1.423579)
q_{-14}=0.35577 (1.098967)	q_{+14}=-0.182106 (–0.938880)	q_{-3}=-0.120160 (–0.569658)	q_{+3}=0.278993 (1.335309)
q_{-13}=0.53238 (1.441539)	q_{+13}=-0.278395 (–1.530213)	q_{-2}=-0.001432 (–0.008174)	q_{+2}=0.200610 (1.237932)
q_{-12}=0.27241 (1.031283)	q_{+12}=-0.192162 (–0.885715)	q_{-1}=0.040854 (0.269496)	q_{+1}=-0.186721 (–0.853218)
q_{-11}=-0.242332 (–0.692666)	q_{+11}=-0.306655 (–1.312194)	q_{0}=-0.696247 (–3.706743)	q =-0.089089 (–0.197145)
q_{-10}=-0.253846 (–0.676602)	q_{+10}=0.058958 (0.281343)		

Wald-test (x^2) statistic for the null hypothesis ($\sum_{i=1}^{k} q_k$ =0): 0.491327 (0.483336)

Wald-test (x^2) statistic for the null hypothesis ($\sum_{i=1}^{-k} q_{-k}$ =0): 6.077716 (0.013690)

Notes: This table reports the results for the linear Granger causality test between weekly futures and water reservoir content filtered returns. The sample period is from October 29th, 1997 to September 25th, 2002. The t-statistic for each of the q coefficients is reported in parentheses. The probability that the null of the Wald-test is rejected is reported in the parentheses after the x^2 statistic.

Table 5 Test results for linear Granger causality between 1-month ahead futures and weekly water reservoir content filtered returns
(After ARMA linear filtering but before EGARCH filtering for volatility persistence)

Dependent variable: 1-month ahead futures return   Independent variable: Weekly water reservoir content return

Coefficient estimations for independent variable:

q_{-20} =0.664653 (4.575697)	q_{+20} =0.172022 (1.228656)	q_{-9} =-0.349519 (–2.409824)	q_{+9} =-0.103330 (–0.56038)
q_{-19} =0.051600 (0.421456)	q_{+19} =0.065091 (0.447860)	q_{-8} =0.323739 (1.774296)	q_{+8} =0.034707 (0.273232)
q_{-18} =-0.146412 (-0.812846)	q_{+18} =-0.328138 (–2.269936)	q_{-7} =-0.067884 (–0.435161)	q_{+7} =0.217533 (1.682861)
q_{-17} =-0.034990 (–0.230291)	q_{+17} =-0.120387 (–0.746513)	q_{-6} =0.181602 (1.193024)	q_{+6} =-0.037030 (–0.281705)
q_{-16} =-0.008826 (–0.051139)	q_{+16} =-0.013495 (–0.08109)	q_{-5} =0.039378 (0.221473)	q_{+5} =-0.178178 (–1.11898)
q_{-15} =-0.051469 (–0.259345)	q_{+15} =0.127156 (0.902060)	q_{-4} =-0.222555 (–1.856061)	q_{+4} =0.152654 (0.836088)
q_{-14} =-0.064068 (–0.425207)	q_{+14} =-0.173373 (–1.008129)	q_{-3} =-0.183943 (–1.386181)	q_{+3} =0.305417 (1.743109)
q_{-13} =0.098606 (0.312561)	q_{+13} =-0.283776 (–1.438228)	q_{-2} =0.257092 (1.864478)	q_{+2} =0.190357 (1.220612)
q_{-12} =0.212543 (1.186541)	q_{+12} =-0.233420 (–1.581525)	q_{-1} =-0.039901 (–0.313292)	q_{+1} =-0.128455 (–0.794860)
q_{-11} =0.251597 (1.408985)	q_{+11} =-0.061850 (–0.387154)	q_{0} =-0.142494 (–1.000642)	q =-0.044837 (–0.137103)
q_{-10} =0.590648 (3.4107819	q_{+10} =0.060089 (0.360172)		

Wald-test (x^2) statistic for the null hypothesis ($\sum_{i=1}^{k} q_k$ =0): 2.331969 (0.126741)

Wald-test (x^2) statistic for the null hypothesis ($\sum_{i=1}^{-k} q_{-k}$ =0): 0.743928 (0.388406)

Notes: This table reports the results for the linear Granger causality test between 1- month ahead futures and water reservoir content filtered returns. The sample period is from October 29th, 1997 to September 25th, 2002. The t-statistic for each of the q coefficients is reported in parentheses. The probability that the null of the Wald-test is rejected is reported in the parentheses after the x^2 statistic.

Table 6 Test results for linear Granger causality between 1-year ahead seasonal summer 0 forward and weekly water reservoir content returns
(After ARMA filtering for linearity but before EGARCH filtering for volatility persistence)

Dependent variable: 1-year ahead seasonal summer 0 forward return   Independent variable: Weekly water reservoir content return

Coefficient estimations for independent variable:

q_{-12} =0.055658 (1.402855)	q_{+12} =-0.151175 (-2.656944)	q_{-5} =0.075111 (1.491721)	q_{+5} =-0.112084 (–1.456212)
q_{-11} =-0.052960 (–1.041022)	q_{+11} =-0.092821 (–1.330521)	q_{-4} =-0.060802 (–1.433075)	q_{+4} =0.059264 (0.980202)
q_{-10} =0.033003 (0.568631)	q_{+10} =0.007952 (0.126590)	q_{-3} =-0.012510 –(0.21713)	q_{+3} =0.140098 (1.406599)
q_{-9} =-0.021559 (–0.393740)	q_{+9} =-0.001453 (–0.026264)	q_{-2} =0.033291 (0.623233)	q_{+2} =0.035652 (0.544860)
q_{-8} =-0.091198 (–1.318833)	q_{+8} =0.006140 (0.103076)	q_{-1} =0.106837 (1.599614)	q_{+1} =-0.126262 (–2.152499)
q_{-7} =-0.041108 (–0.774011)	q_{+7} = 0.121548 (1.962377)	q_0 =0.027459 (0.551159)	q =-0.025339 (–0.167538)
q_{-6} =-0.052935 (–0.955805)	q_{+6} =-0.033902 (–0.696602)		

Wald-test (x^2) statistic for the null hypothesis ($\sum_{i=1}^{k} q_k$ =0): 1.326930 (0.249352)

Wald-test (x^2) statistic for the null hypothesis ($\sum_{i=1}^{-k} q_{-k}$ =0):0.013508 (0.907475)

Notes: This table reports the results for the linear Granger causality test between 1-year ahead seasonal summer 2 forward and water reservoir content filtered returns. The sample period is from October 29th, 1997 to September 25th, 2002. The t-statistic for each of the q coefficients is reported in parentheses. The probability that the null of the Wald-test is rejected is reported in the parentheses after the x^2 statistic.

Table 7 Test results for linear Granger causality between 2-years ahead winter 1 forward and weekly water reservoir content filtered return
(After ARMA filtering for linearity but before GARCH filtering for volatility persistence)

Dependent variable: 2-years ahead winter 1 forward return   Independent variable: Weekly water reservoir content return

Coefficient estimations for independent variable:

q_{-12} =0.015464 (0.501789)	q_{+12} =-0.101343 (–2.299076)	q_{-5} =0.068485 (2.001431)	q_{+5} =-0.120669 (–1.662998)
q_{-11} =-0.032694 (-0.991830)	q_{+11} =-0.056640 (–1.030703)	q_{-4} =-0.021611 (–0.714265)	q_{+4} =0.025070 (0.607439)
q_{-10} =-0.011806 (-0.348622)	q_{+10} =-0.041912 (–0.931648)	q_{-3} =0.008954 (0.219959)	q_{+3} =0.145290 (1.523091)
q_{-9} =-0.019244(–0.581309)	q_{+9} =0.004751 (0.100676)	q_{-2} =0.011948 (0.275672)	q_{+2} =0.039054 (1.072621)
q_{-8} =-0.043177 (–1.052112)	q_{+8} =0.023543 (0.409285)	q_{-1} =0.061225 (1.396919)	q_{+1} =-0.067362 (–1.577635)
q_{-7} =-0.055098 (–1.873235)	q_{+7} =0.053210 (1.014458)	q_{0} =0.025985 (0.619447)	q =-0.024012 (–0.224844)
q_{-6} =-0.005479 (–0.190683)	q_{+6} =0.010256 (0.266171)		

Wald-test (x^2) statistic for the null hypothesis ($\sum_{i=1}^{k} q_k$ =0): 1.119061 (0.290121)

Wald-test (x^2) statistic for the null hypothesis ($\sum_{i=1}^{-k} q_{-k}$ =0): 0.052014 (0.819596)

Notes: This table reports the results for the linear Granger causality test between 2-years ahead seasonal winter 1 forward and water reservoir content filtered returns. The sample period is from October 29th, 1997 to September 25th, 2002. The t-statistic for each of the q coefficients is reported in parentheses. The probability that the null of the Wald-test is rejected is reported in the parentheses after the x^2 statistic.

