ELSEVIER

Energy Policy 34 (2006) 1736–1749

ENERGY POLICY

www.elsevier.com/locate/enpol

Electricity markets volatility: estimates, regularities and risk management applications☆

Masao Nakamura[a,*,1], Tomoaki Nakashima[b], Takahide Niimura[c]

[a]Sauder School of Business, University of British Columbia, 2053 Main Mall, Vancouver, BC, Canada V6 T 1Z2
[b]Powerex Corp., Vancouver, BC, Canada V6C 2X8
[c]TNC Systems Technologies, Burnaby, BC, Canada V5 H 2W4

Available online 16 February 2005

Abstract

The recent deregulation of the market for electric power in many parts of the US and Canada has expanded the set of potential tools for managing the types of risks faced by both generators and consumers of electric power. In particular manufacturing and other firms whose operations are powered by electricity now face, on a continuing basis, the engineering management decisions concerning whether they should buy or produce electricity, and if they are to buy or sell electricity, what types of contracts are optimum. These types of risk management decisions typically involve futures, forwards, options and other financial derivatives. The price and volatility of electric power are known to play an essential role in determining which of these instruments should be used. However, electricity as a commodity possesses certain special features not shared by other commodities and hence its risk properties are not yet well understood. In this paper we consider and test certain hypotheses about the properties of electricity price using recent market data. We find that electricity prices possess certain volatility and other systematic properties that can be characterized by the type and method of delivery of electricity. These properties can be used by firms in formulating their optimal demand and supply schedules of electric power.

Keywords: Electricity markets; Volatility; Risk management

1. Introduction

The recent deregulation of the market for electric power in many parts of the US and Canada has led to the rapid development of markets for electricity. This deregulation process has been accompanied by a separation between power generation and power delivery by transmission lines. Industrial firms are now able to enter the electricity market to sell or buy electricity using spot, forward and futures contracts. This development has expanded the set of potential tools for managing the types of risks faced by both generators and consumers of electric power. In particular, many firms in North America whose operations are powered by electricity now face, on a continuing basis, the engineering management decisions on whether they should buy or produce electricity; and if they are to buy or sell electricity, what types of contracts are optimum.[2]

☆Research in part supported by the Social Science and Humanities Research Council of Canada.
*Corresponding author. Tel.: +1 604 822 8434; fax: +1 604 822 8477.
E-mail address: masao.nakamura@sauder.ubc.ca (M. Nakamura).
[1]M. Nakamura is also with UBC's Department of Electrical and Computer Engineering and Institute of Asian Research.

[2]Electricity prices in California were generally stable during the sample period of this study (June 1999–May 2000) and remained below \$50/MW/h). They began increasing in the summer of 2000, reaching the high of more than \$150/MW/h in August. The prices began to skyrocket in the fall of 2000, exceeding \$300/MW/h by January 2001. See, for example, Sweeney (2002) for a detailed analysis of the California electric power crisis. Since the early 1990s many firms in British Columbia with self-power generating capabilities found it more profitable to sell their self-generated electricity in the open market to

0301-4215/\$ - see front matter
doi:10.1016/j.enpol.2004.12.019

These types of risk management decisions often involve futures, forwards, options and other financial derivatives. The price and its volatility of electric power are known to play an essential role in determining which of these instruments should be used.[3] However, unlike agricultural and other commodities for which futures and other financial markets exist,[4] electricity possesses certain special features not shared by other commodities and hence its risk properties are not yet well understood. In this paper we consider and test certain hypotheses regarding the volatility of electric power, as well as other properties using recent market price data.

Our data were observed for the Pennsylvania–New Jersey–Maryland Western Hub and California–Oregon Border markets for the period 1999–2000, which was before the California power crisis. We find that the volatility of electricity prices possesses certain systematic properties, which depend on the delivery type and method. These properties can be used by firms in formulating their optimal demand and supply schedules for electric power.

1.1. Electricity as a commodity[5]

Delivery of sold electricity requires the availability of transmission lines between the seller and the buyer of electricity on a specific delivery date. However, it is important to remember that the availability of electricity transmission lines is subject to strict capacity constraints. Satisfying electricity delivery capacity constraints has become very complex particularly in the areas where electricity is traded as a financial commodity. For example, the transmission capacity, in terms of networks of power lines, must now accommodate transmission requirements induced by an indefinite number of firms who want to sell electricity to their customers on specified future dates. Even so, electricity futures markets typically take no regard to the transmission capacity required to deliver the electricity underlying the futures being traded. Thus, there is a special category of risk associated with electric power markets as compared to markets for other agricultural and mineral commodities.

Another technical factor, which constrains the delivery of electricity by futures contracts is our inability to store electricity in its direct form. This property of electricity is not shared by other energy commodities traded in the futures markets such as natural gas and oil which can be stored in order to satisfy (pipe line) network capacity constraints over time. Electricity can be stored in a number of indirect ways. For example, hydro power can be generated by controlling dam water levels over time, thus allowing water to play the role of stored electricity.[6] The hydro storage capacity of electricity can be valuable in the marketplace but the amount of stored electricity in this form is quite small. It is also constrained by weather conditions and is available only in some geographical areas for certain seasons and time of the day.

The role of ensuring the technical constraints are satisfied, at every instant, in electricity markets, while still matching electricity demands to supplies, is delegated to the Independent System Operator (ISO). Currently, two different management technologies are used by US ISOs to do the job: centralized and decentralized methods. Since no a priori theory exists relating the ISO coordination method to the market behavior of various electricity prices, we will treat the ISO coordination method as a potentially important control factor in our empirical investigation of electricity prices.

The traditional form of electricity trading contract is the bilateral forward contract, which legally binds a seller and a buyer of electricity to exchange a pre-specified amount of electricity at a pre-specified future date. In regulated markets where electricity generators also own the transmission lines, bilateral contracts still provide the main method of organizing electricity delivery. Planning for the delivery of forward contracted electricity is a straightforward matter. Such forward contracts still determine about 50% of all electricity deliveries even in deregulated markets in North America.

In deregulated electricity markets, however, both consumers and producers of electricity can better manage their risk by hedging using not only forward contracts and spot purchases but also futures contracts and other financial derivatives such as options.

The primary objective of this paper is to empirically test certain theoretical hypotheses regarding spot, forward and futures prices. In particular we test these hypotheses in the context of standard models of stochastic processes of the type, which are typically assumed in empirical studies of financial derivatives in

(*footnote continued*)
utilities in California than to use it for their own production activities. These firms have chosen to pay their workers who do no production work while selling their electricity.

[3]See, for example, Bjorgan et al. (1999), Gedra (1994), Gedra and Varaiya (1993), and Kaye et al. (1990). See Hull (2003) for general references on financial derivatives and also the role of volatility in financial risk management involving derivatives.

[4]See, for example, Bellalah (1999), Hudson and Coble (1999), Silvapulle and Moosa (1999) and Susmel and Thompson (1997).

[5]See, for example, Barkovich and Hawk (1996); Hogan (1998), Heneault et al. (1999), Jessome and El-Hawary (1999), and Nakashima (2000).

[6]It is well known that the B.C. Hydro, a Crown Corporation in British Columbia, has taken advantage of its excess dam water capacity in the recent years to export for enormous profits its electricity to California.

efficient markets. This type of hypothesis testing seems essential for our understanding of the rapidly developing electricity markets, since electricity as an underlying asset of its financial derivatives does not have certain properties that many other commodities have. To our knowledge relatively little empirical research exists on this topic in the literature.

In this paper, we deal primarily with hypothesis about the first two moments of electricity spot and futures prices. We also discuss a few applications in which our results could be implemented. Our findings will be useful, for example, for understanding futures and spot price behavior in deregulated electricity markets and for formulating appropriate strategies to deal with the risk management issues facing both consumers and producers of electricity in such markets.

2. Electric power markets and delivery methods

Before the deregulation, the demand for electric power was assumed to be independent of the electricity price. The vertically integrated utility typically owned both the generators and the distribution systems. The operating rule of the utility was to satisfy all the demands while minimizing the total cost subject to certain technical constraints. In this optimization problem (called the optimal power flow problem), the utility decided the outputs of its generators based on the respective generators' marginal cost of production subject to constraints associated with the physical limitations of generators, transmission lines, and security constraints. To improve the security or voltage profile, the utility only had to change the output of generators or install new transmission lines to control the system conditions.

Once competition was introduced into the power generation sector and power generation was separated from power transmission, the problem of matching consumer demands and supplies was delegated to the ISO. The ISO clears the market by setting the market rules and prices.

ISOs are classified into two types based on the type of authority granted to the ISO: the centralized type and the decentralized type.

2.1. Centralized ISO (max-ISO)

The centralized ISO collects all bid information from sellers and buyers in the market and calculates optimal assignments between sellers and buyers by maximizing the social benefits arising from the use of the network subject to technical constraints. The centralized ISO has full control over flows in the network.

Centralized ISOs mimic vertically integrated utilities whose operational objective is to minimize the total cost of the operation while satisfying system-wide reliability constraints as well as generation, transmission, and reserves constraints.

Market participants are asked by the ISO to reveal their supply costs and demand values, and their technical constraints such as output limits. In its optimization process, the ISO must simultaneously take into account both the generation and transmission markets while satisfying a variety of constraints including inter-temporal factors such as startup commitments and constraints on generators' ramping rates. In the centralized ISO system, the ISO (and not the market) decides, for example, which generators will be committed at what time? In making such decisions the ISO uses the shadow prices (or equivalently the opportunity costs) it calculates as Lagrange multipliers for various technical supply demand balance constraints in their optimization problem.

As is well known, any centralized system suffers from issues associated with asymmetric information and moral hazard problems. For example, what incentives are there to prompt each market participant to provide the accurate information required by the ISO? What would prevent market participants from playing game with the ISO? The centralized ISO system also suffers from the potential manipulation by utilities with significant market power.

Examples of centralized ISOs are found in the Pennsylvania–New Jersey–Maryland Hub (PJM) and the UK markets.

2.2. Decentralized ISO (min-ISO)

Decentralized ISOs do not attempt to collect bid information from market participants. Rather, they collect the desired schedules of generator outputs and customer demands from the market participants, and reschedule their outputs and demands to satisfy the technical constraints. In this system, it is essential that the market participants agree to adjust their outputs, demands, prices and other bid parameters as requested by the ISO. Scheduling generator outputs and customer demands is done by power exchanges, which are not part of the ISO. The power exchange market is cleared based on bid information and bilateral contracts between individual market participants. (Note that in the centralized system the ISO plays the role of the power exchange.)

Other differences between decentralized and centralized systems are the following. In the decentralized system, the ISO does not consider dynamic costs or constraints associated with the market participants. For example, the ISO will not consider start-up costs or ramp-up down constraints. As a result it is important that the market participants internalize these costs and constraints before they enter the market. The decentralized ISO will not coordinate electricity and transmission markets either. It merely tries to accommodate the preferred schedules, which are settled on by the energy market outside the ISO, and to manage the transmission market. Failure by market participants, for example, to internalize their costs or to self-schedule accurately may lead to poor coordination.[7]

2.3. Mix-ISO

In practice, there is no pure min-ISO in operation. Rather we have mix-ISO systems in which centralized and decentralized components coexist. They are called a mix-ISO. For notational convenience we call mix-ISOs decentralized systems below. Examples of decentralized ISOs are found, for example, in California prior to its power crisis and Scandinavia.

3. Spot and futures prices of electricity

In this paper we study electricity spot prices observed for the two electricity exchange markets: Pennsylvania–New Jersey–Maryland Western Hub (PJM) and pre-power crisis California–Oregon Border (COB) markets. We also study electricity futures prices observed in the New York Mercantile Exchange (NYMEX) for electricity in the PJM and COB markets. The prices we use are the following daily prices: (1) Spot prices for Dow-Jones (DJ) electricity indexes: non-firm on-peak, non-firm off-peak, firm on peak and firm off-peak prices for COB; and firm on-peak price for PJM. (PJM has only one DJ electricity index.) (2) NYMEX futures prices for 1-month, 2-month and 3-month PJM and COB futures. Our price data are for the period from June 1, 1999–May 31, 2000.