Table 8 Test results for linear Granger causality between 2-years ahead winter 2 forward and weekly water reservoir content filtered returns
(After ARMA filtering for linearity but before GARCH filtering for volatility persistence)

Dependent variable: 2-years ahead seasonal winter 2 forward return   Independent variable: Weekly water reservoir content return

Coefficient estimations for independent variable:

q_{-12} =0.031606 (0.958499)	q_{+12} =-0.095696 (–2.118189)	q_{-5} =0.059975 (1.970588)	q_{+5} =-0.113317 (–1.91010)
q_{-11} =-0.066401 (–1.79554)	q_{+11} =-0.045057 (–0.855143)	q_{-4} =-0.033574 (–1.12172)	q_{+4} =0.013101 (0.295600)
q_{-10} =0.053167 (1.314938)	q_{+10} =-0.048844 (–0.85786)	q_{-3} =0.009902 (0.253338)	q_{+3} =0.142670 (1.394453)
q_{-9} =-0.025781 (–0.638306)	q_{+9} =0.010501 (0.227080)	q_{-2} =0.007709 (0.190206)	q_{+2} =0.037285 (1.076223)
q_{-8} =-0.040746 (–0.837244)	q_{+8} =0.041361 (0.784816)	q_{-1} =0.068518 (1.444906)	q_{+1} =-0.072884 (–1.8254)
q_{-7} =-0.025638 (–0.741144)	q_{+7} =0.053932 (1.048937)	q_{0} =0.013771 (0.335089)	q =0.007787 (0.069314)
q_{-6} =-0.015920 (–0.47406)	q_{+6} =0.008497 (0.223700)		

Wald-test (x^2) statistic for the null hypothesis ($\sum_{i=1}^{k} q_k$ =0): 0.114458 (0.735125)

Wald-test (x^2) statistic for the null hypothesis ($\sum_{i=1}^{-k} q_{-k}$ =0): 0.045088 (0.831842)

Notes: This table reports the results for the linear Granger causality test between 2-years ahead seasonal winter 2 forward and water reservoir content filtered returns. The sample period is from October 29th, 1997 to September 25th, 2002. The t-statistic for each of the q coefficients is reported in parentheses. The probability that the null of the Wald-test is rejected is reported in the parentheses after the x^2 statistic.

Table 9 Test results for nonlinear Granger causality between weekly futures water reservoir content filtered returns

(After ARMA filtering for linearity but before EGARCH filtering for volatility persistence)

Null: Weekly water reservoir content return does not nonlinearly cause weekly futures return

$Lw = Lf$	LAG=1	CS	TVAL	2	CS	TVAL	3	CS	TVAL	4	CS	TVAL	5	CS	TVAL
		-0.0038	-0.594		-0.0017	-0.183		0.0034	0.257		0.0027	0.170		-0.0044	-0.233
	6			7			8			9			10		
		0.0065	0.290		0.0332	1.185		0.0384	1.284		0.0274	0.752		0.0392	0.875
	11			12			13			14			15		
		0.0351	0.621		0.0568	0.975		0.0628	0.961		0.0712	0.930		0.0595	0.614
	16			17			18			19			20		
		0.1670	4.066 ***		0.1759	3.815 ***		0.155	3.778***		0.1528	3.649***			

Null: Weekly futures return does not nonlinearly cause weekly water reservoir content return

$Lw = Lf$	LAG=1	CS	TVAL	2	CS	TVAL	3	CS	TVAL	4	CS	TVAL	5	CS	TVAL
		0.0056	0.563		-0.0123	-1.156		-0.0316	-2.175**		-0.0417	-2.264**		-0.0525	-2.378**
	6			7			8			9			10		
		-0.0584	-2,210**		-0.0726	- 2.091**		-0.0840	-1.941		-0.0772	-1.529		-0.0743	-1.160
	11			12			13			14			15		
		-0.0730	-0.918		-0.0888	-0.884		-0.0989	-0.796		-0.1128	-0.879		-0.1825	-1.232
	16			17			18			19			20		
		-0.2816	-1.820**		-0.3550	-2.030**									

Notes: This table reports the results for the modified Baek and Brock nonlinear Granger causality test using VAR residuals of the linear Granger causality tests on ARMA filtered returns. The sample period is from October 29th, 1997 to September 25th, 2002. Lw and Lf denote the number of lags in the residual series used in the test. The lead length, m, is set to unity. CS and TVAL are the difference between the two conditional probabilities and the standardized test statistic. Under the null hypothesis of nonlinear Granger causality the test statistic is asymptotically distributed, N (0,1). *** denotes significant at the 1% level, ** denotes significant at the 5% level.

Table 10 Test results for nonlinear Granger causality between 1-month ahead futures water reservoir content filtered returns

(After ARMA filtering for linearity but before EGARCH filtering for volatility persistence)

Null: Weekly water reservoir content return does not nonlinearly cause 1-month ahead futures return

$Lw = Lf$	LAG=1	CS	TVAL	2	CS	TVAL	3	CS	TVAL	4	CS	TVAL	5	CS	TVAL
		-0.0040	-0.732		-0.0084	-0.966		-0.0136	-1.210		-0.0196	-1.392		-0.0107	-0.637
	6			7			8			9			10		
		-0.0288	-1.329		-0.0356	-1.270		-0.0322	-0.952		-0.0396	-1.067		-0.0329	-0.716
	11			12			13			14			15		
		0.0093	0.192		-0.0171	-.276		-0.0224	-0.272		-0.0035	-0.044		0.0457	0.548
	16			17			18			19			20		
		0.0493	0.367		0.1582	3.428***									

Null: 1-month ahead futures return does not nonlinearly cause weekly water reservoir content return

$Lw = Lf$	LAG=1	CS	TVAL	2	CS	TVAL	3	CS	TVAL	4	CS	TVAL	5	CS	TVAL
		-0.0002	-0.022		-0.0048	-0.489		-0.0033	-0.255		0.0002	0.010		0.0037	0.189
	6			7			8			9			10		
		-0.0037	-0.162		-0.0208	-0.700		-0.0237	-0.663		-0.0469	-1.141		-0.0651	-1.207
	11			12			13			14			15		
		-0.0730	-1.086		-0.0967	-1.165		-0.1550	-1.423		-0.2037	-1.769**		-0.2681	-1.902**
	16			17			18			19			20		
		-0.3530	-2.296**												

Notes: This table reports the results for the modified Baek and Brock nonlinear Granger causality test using VAR residuals of the linear Granger causality tests on ARMA filtered returns. The sample period is from October 29th, 1997 to September 25th, 2002. Lw and Lf denote the number of lags in the residual series used in the test. The lead length, m, is set to unity. CS and TVAL are the difference between the two conditional probabilities and the standardized test statistic. Under the null hypothesis of nonlinear Granger causality the test statistic is asymptotically distributed, N (0,1). *** denotes significant at the 1% level, ** denotes significant at the 5% level.

Table 11 Test results for nonlinear Granger causality between 1-year ahead seasonal summer 0 forward and weekly water reservoir content filtered returns

(After ARMA filtering for linearity but before EGARCH filtering for volatility persistence)

Null: Weekly water reservoir content return does not nonlinearly cause 1-year ahead seasonal summer 0 forward return

$Lw = Lf$	LAG=1	CS	TVAL	2	CS	TVAL	3	CS	TVAL	4	CS	TVAL	5	CS	TVAL
		0.0031	0.309		-0.0014	-0.105		-0.0009	-0.057		-0.0162	-1.201		-0.0249	-1.581
	6			7			8			9			10		
		-0.0247	-1.399		-0.0421	-2.200**		-0.0531	-2.470***		-0.0683	-2.742***		-0.0800	-2.935***
	11			12			13			14			15		
		-0.0968	-3.002***		-0.1247	-3.235***		-0.1187	-2.637 ***		-0.1054	-1.883**		-0.1108	-1.624
	16			17			18			19			20		
		-0.1620	-2.095**		-0.1712	-2.288**		-0.1712	1.930**		-0.2193	-1.790**		-0.2123	-1.225

Null: 1-year ahead seasonal summer 0 forward return does not nonlinearly cause weekly water reservoir content return

$Lw = Lf$	LAG=1	CS	TVAL	2	CS	TVAL	3	CS	TVAL	4	CS	TVAL	5	CS	TVAL
		-0.0055	-0.887		-0.0100	-1.109		-0.0089	-0.790		0.0052	0.359		0.0094	0.559
	6			7			8			9			10		
		0.0091	0.481		0.0102	0.432		0.0124	0.464		0.0189	0.810		0.0286	1.170
	11			12			13			14			15		
		0.0382	1.379		0.0427	1.268		0.0496	1.246		0.0307	0.594		0.0960	2.663***
	16			17			18			19			20		
		0.1085	2.771***		0.1079	2.291***		0.0966	1.684**		0.1200	1.944**		0.1752	3.227***

Notes: This table reports the results for the modified Baek and Brock nonlinear Granger causality test using VAR residuals of the linear Granger causality tests on ARMA filtered returns. The sample period is from October 29th, 1997 to September 25th, 2002. Lw and Lf denote the number of lags in the residual series used in the test. The lead length, m, is set to unity. CS and TVAL are the difference between the two conditional probabilities and the standardized test statistic. Under the null hypothesis of nonlinear Granger causality the test statistic is asymptotically distributed, N (0,1). *** denotes significant at the 1% level, ** denotes significant at the 5% level.