3.1. Spot market

Because electrical systems require that demand and supply be continually balanced, the spot market is operated continuously. A failure to maintain the continuous demand-supply balance will destabilize the transmission system. The continuous balance is achieved by the system operator who conducts real-time balance operations based on engineering (rather than economic) considerations.

Day-ahead markets are used for matching electricity demands to supplies one day prior to the actual transaction dates, thus reducing significantly the number of spot market transactions. Day-ahead markets are used by both California and PJM to balance transmission on major lines. Because real-time energy demand can be typically predicted a day ahead within the 3% margin of error for each hour, spot market (real-time) operations by the system operator are usually limited to transactions involving local transmission lines.

In a fully centralized system a supplier must bid all its operable capacity in the day-ahead market and accept its assignments (real-time dispatches) by the system operator who re-optimizes the entire system every few minutes. In a decentralized system, however, suppliers are not controlled by the system operator. Hence, suppliers can deviate from the day-ahead schedules. Nevertheless the system operator is responsible for balancing the demand and supply at every moment. This reliance on the system operator's arbitrary balancing act is likely to generate a significant amount of economic inefficiency in decentralized systems.

3.2. Forward market

Both consumers and suppliers of electricity may hedge against future fluctuations in spot prices by entering into forward contracts. In the centralized system, consumers must enter into forward contracts with the pool operator and not directly with the suppliers. In the decentralized system consumers are free to enter into forward contracts with any suppliers. The ISOs must take these forward contracts into consideration in order to maintain a continuous balance between demands and supplies. Although the forward is a contract for the physical delivery of electricity, all forward transactions nevertheless are inherently financial since purchases or sales of electricity in the spot market can reverse forward commitments. Market participants often adjust (e.g. cancel) their forward positions before the forward contracts mature, based on contingencies arising in the spot market.

3.3. Futures market

Futures contracts deal with relatively short-term transactions (1–3 months) compared to forward contracts. Unlike in the forward markets, there is no distinction between futures for centralized and decentralized ISO systems. Even though many futures contracts are rolled over and expire prior to maturity, futures may influence electricity exchanges and ISOs' balancing operations to the extent that futures contracts are used to hedge against the future spot price of electricity.

3.4. Transmission rights

In the US, for example, the ISO, which is responsible for clearing the market has open access to the transmission system on nondiscriminatory terms. This

[7]Failures of this sort, caused by improper pricing schemes, may be to a large extent responsible for the recent power shortage problem in California.

does not mean, however, that all demands and supplies are matched precisely as planned because the flow of electricity obeys Kirchhoff's Laws and hence is largely uncontrollable. Consequently, it is typical that a point-to-point injection or withdrawal of electricity results in some transmission losses of electricity.

Transmission rights are actually financial rights, which allow the holder to reimburse the usage fees charged for the transmission of electricity, whether or not she transmits electricity. Hedging against usage fees or firm rights to physical access to transmission lines is an example of financial activities in the transmission market. We can interpret the transmission rights as consisting of the right to inject or withdraw power from the transmission grid at specific locations. When the right includes a scheduling priority, physical access is virtually assured.

In centralized systems like PJM, a financial right specifies injection and withdrawal points. This is necessary for optimization procedures for deriving nodal prices. It also allows us to set the auction price of the right to be the difference between the nodal prices. In decentralized systems like the one in California, each right pertains to the interface between two zones and includes both a financial hedge and scheduling priority.

4. Our models and hypotheses

4.1. Models

We assume that the electricity spot price, $S(t)$, follows the following stochastic process (an Ito process):

$$(\mathrm{d}S/S) = \mu\,\mathrm{d}t + \sigma\,\mathrm{d}z, \tag{1}$$

where $z(t)$ is a Wiener process and μ and σ are given scalar parameters characterizing, respectively, the instantaneous expected drift rate μS and the instantaneous variance rate $\sigma^2\ S^2$ (see, for example, Hull, 2003).[8] The parameter of our interest is σ which is also called the electricity price volatility.

Denoting the current time and the maturity date of a futures contract by t and T, respectively, the futures price for the underlying commodity, with no storage cost, is

$$F = S\mathrm{e}^{r(T-t)}, \tag{2a}$$

where r is the risk-free interest rate. On the other hand, suppose there are storage costs. Then if we denote by U the present value of all storage costs that are incurred during the life of the futures contract, then the futures price is given by

$$F = (S+U)\mathrm{e}^{r(T-t)}. \tag{2b}$$

If the storage costs are proportional to the price of the commodity, then $U = S\mathrm{e}^{u(T-t)}$ where u represents the storage cost as a proportion of the commodity price. Thus, (2b) becomes

$$F = S\mathrm{e}^{(r+u)(T-t)}. \tag{2c}$$

Using Ito's lemma[9] it can be shown that the futures price (2c) follows the following stochastic differential equation:

$$(\mathrm{d}F/F) = (\mu - r - u)\,\mathrm{d}t + \sigma\,\mathrm{d}z. \tag{3}$$

The above models assume that the investors hold the underlying commodities for investment purposes. (For example, silver and gold are thought to be such commodities.) There are also commodities, which are held by companies and individuals primarily for consumption purposes. When an underlying asset has consumption value, (2c), for example, need not hold. Rather we have

$$F \leqslant S\mathrm{e}^{(r+u)(T-t)}. \tag{4}$$

(Note, however, that arbitrageurs would not allow the inequality $F \leqslant S\mathrm{e}^{(r+u)(T-t)}$ to hold for too long.)[10]

The difference between the right and left sides of the inequality (4) is the convenience yield that corresponds to the net benefit to the owner of actually holding the underlying commodity. In general, the convenience yield depends on the likelihood of future shortages of the underlying commodity, particularly those, which are used in everyday production. If there are large local inventories of the commodity, then the convenience yield is likely to be small, reflecting little chance of shortages. (See, for example, Heinkel et al. (1990) and Susmel and Thompson (1997)).

The convenience yield, y, in the context of model (4) is defined as follows:

$$F = S\mathrm{e}^{(r+u-y)(T-t)}. \tag{5a}$$

Denoting the cost of carry by $c = r + u$, Eq. (5a) can be rewritten as

$$F(t) = S(t)\mathrm{e}^{(c-y)(T-t)}. \tag{5b}$$

One hypothesis which has been empirically tested for many underlying commodities is that the current futures price is an unbised estimate of the predicted future spot price:

$$F(t) = E_t(S(T)), \tag{6a}$$

which combined with (5b), implies that

[8] More generally, μ can be a function of time. Another type of model which is used to describe prices of electricity and other commodities incorporates the property of mean reversion and is given by $\mathrm{d}\ln S = [\theta(t) - a\ln S]\mathrm{d}t + \sigma\,\mathrm{d}z$, where a and σ are constants and $\theta(t)$ captures seasonality and trends. Our results below hold with minor modifications for this model with mean reversion.

[9] See, for example, Hull (2003, pp. 226–227). ITO's lemma.

[10] See, for example, Hull (2003).

$$E_t(S(T)) = S(t)e^{(c-y)(T-t)}. \tag{6b}$$

(Throughout this paper $E_t X$ denotes the expectation of random variable X conditional on all information available up to time t.)

Another hypothesis we consider below is derived from (5b) and relates the current futures price to the current spot price:

$$\ln S(t) = \ln F(t) - (c-y)(T-t), \tag{7}$$

where ln represents natural logarithm. If $y = 0$, then the log futures price exceeds the log spot price by the amount of the carrying cost. On the other hand, if $y > 0$, then $\ln F$ may be larger or smaller than $\ln S$ depending on the sign and magnitude of $(c-y)$. Eq. (7) implies, however, that as t approaches T, the difference in absolute value between $\ln S(t)$ and $\ln F(t)$ approaches zero and that the speed of convergence is $(c-y)$. As discussed above, the nature of convenience yields is unclear in the case of electricity; consequently it is of interest to empirically test (7) for electricity.

4.2. Hypotheses

4.2.1. Volatility

The first hypothesis we investigate in this paper is concerned with volatility of the spot price $S(t)$ and the futures price $F(t)$. The volatility of the commodity spot and futures prices has been of interest to both practitioners and researchers for a long time (e.g. Hennessy and Wahl, 1996). Volatility plays the central role in the risk management for the participants of markets involving uncertainty. For example, it is important for risk-averse consumers to know that the volatility of many commodity spot prices exhibits seasonality-in particular, it peaks in the summer (Anderson and Danthine, 1983; Kenyon et al., 1993). It is of interest to verify that this is also the case for electricity.

Electricity spot prices are also influenced by the delivery type and method: firm vs. non-firm delivery, and peak vs. off-peak delivery. In the first case, the demand for non-firm electricity is likely to be more random than the demand for firm electricity, the volatility for the non-firm electricity prices is expected to be higher than the volatility for the firm electricity prices. In the second case, on-peak periods involve more transactions of electricity than off-peak periods and hence the volatility for on-peak electricity prices is expected to be higher than the volatility for off-peak electricity prices.

Optimal hedging for producers and buyers of certain commodities involves the use of options on futures (Moschini and Lapan, 1995). Since the value of options on futures contracts depends on the second and higher moments of the futures prices, the volatility of futures prices is potentially important to producers of electricity. One of the most important hypotheses about the variability of futures price states that volatility increases as the time to the maturity of futures contracts approaches zero (time-to-maturity (TTM) hypothesis). The TTM hypotheses was originally conjectured by Telser (1958) and was later refined by Samuelson (1965). There are alternative interpretations of the TTM hypotheses. The hypothesis is consistent, for example, with the notion that volatility increases as the date of expiration draws near because the amount of information about market conditions at contract expiration that becomes available to market participants increases as the date of expiration approaches (Anderson and Danthine, 1983). We are interested in empirically testing the TTM hypothesis using publicly available data on electricity futures.

We summarize our hypotheses about volatility as follows:

(VH1) The volatility of electricity spot prices exhibits seasonality and peaks in summer.

(VH2) The volatility of electricity spot prices depends on the type of delivery. In particular, the volatility is higher for non-firm electricity than for firm electricity; and the volatility is higher for on-peak electricity than for off-peak electricity.

(VH3) The volatility of electricity futures prices increases as the time to the maturity (TTM) of the futures contracts approaches zero (time-to-maturity (TTM) hypothesis).

4.2.2. The relationship between futures and spot prices

We first consider the hypothesis given by Eq. (6a). Houthakker (1957) presents some evidence for wheat, cotton and corn prices during the period 1926–1950 that $F(t) < E_t(S(T))$, which suggests that it is possible to make profits by investing in long futures positions. More recently, Chang (1985) presents evidence which is consistent with Houthakker's conclusions. Telser (1958) studies cotton prices for the period 1926–1950 and wheat prices for the period 1927–1954. Gray (1961) studies corn prices for the priod 1921–1959. Both Telser and Gray concluded that (6a) couldn't be rejected. These results are of interest since, for example, the hedging strategies of the participants of electricity markets depend on whether (6a), or $F(t) < E_t(S(T))$ holds. To our knowledge this hypothesis has not been yet considered for the case of electricity.[11]

The second hypothesis we consider is based on (7). Because they share the same underlying asset (electricity in our case), spot and futures prices are expected to be closely related to each other. Eq. (7) represents such a relationship under our maintained hypothesized model (1). The commercial product characteristics used to

[11] Silvapulle and Moosa (1999) study this issue for crude oil.

price electricity are different for spot and futures markets. For example, spot prices depend on whether the electricity is to be delivered during peak hours, and on whether it to be delivered on a firm contract. However, there is no electricity futures contract, which is written for electricity with exactly the same type of product characteristics (i.e. firm and on-peak delivery). (This is in contrast, for example, to gold futures and spot prices, which are both measured per ounce of gold.) For these reasons we cannot directly test (6a) nor (7).