Table 12 Test results for nonlinear Granger causality between 2-years ahead seasonal winter 1 forward and weekly water reservoir content filtered returns
(After ARMA filtering for linearity but before EGARCH filtering for volatility persistence)

Null: Weekly water reservoir content return does not nonlinearly cause 2-year ahead seasonal winter 1 forward return

$Lw = Lf$	LAG=1	CS	TVAL	2	CS	TVAL	3	CS	TVAL	4	CS	TVAL	5	CS	TVAL
		0.0017	0.211		0.0003	0.025		-0.0042	-0.374		-0.0129	-1.129		-0.0135	-1.066
	6			7			8			9			10		
		-0.0236	-1.696**		-0.0362	-2.092***		-0.0378	-1.960**		-0.0496	-2.120**		-0.0491	-2.041**
	11			12			13			14			15		
		-0.0640	-2.417 ***		-0.0860	-2.854***		-0.0843	-2.486***		-0.0960	-2.387***		-0.0955	-1.989**
	16			17			18			19			20		
		-0.0978	-1.665**		-0.0638	-1.192		-0.1024	-1.421		-0.1170	-1.425		-0.1155	-1.349

Null: 2-year ahead seasonal winter 1 forward return does not nonlinearly cause water reservoir content return

$Lw = Lf$	LAG=1	CS	TVAL	2	CS	TVAL	3	CS	TVAL	4	CS	TVAL	5	CS	TVAL
		-0.0058	-0.918		-0.0030	-0.316		0.0077	0.670		0.0120	0.802		0.0155	0.789
	6			7			8			9			10		
		0.0117	0.542		0.0094	0.396		0.0096	0.364		0.0084	0.339		0.0182	0.667
	11			12			13			14			15		
		0.0193	0.591		0.0512	1.845**		0.0643	2.236**		0.0705	2.278**		0.0721	2.060**
	16			17			18			19			20		
		0.0592	1.409		0.0397	0.894		0.0235	0.457		0.0084	0.140		0.0277	0.440

Notes: This table reports the results for the modified Baek and Brock nonlinear Granger causality test using VAR residuals of the linear Granger causality tests on ARMA filtered returns. The sample period is from October 29th, 1997 to September 25th, 2002. Lw and Lf denote the number of lags in the residual series used in the test. The lead length, m, is set to unity. CS and TVAL are the difference between the two conditional probabilities and the standardized test statistic. Under the null hypothesis of nonlinear Granger causality the test statistic is asymptotically distributed, N (0,1). *** denotes significant at the 1% level, ** denotes significant at the 5% level.

Table 13 Test results for nonlinear Granger causality between 2-years ahead seasonal winter 2 forward and weekly water reservoir content filtered returns

(After ARMA filtering for linearity but before EGARCH filtering for volatility persistence)

Null: Weekly water reservoir content return does not nonlinearly cause 2-years ahead seasonal winter 2 forward return

$Lw = Lf$	LAG=1	CS	TVAL	2	CS	TVAL	3	CS	TVAL	4	CS	TVAL	5	CS	TVAL
		-0.0058	-0.918		-0.0030	-0.316		0.0077	0.670		0.0120	0.802		0.0155	0.789
	6			7			8			9			10		
		0.0117	0.542		0.0094	0.396		0.0096	0.364		0.0084	0.339		0.0182	0.667
	11			12			13			14			15		
		0.0193	0.591		0.0512	1.845**		0.0643	2.236**		0.0705	2.278**		0.0721	2.060**
	16			17			18			19			20		
		0.0592	1.409		0.0397	0.894		0.0235	0.457		0.0084	0.140		0.0277	0.440

Null: 2-years ahead seasonal winter 2 forward return does not nonlinearly cause weekly water reservoir content return

$Lw = Lf$	LAG=1	CS	TVAL	2	CS	TVAL	3	CS	TVAL	4	CS	TVAL	5	CS	TVAL
		-0.0043	-0.626		-0.0073	-0.869		-0.0095	-0.976		-0.0046	-0.348		-0.0051	-0.295
	6			7			8			9			10		
		-0.0121	-0.588		-0.0152	-0.651		-0.0209	-0.796		-0.0121	-0.531		0.0088	0.306
	11			12			13			14			15		
		0.0068	0.212		0.0440	1.598		0.0481	1.679**		0.0514	1.601		0.0603	1.672**
	16			17			18			19			20		
		0.0567	1.404		0.0540	1.291		0.0327	0.661		0.0067	0.112		0.0303	0.467

Notes: This table reports the results for the modified Baek and Brock nonlinear Granger causality test using VAR residuals of the linear Granger causality tests on ARMA filtered returns. The sample period is from October 29th, 1997 to September 25th, 2002. Lw and Lf denote the number of lags in the residual series used in the test. The lead length, m, is set to unity. CS and TVAL are the difference between the two conditional probabilities and the standardized test statistic. Under the null hypothesis of nonlinear Granger causality the test statistic is asymptotically distributed, N (0,1). *** denotes significant at the 1% level, ** denotes significant at the 5% level.

Table 14 Test results for linear Granger causality between weekly futures and weekly water reservoir content filtered returns (After ARMA filtering for linearity and EGARCH filtering for volatility persistence)

Dependent variable: Weekly futures return   Independent variable: Weekly water reservoir content return

Coefficient estimations for independent variable:

q_{-20} = 0.125260 (1.953102)	q_{+20} =0.063636 (0.934437)	q_{-9} =-0.075587 (-1.171941)	q_{+9} =-0.080378 (–1.265751)
q_{-19} =0.134731 (2.023952)	q_{+19} =0.020365 (0.302244)	q_{-8} =-0.080929 (–1.097609)	q_{+8} =-0.133980 (–2.319218)
q_{-18} =-0.046889 (–0.77299)	q_{+18} =-0.130526 (–2.643979)	q_{-7} =0.074623 (1.370952)	q_{+7} =0.020921 (0.461018)
q_{-17} =0.032895 (0.554324)	q_{+17} =-0.023187 (–0.326847)	q_{-6} =-0.018868 (–0.269693)	q_{+6} =-0.126471 (–2.330319)
q_{-16} =0.034705 (0.545947)	q_{+16} =-0.039315 (-0.712703)	q_{-5} =0.104599 (1.755236)	q_{+5} =-0.181998 (–3.71510)
q_{-15} =0.073704 (1.455813)	q_{+15} =-0.062615 (–0.988868)	q_{-4} =-0.157752 (–2.751761)	q_{+4} =0.038050 (0.488502)
q_{-14} =0.117606 (1.184837)	q_{+14} =-0.049859 (–1.167309)	q_{-3} =-0.127911 (–1.754453)	q_{+3} =0.108484 (2.077869)
q_{-13} =-0.003011 (–0.037083)	q_{+13} =-0.076243 (-1.198034)	q_{-2} =-0.024077 (–0.426038)	q_{+2} =0.014581 (0.355851)
q_{-12} =-0.001348 (–0.020841)	q_{+12} =-0.083955 (–1.933861)	q_{-1} =-0.065748 (–1.361744)	q_{+1} =-0.101978 (–1.454406)
q_{-11} =-0.141498 (–1.392830)	q_{+11} =-0.108490 (–2.105349)	q_{0} =-0.246265 (–4.213958)	q =-0.020582 (–0.385590)
q_{-10} =-0.080642 (–0.884943)	q_{+10} =-0.173021 (–3.069884)		

Wald-test (x^2) statistic for the null hypothesis ($\sum_{i=1}^{k} q_k$ =0): 0.035107 (0.851372)

Wald-test (x^2) statistic for the null hypothesis ($\sum_{i=1}^{-k} q_{-k}$ =0): 21.34137 (0.000004)

Notes: This table reports the results for the linear Granger causality test between weekly futures and water reservoir content filtered returns. The sample period is from October 29th, 1997 to September 25th, 2002. The t-statistic for each of the q coefficients is reported in parentheses. The probability that the null of the Wald-test is rejected is reported in the parentheses after the x^2 statistic.