We will also test how the absolute difference between the left-hand and right-hand sides of (6a) or (7) behaves as t approaches the maturity date (T) of the futures contract. In the case of (6a) we expect that, as the information set at time t used for forecasting $S(T)$ becomes larger as t increases towards T, the absolute difference between $F(t)$ and $S(T)$ would decrease. Moreover, we would also expect the absolute difference between $\ln S(t)$ and $\ln F(t)$ (and hence $S(t)-F(t)$) decreases as $(T-t)$ decreases.[12] We summarize our hypotheses regarding the relationships between spot and futures prices as follows:

(RH1a) The futures prices $F(t)$ predicts the future spot price at $t=T$ (the futures contract maturity).

(RH1b) The difference in absolute value between the current futures price $F(t)$ and the future spot price at maturity $S(T)$ (equivalently $|\ln S(T)–\ln F(t)|$) shrinks as t approaches T, the time when the futures contract matures, or as $(T-t)$ approaches zero.

(RH2) The difference in absolute value between $\ln S(t)$ and $\ln F(t)$ shrinks as t approaches T, the time when the futures contract matures, or as $(T-t)$ approaches zero.

5. Empirical results

5.1. Volatility

The volatility of the spot price $S(t)$ is typically measured as standard error (s) or variance (s^2) of the first difference in the natural logarithm of $S(t)$ and is calculated as follows for discretely observed spot prices $\{S(t),\ t=0,1,2,\dots,T\}$ where $S(t)$ is the spot price observed at the end of period t:

$$s=\left[(1/T-1)\sum_{i=1}^{T}(u_i-u^*)^2\right]^{(1/2)}, \tag{8}$$

where

$$u_i=\ln(S_i/S_{i-1}),\quad i=1,2,\dots,T$$

[12]It is assumed throughout this paper that both $S(t)$ and $F(t)$ are positive for all values of t. We should note, however, that electricity prices could become negative because of the technical nature of electricity production.

and u^* is mean of the u_i. Assuming, for simplicity, that each time period is of length 1, s is a consistent estimate of σ in (1) with standard error given by $s/(2\,\mathrm{T})^{(1/2)}$. (See, for example, Hull, 2003, pp. 368–369.)

5.2. Hypothesis VH1

Tables 1A and B give estimates for s calculated using daily data for different time periods and also for different types of spot prices. Although precise statistical testing of seasonality in price volatility is not possible using only data for a single year, we see from both Tables 1A and B that volatility is generally higher for summer months than for other months (Hypothesis VH1). Tables 2A and B present volatility estimates for electricity futures prices. While we see that the volatility for the summer months tends to be higher than for other months, multiple years of data would be needed to identifying different types of seasonal patterns.

5.3. Hypothesis VH2

Next we consider Hypothesis (VH2). Table 1A gives our results for the volatility of COB spot prices. (Note that there are 30 volatility estimates for each of the 4 types of electricity (non-firm, on-peak; non-firm, off-peak; firm, on-peak; and firm, off-peak).) (i) On-peak electricity. The volatility estimates for non-firm electricity exceed the volatility estimates for firm electricity for 30 out of 30 cases. (ii) Off-peak electricity. The volatility estimates for non-firm electricity exceed the volatility estimates for firm electricity for 30 out of 30 cases. (iii) Non-firm electricity. The volatility estimates for on-peak electricity exceed volatility estimates for off-peak electricity for 20 out of 30 cases. (iv) Firm electricity. The volatility estimates for on-peak electricity exceed the volatility estimates for off-peak electricity for 27 out of 30 cases.

In order to investigate Hypothesis (VH2) further we ran a regression using our monthly volatility estimates using the four types of delivery data as the dependent variable.

The regression results reported in Table 3 show that volatility for the COB firm prices is significantly smaller than that for COB non-firm prices. The peak demand dummy, however, does not seem to have statistically significant effects on the spot price volatility. Also the presence of heteroskedasticity due to price becomes evident particularly when the monthly effects (seasonality effects) are controlled for, as in model (1) in Table 3. PJM prices show some positive price effects and monthly effects but they are not statistically significant due to the small sample size.

We conclude that our descriptive results (i)–(iv) generally support Hypothesis (VH2) for COB spot prices and that our regression results support the