Table 15 Test results for linear Granger causality between 1-month ahead futures and weekly water reservoir content returns (After ARMA linear filtering and EGARCH filtering for volatility persistence)

Dependent variable: 1-month ahead futures return   Independent variable: Weekly water reservoir content return

Coefficient estimations for independent variable:

q_{-20}=0.185374 (3.051870)	q_{+20}=0.064381 (0.909012)	q_{-9}=-0.116050 (–2.30325)	q_{+9}=-0.008389 (–0.15218)
q_{-19}=0.064381 (1.413269)	q_{+19}=-0.031039(–0.596496)	q_{-8}=0.108964 (1.367560)	q_{+8}=0.011089 (0.219817)
q_{-18}=-0.080054 (–1.102678)	q_{+18}=-0.097431 (–1.610144)	q_{-7}=-0.033120 (–0.52704)	q_{+7}=0.074174 (1.325687)
q_{-17}=-0.041156 (–0.644757)	q_{+17}=-0.044400 (–0.627545)	q_{-6}=0.030228 (0.471412)	q_{+6}=-0.022366 (–0.349739)
q_{-16}=-0.060797 (–1.02259)	q_{+16}=-0.021486 (–0.38607)	q_{-5}=0.042673 (0.609441)	q_{+5}=-0.135985 (–2.18628)
q_{-15}=0.058802 (0.940354)	q_{+15}=0.034603 (0.589891)	q_{-4}=-0.052757 (–1.069477)	q_{+4}=0.059488 (0.791090)
q_{-14}=-0.018186 (–0.28253)	q_{+14}=-0.044250 (–0.818529)	q_{-3}=-0.132716 (–2.120346)	q_{+3}=0.119071 (1.412824)
q_{-13}=0.086783 (0.834732)	q_{+13}=-0.118559 (–1.633201)	q_{-2}=0.127499 (2.184320)	q_{+2}=0.040199 (0.663186)
q_{-12}=0.082030 (0.904925)	q_{+12}=-0.142560 (–2.381084)	q_{-1}=-0.047698 (–0.855516)	q_{+1}=3.015757 (0.226593)
q_{-11}=0.044309 (0.822830)	q_{+11}=-0.039458 (–0.621159)	q_{0}=-0.108757 (–2.030921)	q =-0.010107 (–0.176504)
q_{-10}=0.230496 (4.032216)	q_{+10}=-0.099043 (–1.60981)		

Wald-test (x^2) statistic for the null hypothesis ($\sum_{i=1}^{k} q_k$ =0): 1.353238 (0.244713)

Wald-test (x^2) statistic for the null hypothesis ($\sum_{i=1}^{-k} q_{-k}$ =0): 2.055670 (0.151641)

Notes: This table reports the results for the linear Granger causality test between 1- month ahead futures and water reservoir content filtered returns. The sample period is from October 29th, 1997 to September 25th, 2002. The t-statistic for each of the q coefficients is reported in parentheses. The probability that the null of the Wald-test is rejected is reported in the parentheses after the x^2 statistic.

Table 16 Test results for linear Granger causality between various seasonal forward and weekly water reservoir content returns (After ARMA filtering for linearity and EGARCH filtering for volatility persistence)

Dependent variable: 1-year ahead seasonal summer 0 forward return Independent variable: Weekly water reservoir content return

Coefficient estimations for independent variable:

q_{-3} =-0.03613 (–0.64096)	q_{+3} =0.130410 (1.664784)	q_{-1} =0.078698 (1.191393)	q_{+1} =-0.083108 (–1.450474)
q_{-2} =0.059041 (1.058634)	q_{+2} =0.007678 (0.135321)	q_0 =-0.009654 (–0.189817)	q =-0.017199 (–0.246346)

Wald-test (x^2) statistic for the null hypothesis ($\sum_{i=1}^{k} q_k$ =0): 0.003074 (0.955784) Wald-test (x^2) statistic for the null hypothesis ($\sum_{i=1}^{-k} q_{-k}$ =0): 1.028318 (0.310554)

Dependent variable: 2-years ahead seasonal winter 1 forward return Independent variable: Weekly water reservoir content return

Coefficient estimations for independent variable:

q_{-3} = 0.027626 (0.478890)	q_{+3} =0.142637 (1.664284)	q_{-1} =0.032141 (0.523233)	q_{+1} =-0.032793 (–0.613023)
q_{-2} =0.044851 (0.714741)	q_{+2} =0.030641 (0.505691)	q_0 =-0.025247 (–0.506917)	q =-0.015967 (–0.230586)

Wald-test (x^2) statistic for the null hypothesis ($\sum_{i=1}^{k} q_k$ =0): 0.366435 (0.544953) Wald-test (x^2) statistic for the null hypothesis ($\sum_{i=1}^{-k} q_{-k}$ =0): 0.104794 (0.746150)

Dependent variable: 2-years ahead seasonal winter 2 forward return Independent variable: Weekly water reservoir content return

Coefficient estimations for independent variable:

q_{-3} =-0.006763 (–0.116577)	q_{+3} = 0.118792 (1.532187)	q_{-1} =0.063154 (1.064511)	q_{+1} = -0.069882 (–1.383931)
q_{-2} =0.051667 (0.845390)	q_{+2} = 0.055161 (0.922838)	q_0 =-0.053974 (–0.866102)	q = -0.015835 (–0.227685)

Wald-test (x^2) statistic for the null hypothesis ($\sum_{i=1}^{k} q_k$ =0): 0.090870 (0.763074) Wald-test (x^2) statistic for the null hypothesis ($\sum_{i=1}^{-k} q_{-k}$ =0): 0.568090 (0.451019)

Notes: This table reports the results for the linear Granger causality test between various seasonal forward and water reservoir content filtered returns. The sample period is from October 29th, 1997 to September 25th, 2002. The t-statistic for each of the q coefficients is reported in parentheses. The probability that the null of the Wald-test is rejected is reported in the parentheses after the x^2 statistic.

Table 17 Test results for nonlinear Granger causality between weekly futures water reservoir content filtered returns

(After ARMA(p,q)-EGARCH(1,1) filtering for linearity and volatility persistence)

Null: Weekly water reservoir content return does not nonlinearly cause weekly futures return

$Lw = Lf$	LAG=1	CS	TVAL	2	CS	TVAL	3	CS	TVAL	4	CS	TVAL	5	CS	TVAL
		0.0007	0.113		0.0019	0.207		0.0115	0.900		0.0182	1.106		0.0306	1.533
	6			7			8			9			10		
		0.0396	1.638		0.0421	1.385		0.0542	1.340		0.0098	0.168		0.0264	0.355
	11			12			13			14			15		
		0.0460	0.463		0.0824	0.793		0.0629	0.451		0.1424	0.845		0.2535	4.638***
	16			17			18			19			20		

Null: Weekly futures return does not nonlinearly cause weekly water reservoir content return

$Lw = Lf$	LAG=1	CS	TVAL	2	CS	TVAL	3	CS	TVAL	4	CS	TVAL	5	CS	TVAL
		0.0061	0.679		-0.0028	-0.234		-0.0191	-1.197		-0.0293	-1.588		-0.0246	-1.091
	6			7			8			9			10		
		-0.0245	-0.963		-0.0393	-1.020		-0.0624	-1.524		-0.0407	-0.854		-0.0652	-0.971
	11			12			13			14			15		
		0.0015	0.018		-0.0520	-0.426		-0.0588	-0.385		-0.1508	-0.733			
	16			17			18		19		20				

Notes: This table reports the results for the modified Baek and Brock nonlinear Granger causality test applied to the standardized VAR residuals from linear Granger causality on ARMA(p,q)- EGARCH (1,1) filtered raw returns. The sample period is from October 29th, 1997 to September 25th, 2002. Lw and Lf denote the number of lags in the residual series used in the test. The lead length, m, is set to unity. CS and TVAL are the difference between the two conditional probabilities and the standardized test statistic. Under the null hypothesis of nonlinear Granger causality the test statistic is asymptotically distributed, N (0,1). *** denotes significant at the 1% level, ** denotes significant at the 5% level.

Table 18 Test results for nonlinear Granger causality between 1-month ahead futures water reservoir content filtered returns (After ARMA(p,q)-EGARCH(1,1) filtering for linearity and volatility persistence)

Null: Weekly water reservoir content return does not nonlinearly cause 1-month ahead futures return

$Lw = Lf$	LAG=1 CS	TVAL	2 CS	TVAL	3 CS	TVAL	4 CS	TVAL	5 CS	TVAL
	-0.0023	-0.348	-0.0041	-0.481	-0.0067	-0.576	-0.0026	-0.165	-0.0029	-0.137
	6		7		8		9		10	
	-0.0019	-0.082	0.0165	0.556	0.0133	0.369	-0.0271	-0.527	-0.0288	-0.397
	11		12		13		14		15	
	-0.0186	-0.177	-0.0208	-0.144	-0.0230	-0.102				
	16		17		18		19		20	

Null: 1-month ahead futures return does not nonlinearly cause weekly water reservoir content return

$Lw = Lf$	LAG=1 CS	TVAL	2 CS	TVAL	3 CS	TVAL	4 CS	TVAL	5 CS	TVAL
	-0.0007	-0.091	-0.0003	-0.030	0.0042	0.291	0.0065	0.377	0.0182	0.879
	6		7		8		9		10	
	0.0059	0.226	-0.0118	-0.339	-0.0122	-0.300	-0.0640	-1.198	-0.1154	-1.631
	11		12		13		14		15	
	-0.1902	-1.669**	-0.3020	-1.928**	-0.4171	-2.381***				
	16		17		18		19		20	

Notes: This table reports the results for the modified Baek and Brock nonlinear Granger causality test applied to the standardized VAR residuals from linear Granger causality on ARMA(p,q)- EGARCH (1,1) filtered raw returns. The sample period is from October 29th, 1997 to September 25th, 2002. Lw and Lf denote the number of lags in the residual series used in the test. The lead length, m, is set to unity. CS and TVAL are the difference between the two conditional probabilities and the standardized test statistic. Under the null hypothesis of nonlinear Granger causality the test statistic is asymptotically distributed, N (0,1). *** denotes significant at the 1% level, ** denotes significant at the 5% level.

Table 19 Test results for nonlinear Granger causality between 1-year ahead seasonal summer 0 forward return and weekly water reservoir content returns
(After ARMA(p,q)-EGARCH(1,1) filtering for linearity and volatility persistence)

Null: Weekly water reservoir content return does not nonlinearly cause 1-year ahead seasonal summer 0 forward return

$Lw = Lf$	LAG=1	CS	TVAL	2	CS	TVAL	3	CS	TVAL	4	CS	TVAL	5	CS	TVAL
		-0.0087	-1.341		-0.0051	-0.500		0.0005	0.033		-0.0150	-0.840		-0.0209	-0.974
	6			7			8			9			10		
		-0.0014	-0.047		-0.0200	-0.543		-0.0201	-0.466		-0.0689	-1.191		-0.0764	-1.044
	11			12			13			14			15		
		-0.0946	-1.042		-0.0873	-0.659									
	16			17			18			19			20		

Null: 1-year ahead seasonal summer 0 forward return does not nonlinearly cause weekly water reservoir content return

$Lw = Lf$	LAG=1	CS	TVAL	2	CS	TVAL	3	CS	TVAL	4	CS	TVAL	5	CS	TVAL
		-0.0072	-1.204		-0.0198	-2.347***		-0.0245	-1.956**		-0.0160	-1.023		-0.0120	-0.590
	6			7			8			9			10		
		0.0012	0.048		0.0210	0.695		0.0080	0.221		-0.0078	-0.200		-0.0120	-0.219
	11			12			13			14			15		
		-0.0229	-0.283		-0.1494	-1.236									
	16			17			18			19			20		

Notes: This table reports the results for the modified Baek and Brock nonlinear Granger causality test applied to the standardized VAR residuals from linear Granger causality on ARMA(p,q)- EGARCH (1,1) filtered raw returns. The sample period is from October 29th, 1997 to September 25th, 2002. Lw and Lf denote the number of lags in the residual series used in the test. The lead length, m, is set to unity. CS and TVAL are the difference between the two conditional probabilities and the standardized test statistic. Under the null hypothesis of nonlinear Granger causality the test statistic is asymptotically distributed, N (0,1). *** denotes significant at the 1% level, ** denotes significant at the 5% level.

Table 20 Test results for nonlinear Granger causality between 2-years ahead seasonal winter 1 forward return and weekly water reservoir content returns

(After ARMA(p,q)-EGARCH(1,1) filtering for linearity and volatility persistence)

Null: Weekly water reservoir content return does not nonlinearly cause 2-year ahead seasonal winter 1 forward return

$Lw = Lf$	LAG=1 CS	TVAL	2 CS	TVAL	3 CS	TVAL	4 CS	TVAL	5 CS	TVAL
	-0.0028	-0.500	0.0012	0.113	0.0065	0.449	0.0005	0.027	-0.0040	-0.193
	6		7		8		9		10	
	-0.0112	-0.503	-0.0345	-1.107	-0.0181	-0.475	-0.0238	-0.496	-0.0292	-0.470
	11		12		13		14		15	
	-0.1203	-1.161	-0.1020	-0.550						
	16		17		18		19		20	

Null: 2-year ahead seasonal winter 1 forward return does not nonlinearly cause water reservoir content return

$Lw = Lf$	LAG=1 CS	TVAL	2 CS	TVAL	3 CS	TVAL	4 CS	TVAL	5 CS	TVAL
	-0.0112	-2.328***	-0.0146	-1.407	-0.0092	-0.699	0.0008	0.050	-0.0087	-0.380
	6		7		8		9		10	
	-0.0110	-0.339	0.0000	0.001	-0.0331	-0.754	-0.0483	-0.774	-0.0321	-0.452
	11		12		13		14		15	
	-0.1200	-1.082	-0.0847	-0.539						
	16		17		18		19		20	

Notes: This table reports the results for the modified Baek and Brock nonlinear Granger causality test applied to the standardized VAR residuals from linear Granger causality on ARMA(p,q)- EGARCH (1,1) filtered raw returns. The sample period is from October 29th, 1997 to September 25th, 2002. Lw and Lf denote the number of lags in the residual series used in the test. The lead length, m, is set to unity. CS and TVAL are the difference between the two conditional probabilities and the standardized test statistic. Under the null hypothesis of nonlinear Granger causality the test statistic is asymptotically distributed, N (0,1). *** denotes significant at the 1% level, ** denotes significant at the 5% level.

Table 21 Test results for nonlinear Granger causality between 2-years ahead seasonal winter 2 forward return and weekly water reservoir content returns

(After ARMA(p,q)-EGARCH(1,1) filtering for linearity and volatility persistence)

Null: Weekly water reservoir content return does not nonlinearly cause 2-years ahead seasonal winter 2 forward return

$Lw = Lf$	LAG=1	CS	TVAL	2	CS	TVAL	3	CS	TVAL	4	CS	TVAL	5	CS	TVAL
		-0.0047	-0.813		-0.0048	-0.455		-0.0029	-0.183		-0.0104	-0.547		-0.0174	-0.727
	6			7			8			9			10		
		-0.0284	-0.945		-0.0359	-0.984		-0.0588	-1.419		-0.0468	-0.923		-0.0412	-0.701
	11			12			13			14			15		
		-0.0359	-0.459		-0.0721	-0.595									
	16			17			18			19			20		

Null: 2-years ahead seasonal winter 2 forward return does not nonlinearly cause weekly water reservoir content return

$Lw = Lf$	LAG=1	CS	TVAL	2	CS	TVAL	3	CS	TVAL	4	CS	TVAL	5	CS	TVAL
		-0.0063	-0.860		-0.0077	-0.690		-0.0167	-1.265		-0.0148	-0.838		-0.0243	-1.098
	6			7			8			9			10		
		-0.0202	-0.660		-0.0215	-0.572		-0.0508	-1.102		-0.0280	-0.670		-0.0635	-1.141
	11			12			13			14			15		
		-0.0652	-0.837		-0.0312	-0.297									
	16			17			18			19			20		

Notes: This table reports the results for the modified Baek and Brock nonlinear Granger causality test applied to the standardized VAR residuals from linear Granger causality on ARMA(p,q)- EGARCH (1,1) filtered raw returns. The sample period is from October 29th, 1997 to September 25th, 2002. Lw and Lf denote the number of lags in the residual series used in the test. The lead length, m, is set to unity. CS and TVAL are the difference between the two conditional probabilities and the standardized test statistic. Under the null hypothesis of nonlinear Granger causality the test statistic is asymptotically distributed, N (0,1). *** denotes significant at the 1% level, ** denotes significant at the 5% level.