Table 1
Volatility (standard deviation) for electricity spot prices

		Jun-99	Jul-99	Aug-99	Sep-99	Oct-99	Nov-99	Dec-99	Jan-00	Feb-00	Mar-00	Apr-00	May-00
(A) California– Oregon Border (Dow Jones Cob), June 1999– May 2000													
DJ COB non-firm on-peak	1 month	28.88%[a]	60.01%	47.07%	26.62%	22.92%	12.41%	15.89%	11.35%	17.90%	8.84%	28.19%	72.33%
	3 months	46.31%[b]	45.90%	33.64%	21.69%	17.68%	13.63%	15.33%	12.92%	19.25%	44.45%		
	6 months	36.29%[c]	34.84%	25.89%	18.73%	15.54%	16.67%	33.48%					
	12 months	34.81%[d]											
DJ COB non-firm off-peak	1 month	19.75%	32.19%	41.50%	23.62%	21.75%	20.85%	19.14%	12.32%	11.08%	11.82%	63.09%	28.49%
	3 months	31.85%	32.85%	29.95%	22.14%	20.71%	17.47%	14.55%	11.80%	36.79%	39.47%		
	6 months	27.46%	27.38%	24.73%	18.68%	16.79%	28.79%	29.85%					
	12 months	28.60%											
DJ COB firm on-peak	1 month	21.03%	28.06%	15.41%	18.13%	11.29%	15.80%	10.16%	9.75%	4.55%	2.87%	7.83%	33.64%
	3 months	21.88%	20.96%	14.90%	15.07%	12.40%	12.21%	8.58%	6.11%	5.30%	19.49%		
	6 months	18.74%	17.21%	13.60%	12.26%	9.83%	9.25%	15.14%					
	12 months	17.00%											
DJ COB firm off-peak	1 month	19.41%	11.21%	10.74%	8.26%	5.14%	11.57%	5.50%	5.43%	3.89%	4.65%	14.11%	13.35%
	3 months	14.04%	10.01%	8.25%	8.70%	7.99%	8.09%	4.88%	4.58%	8.56%	11.39%		
	6 months	11.67%	9.05%	8.16%	7.09%	6.48%	8.29%	8.82%					
	12 months	10.33%											
(B) Pennsylvania, New Jersey, Maryland Western Hub (Dow Jones PJM, Firm on-peak), June 1999– May 2000													
DJ PJM firm on-peak	1 month	50.69%[a]	72.24%	60.21%	13.71%	5.49%	14.07%	12.35%	24.57%	9.62%	8.74%	11.74%	39.36%
	3 months	61.08[b]	54.96%	35.45%	11.53%	10.92%	17.70%	16.98%	15.51%	9.78%	23.60%		
	6 months	44.10%[c]	39.48%	27.99%	14.42%	13.68%	14.29%	20.46%					
	12 months	34.19%[d]											

Note: these figures represent standard deviations calculated using the DJ day-ahead daily price index data. (See (8) and Data Appendix A in the text.)
[a,b,c,d]These figures represent standard deviations calculated using Dow Jones COB data for June 1999, for June–August 1999, for June–November 1999 and for June 1999–May 2000, respectively. Also, note that our notation used here for rolling volatility does not coincide with the industry practice. For example, 3-month August-99 volatility for DJ COB (non-firm, on-peak) reported in this table is calculated using data for August-99, September-99 and October-99. In industry this volatility is typically calculated using data for July-99, August-99 and September-99.

monthly seasonal patterns are statistically significant. However, the regression results do not support significant peak period effects (Table 3).[13]

5.4. Hypothesis VH3

In order to test the time-to-maturity (TTM) hypothesis (Hypothesis VH3) regarding futures price volatility, we consider the following regression specification:

$$V_t = a_0 + a_1(\mathrm{ttm})_t + \{\text{monthly dummy terms}\} + \varepsilon_t, \quad (9)$$

where V_t is volatility for futures contracts during month t, $(\mathrm{ttm})_t$ denotes time to maturity in months for the futures contract in month t, {monthly dummy terms} denotes dummies which control for monthly factors and ε_t denotes the equation error term. Under the TTM hypothesis we expect a_1 to be negative.

Estimation results for regression Eq. (9) are presented in Table 4. As expected under Hypothesis VH3, estimated coefficients of time to maturity $(\mathrm{ttm})_t$ in Table 4 are all negative (i.e. a_1 is negative in (9)) for each of the two specifications for both COB and PJM markets. This suggests that as futures contracts approach their maturity dates, their volatility increases, as expected. In particular, we are reasonably confident that this is the case for the COB market given that the estimated coefficients of $(\mathrm{ttm})_t$ for COB are both statistically significant. We are less confident to conclude that hypothesis VH3 holds equally well for the PJM market given that the estimated coefficients of $(\mathrm{ttm})_t$ for PJM in Table 4 are negative but not statistically significant. We tentatively conclude that the TTM hypothesis holds for COB futures prices well but not quite well for PJM futures prices. Further research would be required to determine whether this difference results from differences in the organization of COB and PJM electricity markets. We also see from models (2) and (4) in Table 4 that futures prices absorb some of the monthly (seasonality) effects for both COB and PJM markets, as expected.

5.5. Hypotheses RH1a, RH1b, RH2: the relationship between spot and futures prices

Using (6a) we can test Hypothesis RH1a using the specification

$$S(T) = b_0 + b_1 F(t) + b_2(T - t) + \mu_t, \quad (10)$$

[13]We do not have an explanation for this yet.

Table 2
Volatility (standard deviation) for electricity futures

	Jun-99	Jul-99	Aug-99	Sep-99	Oct-99	Nov-99	Dec-99	Jan-00	Feb-00	Mar-00	Apr-00	May-00
(A) California–Oregon Border (COB), Nymex, June 1999–May 2000												
Jul-99	4.35%[a]											
Aug-99	2.47%[b]	2.56%										
Sept-99	2.36%[c]	2.34%	2.51%									
Oct-99		1.44%	2.28%	2.46%								
Nov-99			1.63%	2.37%	1.65%							
Dec-99				1.72%	1.77%	3.13%						
Jan-00					1.54%	4.66%	1.97%					
Feb-00						1.58%	1.83%	2.72%				
Mar-00							2.11%	1.44%	2.00%			
Apr-00								1.64%	2.38%	1.46%		
May-00									2.20%	1.38%	1.45%	
Jun-00										1.29%	6.13%	5.60%
Jul-00											1.40%	5.66%
Aug-00												4.04%
(B) Volatility for electricity futures: Pennsylvania–New Jersey–Maryland Western Hub (PJM), Nymex, JUNE 1999–February 2000												
Jul-99	6.25%[a]											
Aug-99	3.45%[b]	5.26%										
Sept-99	1.70%[c]	1.38%	3.69%									
Oct-99		1.24%	0.45%	1.11%								
Nov-99			0.29%	0.58%	1.52%							
Dec-99				0.46%	0.71%	1.17%						
Jan-00					0.00%	2.17%	3.09%					
Feb-00						2.95%	1.91%	2.47%				
Mar-00							1.71%	0.31%	1.74%			
Apr-00								7.59%	1.60%	1.19%		
May-00									0.64%	19.65%	4.21%	
Jun-00										0.98%	2.29%	8.47%
Jul-00											1.47%	5.26%
Aug-00												5.17%

Note: these figures represent standard deviations calculated using daily futures price data. (See (8) in the text.)
[a,b,c]These figures represent standard deviations calculated using daily prices observed in July of 1-month futures (which expire at the end of July 1999), 2-month futures (which expire at the end of August, 1999) and 3-month futures (which expire at the end of September, 1999).

where b_0 and b_1 are regression coefficients and μ_t is a regression error term which is assumed to be independent over t and have mean zero. According to Hypothesis RH1, $b_1 > 0$ should be close to one if $F(t)$ is a good predictor of $S(T)$. We ran regressions with and without $(T-t)$ to see whether there was any time-to-maturity effect.