Essay III

Convenience yield behavior at the Nord Pool power exchange

Daniel Deng

Center for Finance
Department of Economics
School of Economics and Commercial Law
Gothenburg University
P.O.Box 640, SE-60530, Gothenburg
Sweden

E-mail: Daniel.Deng@handels.gu.se

I want to thank Hans Byström, Erik Hjalmarsson and Lennart Hjalmarsson for helpful comments. I also want to thank Kenneth Andreassen and Jan Foyn at the Nord Pool power exchange for providing the data used in this study.

Abstract

This paper investigates convenience yield behavior at the Nord Pool power exchange given the considerable storable hydropower being traded. Several hypotheses are tested concerning the behavior and determinants of convenience yield from holding hydropower as inventory. The results reveal that 1) convenience yield has a negative relationship with hydro reservoir content as inventory, 2) convenience yield behavior can be statistically explained within a standard financial call option framework, and the call option component can explain a large portion of variability in convenience yield, 3) convenience yield varies on both a yearly and a monthly basis, and 4) there is an asymmetry of volatility of convenience yield during high/low hydro inventory periods.

Keywords: Nord Pool, convenience yield, inventory, call option, yearly and monthly effect, volatility asymmetry.

1. Introduction

The theory of storage proposed in Kaldor (1939), Working (1949) and Brennan (1958) has successfully explained the futures price behavior of seasonally harvested storable commodities and is the dominant theory concerning commodity prices. The theory essentially states that the price difference between spot and futures prices equals the marginal cost of storage minus the marginal convenience yield of holding the current stock of a commodity. The storage cost includes interest expense, insurance and a physical storage cost for the commodity. The marginal convenience yield is defined as an inventory holder benefit accrued from the increased utility associated with availability during periods of scarce supplies. This concept is taken as a negative component of carrying charges in an effort to explain the existence of spot prices being greater than futures prices. The convenience yield is negatively related to the level of stock; it rises at an increasing rate when stock level decreases and vice versa.

Empirical works such as Brennan (1958), Telser (1958) and Fama and French (1987) have provided strong empirical support for the negative relationship between convenience yield and inventory levels. In particular, Fama and French (1987) argued that seasonal variation in the supply mechanism produces differential behavior in convenience yield.

A more recent development in modeling convenience yield incorporates the application of option pricing theory (Heinkel, Howe and Hughes, 1990; Milonas and Thomadakis, 1997). This line of argument considers convenience yield as a financial call option written on a futures contract with an expiration time some intermediate period before maturity and with a strike price that is the maximum within the intermediate period given the available supply. Empirical results on four commodities including soybeans, corn, wheat and copper have provided strong support for this theoretical extension.

The purpose of this study is to empirically estimate the convenience yield and to investigate its behavior and determinants generated by the hydropower inventory at the spot and futures power markets at the Nord Pool power exchange. The applicability of the concept of convenience yield to a commodity like electricity lies in the fact that the proportion of hydropower traded at Nord Pool is considerably high (nearly 50%) and the hydropower is typically regarded as storable via hydro-reservoir inventory holding. Although other sources of electricity generation such as nuclear power, wind power, coal power, etc. are also traded at Nord Pool, the system price matching the supply and demand conditions is a uniform price for all sources of electricity generation, including hydropower. Hence it is reasonable to implement the concept of convenience yield to interpret the benefit associated with holding hydro-reservoir inventory, in particular when the reservoir content is low.

This study appears to be the first to systematically investigate the convenience yield in the context of a power exchange. As is well known in the academic literature, convenience yield is not only an important factor contributing to the interpretation of the commodity spot-futures spread, but also has an effect on the pricing of commodity derivative contracts (see Jarrow and Turnbull 1997; Schwartz, 1998; Miltersen and Schwartz, 1998). However, nothing is yet known about the factors influencing convenience yield in the Nord Pool power markets. Thus it is crucial to conduct an empirical investigation to ascertain the dynamics and the determinants of convenience yield. Such an endeavor should greatly improve our understanding of the electricity market and is highly relevant to the design of hedging practice. Specifically, this study begins with verifying the famous Kaldor-Working-Brennan hypothesis that hydro reservoir content as inventory has a negative relationship with convenience yield in the context of Nord Pool. Furthermore, following the latest theoretical development on convenience yield, I empirically investigate if an inventory holder's decision to sell reservoir water stocks is like deciding whether or not to exercise a financial call option. Third, given the seasonal nature of the hydro inventory supply mechanism, I explore the differential behaviors of convenience yield on both an inter-year and an intra-year basis. Fourth, I test whether or not there is an asymmetry of volatility of convenience yield associated with high/low reservoir contents.

The findings show that convenience yield is negatively associated with hydro reservoir content. Convenience yield can be statistically explained as a financial call option, and the call option component can account for a large portion of variability in convenience yield. Furthermore, the results suggest that convenience yield may differ from year to year and from month to month. Finally, the volatility of convenience yield shows an asymmetric pattern over periods of high/low water reservoir contents.

The rest of the paper is organized as follows. In Section 2, I present the theory of storage, hypotheses to be empirically tackled and the specific testing procedures. In Sections 3-5, I discuss the data and present the methodology for calculating the convenience yield and the descriptive data statistical analysis, respectively. In Section 6, I report the empirical findings. Finally, Section 7 provides a summary and a conclusion.

2. Theory and hypotheses

The storage model assumes that the inventory holders derive a benefit termed convenience yield from holding inventory. When inventory is adequate, there is no temporary supply shortage and hence no advantage of holding physical stocks of a commodity, and futures price exceeds spot price. When inventory is scarce, the high opportunity cost of a shortage pushes the current price of inventory stocks higher relative to their expected future price. Such an occurrence leads to a positive convenience yield. In the context of the Nord Pool power exchange, there is a large proportion of traded power supplied by hydro technology. In times of drought, the benefit of holding a physical inventory of hydropower is higher and hence a large convenience yield occurs.

Roughly following the theoretical development concerning convenience yield discussed in the introduction, I set up hypotheses for empirical testing as follows:

Hypothesis 1. Convenience yield generated by hydropower inventory has a negative relationship with the hydro reservoir content as inventory.

This is of course the Kaldor-Working-Brennan hypothesis applied in the context of a power market. It is important to empirically characterize the relationship between convenience yield and hydro inventory as a starting point for testing the rest of the hypotheses. The empirical procedure is carried out by regressing the water reservoir content at its natural logarithm ($\ln(WR_t)$) on to the convenience yield (CY_t). Taking the natural logarithm of water reservoir content is necessary because it incorporates the nonlinear relationship between the convenience yield and inventory, as mentioned in Cho and McDougall (1990). Since the available water reservoir content series has a weekly frequency, the corresponding weekly convenience yield series is calculated based on the average of the daily convenience yield. The hypothesis predicts that the coefficient of the inventory regressor should be negative and statistically significant.

Hypothesis 2. Convenience yield behaves like a financial call option.

That the convenience yield behaves like a financial option can be illustrated in terms of inventory decision-making for profit maximization. We assume that at time t, the inventory holder faces a choice of whether to sell the inventory withheld from the previous period ($t-1$) or to wait until the future period ($t+1$). We further assume that the asset price follows a binomial process with price either going up to mS or down to dS in each period ($m>1; d<1$). In this way, if the current price at time t is higher than the carrying charges, then the benefit of withholding the inventory stocks at time t is positive. On the other hand, if the current price turns out to be less than that amount, then holding inventory does not reward the holder with a positive benefit. Hence, inventory decision making is like whether to exercise a financial call option, with the former situation as a call option that is in the money and the later situation as a call option that is out of the money. Consequently, the deeper in the money the option is, the greater the incentives to exercise the option by the inventory holder. However, with an option that is out of the money, the inventory holder will opt to wait to sell until the asset price goes up in the future. In other words, the decision making is based on a comparison of the current spot price with a corresponding futures price, *i.e.* the strike price. Thus, it resembles a standard financial call option with the following valuation formula:

$$COPT = SN(w_1) - Xe^{-r(T-t)/365} N(w_2)\,, \qquad (1)$$

where

$$w_1 = \frac{\ln(S/X) + (r/365 + s^2/2)(T-t)}{s\sqrt{T-t}}, \; w_2 = w_1 - s\sqrt{T-t}\,.$$

In Equation (1), S is the spot price, X is the futures price, r is the annualized risk-free 3-month Treasury bill rate, s^2 is the underlying asset price volatility calculated on a yearly basis (250 days), and $T-t$ is the number of days left before contract maturity. The time measurement is on a daily basis. N denotes the cumulative normal distribution function.

Empirically, the hypothesis that convenience yield behaves like a call option can be explored by the following regression:

$$CY_t = a + a_1 COPT_t + x_t\,, \qquad (2)$$

where CY_t is the convenience yield at time t and $COPT_t$ is the call option value at time t written on the futures contract before maturity.

In Equation (2), if a_1 is statistically significant, then the option value is able to explain the variation of convenience yield in a statistically significant way. Moreover, in the case of a =0 and a_1 =1, the option value can be regarded as an unbiased estimator of the convenience yield in its magnitude.

Hypothesis 3. Seasonal hydropower supply results in seasonal convenience yield variation with a higher convenience yield occurring in the spring-summer months than in the autumn-winter months, and that the inter-year hydropower supply variations have a yearly effect on the convenience yield.

The variation of the reservoir content is highly seasonal due to rains, melting snow and precipitation, etc. Usually, peak reservoir contents are observed roughly in September-December and valley values in April-May. Consequently, the low hydro-inventory holding in April-May should result in a higher convenience yield than in September-December.[1] On an inter-year basis, convenience yield should be higher during a drought year than a year with relatively normal climatic conditions.

To test the seasonal pattern of convenience yield on both an inter-year and an intra-year basis, I conduct the nonparametric Kruskal-Wallis test (Hollander and Wolfe, 1973). This test compares the means of the columns of the n-by-k matrix X, where each column represents an independent sample containing n mutually independent observations. Specifically, the Kruskal-Wallis (KW) value is calculated as follows:

$$KW = \frac{12}{n(n+1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(n+1), \tag{3}$$

where n_i (i=1,2,... k) represent the sample sizes for each of the groups and R_i are the sum of ranks for group i in the data.

The procedure is to rank the combined sample by ordering the data from the smallest to largest across the data, taking the numeric index of this ordering. The Kruskal-Wallis statistic approximates a Chi-square distribution with k-1 degrees of freedom. If the p-

[1] Electricity demand is also seasonal with higher demand occurring in the winter for heating. However, since the hydro inventory level is relatively high in the winter, convenience yield in the winter months is relatively low.

value for the null hypothesis that all samples in X are drawn from the same population (or from different populations with the same mean) is less than 0.05 or 0.01, we may reject the null hypothesis. This suggests that at least one sample mean is significantly different than the other sample means.

Hypothesis 4. The volatility of convenience yield during a low hydro-reservoir content period is greater than the volatility of convenience yield during a high hydro-reservoir content period.

The large proportion of hydropower traded at Nord Pool implies that a demand shock to the system can be smoothed out to some extent by the simultaneous increase of hydropower production. However, as implied by the theory of storage, it is assumed that the elasticity of supply and demand in the short run is smaller than in the long run. With a demand shock at low reservoir content periods, the probability of stock-out increases and hence the spot price reacts in a larger magnitude than the futures price, leading to a greater increase of spot price volatility than that of futures prices. Consequently the spot-futures spread becomes widened, the convenience yield becomes positive and its volatility increases, because a low inventory level is unable to absorb the price pressure due to the sudden shift in demand, given the short-run inelastic supply curve. This should not be the case during the high reservoir content period when a sudden increase in demand can be absorbed by an increase of supply from the adequate hydro inventory holding. Consequently, the volatility of spot prices is very similar to the volatility of futures prices. Therefore, the spot-futures price spread remains stable, and the volatility of the convenience yield during the high reservoir content period is smaller than during low reservoir content periods.

To test the hypothesis on the asymmetric volatility behavior of the convenience yield during high versus low reservoir content periods, I implement the Exponential GARCH (EGARCH) modeling framework (Nelson, 1991) that has the following specification:

$$CY_t = g_0 + g_1 COPT_t + x_t, \qquad x_t \sim N(0, h_t^2)$$
$$\log(h_t^2) = q_0 + q_1 \log(h_{t-1}^2) + h_1 |x_{t-1} / h_{t-1}| + h_2 (x_{t-1} / h_{t-1}), \tag{4}$$

where CY_t is the daily convenience yield, $COPT_t$ is the daily call option value for convenience yield and x_t is the error term from the EGARCH process. While $\log(h_{t-1}^2)$ in the variance equation is chosen to capture the persistence of variance over time, the $|x_{t-1} / h_{t-1}|$ and (x_{t-1} / h_{t-1}) terms are designed to model the asymmetric volatility in convenience yield.

In performing the hypothesis testing, the null hypothesis states that the volatility of the convenience yield is the same during both low and high reservoir content periods. This is equivalent to testing h_2 =0. The alternative hypothesis is that h_2 <0.

3. Data, convenience yield calculation and data statistical analysis

Daily closing spot and 1-week ahead futures prices from June 27th, 1996 to June 17th, 2005 are collected from the Nord Pool power exchange. The corresponding annualized 3-month Treasury bill rates are sampled from the Norwegian Central Bank. Weekly water reservoir content series for the same period are obtained from Nord Pool.

Following the methodology outlined by Brennan (1996) and Milonas and Thomadakis (1997), I estimate the convenience yield as the difference between the spot price and the present value of the futures prices discounted to the time of observation t at the risk-free rate using the 3-month Treasury bill rate:[2]

$$CY_t = S_t - F_t e^{-r(T-t)/365}, \tag{5}$$

[2] Except for the investment cost of constructing the reservoirs, there is no warehouse fee for hydro inventory holding. Considering the life duration of the reservoirs, we assume that the warehouse fee per contract is ignorable.

where CY_t is the convenience yield, S_t is the spot price, F_t is the futures price before contract maturity, r is the annualized 3-month Treasury bill rate and $T-t$ is the number of remaining days before futures contract maturity.

Prior to conducting hypothesis testing on the convenience yield, a descriptive analysis of the data is presented in Table (1). This analysis will provide important basic statistical support relevant to the testing. The mean of the calculated convenience yield based on the 2,234 daily values is 1.29, indicating the positive benefit the hydropower inventory holders accrue from the increased utility associated with the availability of hydro inventory on average. The distribution of the convenience yield is non-normal, evidenced by the significant Jarque-Bera (1980) statistic. The empirical design of using EGARCH modeling for the testing of Hypothesis 4 is able to account for the significant conditional skewnesss in the convenience yield.

4. Empirical results

Table (2) indicates the negative relationship between convenience yield and hydro reservoir content.[3] The hydro reservoir content has a negative and significant coefficient. However, the rather low adjusted R^2 (only 2%) suggests that there may be other variables, such as convenience yield as a call option, that have additional explanatory power beyond the hydro reservoir content.

Table (3) presents evidence on the option-like character of convenience yield. As the hydro reservoir content's variation is highly persistent, the associated convenience yield demonstrates persistence in distribution. An initial OLS regression of option value series onto the convenience yield exhibits serial correlation. To deal with this serial correlation, I include both current and lagged dependent and independent variables, and it turns out that

[3] All series are tested for non-stationarity using the augmented Dickey-Fuller test, Phillips-Perron test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. Results show that all series are stationary processes.

the residual series obtained from the regression is a white noise process.[4] The current option value series coefficient is 1.18, statistically significant and positive, implying that convenience yield does possess an option-like character and therefore can be modeled as a call option. The adjusted R^2 is 83%,[5] indicating that the option component accounts for a large portion of the variability in convenience yield.[6]

Table (4) shows the monthly means of convenience yield and the corresponding non-parametric Kruskal-Wallis test values. The mean values calculated for each month of the year show the differences in convenience yield across the 12 months, with high and positive convenience yield occurring in spring/summer months and low and negative convenience yield taking place in autumn/winter months, except for a slight positive convenience yield in September. The Kruskal-Wallis test verifies that this monthly effect is statistically significant (at the 1% level). Furthermore, convenience yield differing from year to year is evidenced by the mean value of convenience yield calculated on a yearly basis, with high and positive convenience yields appearing in 1997 and 2001, which is consistent with the timing of droughts.[7] The significance of the yearly effect is confirmed by the Kruskal-Wallis test at the 1% level. Hence convenience yield has both a yearly and a

[4] On a daily basis, weather seasonality is not significant. I also consider daily seasonal dummy variables in the regression to account for possible daily effects. However, the result indicates that none of the dummy variables is significant.

[5] Experimenting by regressing one lagged convenience yield on to daily convenience yield reveals that one-lagged convenience yield can explain 43% of the variability of convenience yield; experimenting by regressing the option component onto daily convenience yield shows that option component alone can explain 55% of the variability of convenience yield. Although the regression may be misspecified, it indicates that the option component is a more powerful variable in explaining convenience yield variability than the lagged convenience yield.

[6] It is inappropriate to directly compare adjusted R^2 obtained from the regression of the call option component with that from hydro inventory. This is because the two regressions use data of different frequencies; the former uses daily data, and the latter uses weekly data. However, regressing the option component onto convenience yield using weekly data obtains an adjusted R^2 of 56%, suggesting that the call option component has a much higher explanatory power than the hydro inventory variable over the variability of convenience yield.