We can test Hypothesis RH1b using the specification

$$|\ln S(T) - \ln F(t)| = c_0 + c_1(T-t) + \gamma_t, \quad (11)$$

where c_0 and c_1 are regression coefficients and γ_t is a regression error term which is assumed to be independent over t and have mean zero. According to Hypothesis RH1b, $c_1 > 0$; thus, as $(T-t)$ approaches zero, the expected absolute forecasting error approaches zero. We can test Hypothesis RH2 using the specification (12)

$$|\ln S(t) - \ln F(t)| = d_0 + d_1(T-t) + \eta_t. \quad (12)$$

where d_0 and d_1 are regression coefficients and η_t is a regression error term which is assumed to be independent over t and have mean zero. According to Hypothesis RH2, $d_1 > 0$; thus, as $(T-t)$ approaches zero, the expected absolute forecasting error approaches zero.

Electricity futures contracts stipulate that the prespecified amount of electricity be delivered during the month following the contract expiry date. Consequently, in determining how to hedge their electricity futures, investors might use the spot price expected to prevail over the period $[T,\ T+1$ month$]$, rather than the expected spot price at time T. For this reason we estimate (10) using both the actual spot price observed on day T and the spot price averaged over the entire month as proxies for $S(T)$ in computing the dependent variable $|\ln S(T) - \ln F(t)|$.

Table 5 shows regression results for (10) and (11) for both COB and PJM markets using firm and on-peak spot prices. Model (1), for both COB and PJM markets,

Table 3
Spot price volatility regressions

	(1) COB	(2) COB	(3) PJM
Constant	0.019 (.116)[a]	.176*** (3.00)	−.078 (.440)
Price	0.010*** (2.59)	.003 (1.56)	.007 (1.15)
Firm	−0.180*** (6.00)	−.161*** (4.19)	—
Peak	−0.060 (1.20)	.010 (.235)	—
June	0.149 (1.12)	—	.221 (1.47)
July	0.195* (1.71)	—	−.225 (.315)
August	0.142 (1.29)	—	.279 (1.55)
September	−0.018 (.194)	—	—
October	−0.171** (2.41)	—	—
November	−0.044 (.461)	—	—
December	−0.022 (.204)	—	—
January	−0.079 (.651)	—	—
February	−0.079 (.758)	—	—
March	−0.100(.978)	—	—
April	0.148(1.31)	—	—
May	—	—	.097 (.606)
Adjusted R^2	.603	.265	.942
No. obs.	48	48	12

Note: Monthly volatility (see Tables 1A and 1B) is the dependent variable. Price is the monthly average spot price. Firm and peak denote, respectively, dummy variables, which equal one for firm and peak delivery and equal zero otherwise. June–May are monthly dummies.
*, ** and *** denote significance levels at 90%, 95% and 99%, respectively.
[a]Numbers in parentheses are standard errors.

shows that the futures price $F(t)$ does predict $S(T)$, the spot price at $t = T$, reasonably well. After controlling for time to maturity, $F(t)$ is an important predictor of $S(T)$. This seems to be consistent with hypothesis (RH1a).[14] The time to maturity variable, however, has a significantly positive coefficient for COB and a significantly negative coefficient for PJM. The same difference between the results for the two electricity markets is also found in models (3) and (4) in Table 5. As time t approaches the maturity date T of the futures contracts, the absolute log difference between the futures price $F(t)$ and the spot price at $t = T$ (or average $S(T + s)$) shrinks for both the decentralized (COB) and the centralized (PJM) market. This is consistent with RH1b. It is unclear at this time, however, whether the observed difference in the behavior of time to maturity between the Cob and PJM markets is caused by the difference in the structure (type) of the market.

Table 6 shows regression results for (12) for the COB and PJM markets. The dependent variable for these regressions is the absolute difference between log of spot and future prices at each point in time, t. The estimated slopes, the coefficients of the TTM terms, are positive, statistically significant and similar in magnitude for the COB and PJM markets. This suggests that electricity futures and spot prices tend to converge in absolute value as futures contracts approach their maturity dates. This is consistent with Hypothesis RH2. Theoretically, the coefficient of TTM represents the difference between the convenience yield (y) and the cost of carry ($c = r + u =$ interest + storage cost) for electricity. (See (5a) and (7).)

As we discussed earlier, the cost of carry (particularly storage cost) is likely to be very high for electricity but at the same time there is no known estimate for convenience yield for electricity and hence we have no a priori expectations about the sign or magnitude of $y - c$. Our estimation results for models (1) and (2) in Table 6 suggest that the convenience yield is higher than the cost of carry for electricity for both the COB and PJM markets. This is consistent with the notion that investors value the current secured supply of electricity at least as much as the future supply of electricity. The estimated constant term is considerably larger for the PJM market than for the COB market. This means that the absolute deviation of the futures prices from the spot prices after controlling for the time to maturity is on average larger for PJM than for COB markets. It is yet unclear whether this difference is due to the difference in the management style of the respective ISOs.

It is interesting to note that our regression results for the COB market (Table 6, model (1)) are similar to the results reported for model (3, COB) in Table 5 in which the dependent variable is the absolute difference between the log future price at maturity (($\ln S(T)$) and the log spot price ($\ln F(t)$). This is not the case for the PJM market (see model (3, PJM) in Table 5). We do not have a satisfactory explanation for this phenomenon.