[7] The data duration for convenience yield in 2005 is from January to June. This period usually corresponds to low water reservoir content periods, with a positive convenience yield. This is why the yearly convenience yield is positive and high for the year 2005. Similarly, the negative and high convenience yield in 1996 is based on data from June to December, corresponding to high hydro inventory periods.

monthly effect, consistent with our assertion that convenience yield varies on an inter-year and an intra-year basis.

Table (5) reports the empirical result of testing asymmetric volatility of convenience yield under the framework of EGARCH technology. As anticipated, h_2 is -0.54, has the correct sign and is highly statistically significant at the 0.01% level. This empirical result confirms that there is an asymmetry of volatility of convenience yield for periods of high/low reservoir content, consistent with the implication derived from the theory of storage.[8]

5. Summary and conclusion

This paper investigates the determinants and behavior of the convenience yield in the context of the Nord Pool power exchange using data from June 27th, 1996 to June 17th, 2005. I first investigate the relationship between convenience yield and hydro inventory. Second, I evaluate whether daily convenience yield can be modeled under the framework of a financial call option. Third, I examine the seasonal variation of convenience yield on both an inter-year and an intra-year basis. Lastly, I test whether there is an asymmetry in the volatility of convenience yield during high/low hydro reservoir content periods.

Apart from the association between convenience yield and hydro reservoir content, this study presents statistically significant and theoretically consistent evidence of the option-like character of convenience yield. Furthermore, monthly and yearly effects of convenience yield are statistically detected, confirming that convenience yield varies on an inter-year and an intra-year basis. Finally, empirical evidence supports the argument of the existence of an asymmetry of volatility in convenience yield for high/low hydro inventory periods. These findings are consistent with the storage theory that an increase in the probability and the magnitude of stock-out give rise to convenience yield and contribute to

[8] An alternative specification involving a hydro inventory variable in the EGARCH framework using weekly data is also tested. It turns out this variable is significant in explaining the variance of convenience yield. The result is not reported here but is available upon request from the author.

a better understanding of the variation in convenience yield. Given that price hedging may be regarded as a trade-off between price risk and basis (spread) risk, the deeper knowledge on convenience yield may prove to be highly conducive to the construction of a superior hedging strategy in the Nord Pool markets.

References

Brennan, M. (1958). “The supply of storage”, *American Economic Review,* 48 : 50-72.

Brennan, M. (1986). “The cost of convenience and the pricing of commodity contingent claims”, *Working Paper, University of British Columbia, May*.

Cho, D. and McDougall, G. (1990). “The supply of storage in energy futures markets”, *Journal of Futures Markets,* Vol. 10, No.6 : 611-621.

Fama, E. and French, K. (1987). “Commodity futures prices: some evidence on forecast power, premiums and the theory of storage”, *Journal of Business,* 60 : 55-73.

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

Heinkel, R., Howe, M. E. and Hughes, J. S. (1990). “Commodity convenience yields as an option profit”, *The Journal of Futures Markets,* 10 : 519-533.

Hollander, M. and Wolfe, D. (1973). “*Nonparametric statistical methods*”, Wiley.

Jarque, C. and Bera, A. K.(1980).“An efficient large-sample test for normality of observations and regression residuals”, *Manuscript, Department of Statistics, Australian National University*.

Jarrow, R. A. and Turnbull, S. M. (1997). “An integrated approach to the hedging and pricing of Eurodollar derivatives”, *Journal of Risk and Insurance,* 64 : 271–99.

Milonas N. and Thomadakis, S. (1997). “Convenience yield and the option to liquidate for commodities with crop cycle”, *European Review of Agricultural Economics*, 24, No. 2 : 267-283.

Miltersen, K. and Schwartz, E. (1998). “Pricing of options on commodity futures with stochastic term structures of convenience yields and interest rates”, *Journal of Financial and Quantitative Analysis,* 33 : 33-59.

Nelson, D. (1991). “Conditional heteroskedasticity in asset returns: a new approach”, *Econometrica*, 59: 347-370.

Schwartz, E. (1998). “Valuing long-term commodity assets”, *Financial Management,* 27: 57-66.

Telser, L. G. (1958). “Futures trading and the storage of cotton and wheat”, *Journal of Political Economy,* 66 : 233-255.

Working, H. (1949). “The theory of the price of storage”, *American Economic Review*, 39 : 1254-1262.

Appendix: Statistics and empirical results

Table 1 Descriptive data statistical analysis

CY_t	Mean	Variance	Skewness	Kurtosis	Minimum	Maximum	Normality(JB)
	1.29	607.08	-0.99	113.33	-421.97	434.52	1133477 (p -value: 0.001)

Notes: This table reports the descriptive statistical data analysis result. The sample period is from June 27th , 1996 to June 17th , 2005. *JB* denotes Jarque-Bera test for normality.

Table 2 The relationship between convenience yield and hydro-reservoir content

CY_t	intercept	$\ln(WR_t)$
	30.35	-6.91
	(2.99)	(-2.89)
Adj. R^2 =2%		

Notes: The estimates are obtained from the following regression:

$$CY_t = k_0 + k_1 \ln(WR_t) + y_t .$$

The t -statistics are in parentheses with critical values 2.576 (1%). All t -statistics are significant at 1%.

Table 3 Convenience yield as a standard financial call option

CY_t	intercept	$COPT_t$	$COPT_{t-1}$	$COPT_{t-2}$	CY_{t-1}	CY_{t-2}
	-1.02	1.18	-0.86	-0.12	0.74	0.07
	(-4.62)	(71.35)	(-27.61)	(-4.07)	(34.83)	(3.41)
Adj. R^2 =83%						

Notes: The estimates are obtained from the following regression:

$$CY_t = a + a_1 COPT_t + a_2 COPT_{t-1} + a_3 COPT_{t-2} + a_4 CY_{t-1} + a_5 CY_{t-2} + x_t .$$

The t -statistics are in parentheses with critical values 2.576 (1%). All t -statistics are significant at 1%.

Table 4 Inter-year and intra-year convenience yield

Year	Convenience yield
1996	-7.4012
1997	4.2645
1998	3.2896
1999	2.7450
2000	2.7308
2001	6.5203
2002	-8.6125
2003	-0.0902
2004	1.5326
2005	9.1084
Kruskal-Wallis value	403.6085 (p -value<0.0001)

Month	Convenience yield
Jan	0.7178
Feb	4.6355
Mar	8.1658
Apr	7.6364
May	9.5709
Jun	8.5274
Jul	-0.3852
Aug	-3.6841
Sep	0.09993
Oct	-3.3137
Nov	-6.2234
Dec	-9.8723
Kruskal-Wallis value	98.5548 (p -value<0.0001)

Notes: The Kruskal-Wallis test values approximate Chi -square distribution with k -1 degrees of freedom.

Table 5 EGARCH test results for the asymmetric volatility of convenience yield

	Dependent variable: CY_t
Mean equation	
Intercept	-0.65
	(-24.10)
$COPT_t$	1.143
	(483.24)
$COPT_{t-1}$	-0.736
	(-35.45)
$COPT_{t-2}$	-0.151
	(-7.31)
CY_{t-1}	0.657
	(42.90)
CY_{t-2}	0.129
	(7.87)
Variance equation	
Intercept	0.195
	(16.82)
$\log(h_{t-1}^2)$	0.933
	(266.91)
$\vert x_{t-1}/h_{t-1}\vert$	-0.165
	(-23.35)
(x_{t-1}/h_{t-1})	-0.54
	(-45.96)
Adj. R^2=83%	
$Q(8)$	6.55
p-value	(0.586)
$Q^2(8)$	0.90
p-value	(1.00)

Notes: The estimates are obtained from the following EGARCH specification:

$$CY_t = g + g_1 COPT_t + g_2 COPT_{t-1} + g_3 COPT_{t-2} + g_4 CY_{t-1} + g_5 CY_{t-2} + x_t\,,\ x_t \sim N(0, h_t^2)$$
$$\log(h_t^2) = q_0 + q_1 \log(h_{t-1}^2) + h_1 |x_{t-1}/h_{t-1}| + h_2 (x_{t-1}/h_{t-1})\,.$$

z-statistics are in parentheses. The critical value of the z-distribution (df=∞, a =0.01) is 2.33 and the z-distribution (df=∞, a =0.001) is 3.29. All z-statistics are significant at 1%. $Q(8)$ denotes a Ljung-Box statistic for testing autocorrelations in the residuals and $Q^2(8)$ denotes a McLeod-Li statistic for testing autocorrelations in the variance. p-values for tests of autocorrelations in residuals and variance are in parentheses.