6. Possible applications in risk management

Estimated price and volatility behavior is an important input for firms' decisions in risk management. In this section, we discuss a few of such decision problems for which our empirical results presented above could be used.

First, consider an electricity producer who wants to hedge against fluctuating prices. Since volume does not adjust perfectly to price changes in the electricity market, the producer's hedging strategy must consider not only price risk but also volume risk. We assume that volume risk is captured adequately by temperature. Suppose Y, P and T denote, respectively, the firm's profit for a month, average electricity price for the month and appropriate temperature variable for the

[14]The estimated coefficients of $F(t)$ in model (1) for COB and PJM are .882 and 1.02, respectively, and are statistically highly significant. However, the hypothesis that this coefficient is equal to one (the theorized value) is only accepted for PJM (but not COB) at a 99% level. This is also the case for model (2) in Table 5.

Table 4
Futures volatility and ttm hypothesis

	(1) COB	(2) COB	(3) PJM	(4) PJM
Constant	.077***(3.81)[a]	.014*(1.88)	−.084(1.61)	.029*(1.69)
Price	−.0003(.991)	.001***(3.11)	−.000(1.61)	.0003*(1.69)
Time to maturity	−.003*(1.64)	−.004*(1.80)	−.007(.875)	−.007(1.03)
June	−.028***(2.56)	—	−.029(.772)	—
July	−.037***(3.41)	—	−.041(1.01)	—
August	−.039***(3.16)	—	−.054(1.32)	—
September	−.038***(3.15)	—	−.062(1.34)	—
October	−.043***(3.59)	—	−.061(1.34)	—
November	−.030**(2.27)	—	−.048(1.04)	—
December	−.043***(3.04)	—	−.046(1.00)	—
January	−.043***(3.08)	—	−.034(.721)	—
February	−.040***(2.92)	—	−.055(1.20)	—
March	−.047***(3.64)	—	.005(.116)	—
April	−.029***(2.51)	—	−.039(1.12)	—
May	—	—	—	—
Adjusted R^2	.404	.226	.000	.048
No. obs.	36	36	36	36

Note: volatility for futures prices is the dependent variable (Tables 2A and 2B).
*, ** and *** denote significance levels at 90%, 95% and 99%, respectively.
[a]Numbers in parentheses are standard errors.

Table 5
Futures price as predictor of spot prices at maturity

Dependent variable	(1) $S(T)$	(2) av. $S(T+)$	(3) $\|\ln S(T)–\ln F(t)\|$	(4) $\|\ln \mathrm{av}S(T)–\ln F(t)\|$
COB market				
Constant	9.39*** (2.67)[a]	39.47** (2.41)	.207*** (11.2)	.152*** (9.32)
$F(t)$	.882*** (9.48)	–.059 (.903)	—	—
$T-t$	.082*** (3.55)	.004 (.268)	.001*** (3.81)	.001*** (4.35)
Adjusted R^2	.121	.000	.020	.029
No. obs.	653	535	653	595
PJM market				
Constant	2.31 (.994)	1.22* (1.91)	.283*** (17.7)	.188*** (18.0)
$F(t)$	1.02*** (23.5)	1.08*** (26.2)	—	—
$T-t$	−.057* (1.92)	−.056** (2.45)	−.00008** (2.45)	−.00008*** (3.73)
Adjusted R^2	.480	.560	.008	.024
No. obs.	652	594	652	536

*, ** and *** denote significance levels at 90%, 95% and 99%, respectively.
[a]Numbers in parentheses are standard errors.

month. Using historical data the producer first estimate the regression equation

$$Y = a + bP + cT + \varepsilon, \tag{13}$$

where ε is the regression error term. The producer can hedge risks for this month by taking the following positions: *a* position of -*b* in energy forwards or futures and a position of -*c* in weather forwards or futures.[15] Estimates for the prices and volatility of spot and futures prices of electricity are an important input in calculating this type of a hedging position. For example, our results suggest that: the volatility level the producer faces in the next month depends on the type of market (e.g. firm, non-firm, on-peak, off-peak) in which it wants to sell its electricity; and futures prices may predict spot prices reasonably well when the futures' maturity dates are near. The producer may be able to use this information in determining the degree of exposure it wishes to take.

As a second example, consider a peak-load plant, which produces electric power only when either increases in electricity price, decline in fuel prices, or both make electricity production profitable. Assume for simplicity the fuel used is natural gas and the only cost

[15]Hull (2003).

Table 6
Futures and spot prices of electricity

Dependent variable: $\|\ln S(t) - \ln F(t)\|$	(1) COB market	(2) PJM market
Constant	.139*** (10.1)[a]	.317*** (9.41)
$T-t$	.001*** (4.49)	.001** (2.09)
Adjusted R^2	.030	.005
No. obs.	653	652

*, ** and *** denote significance levels at 90%, 95% and 99%, respectively.
[a]Numbers in parentheses are standard errors.

incurred by production is the gas cost. (Thus we ignore such costs as distribution costs, marginal cost of production and maintenance costs.) The plant's profit (Y) is given by

$$Y = \max(S_E - \gamma S_G, 0), \tag{14}$$

where S_E and S_G are, respectively, the prices of electricity and natural gas and are assumed to obey standard stochastic differential equations of type (1) (or its mean-reversion version) and γ is a given heat rate which measures the plant's efficiency with which the plant turns natural gas into electricity. Since the plant is turned on only when profitable, owning the plant is like owning a strip of call options which mature daily.[16] Then, denoting by $F_{E,i}$ and $F_{G,i}$ the time 0 forward prices for electricity and gas delivered at time i, respectively, the value of the plant (V) which operates over the next n days (a given planning horizon) is given by

$$V = \sum_{i=1}^{n} ECall(F_{E,i}, \gamma F_{G,i}, \sigma_i, r, i, r), \tag{15}$$

where $ECall$ (x_1, x_2, x_3, x_4, x_5, x_6) is the European call price given by the Black-Scholes formula for the underlying asset price (x_1), the strike price (x_2), the volatility of the underlying asset (x_3), risk-free rate (x_4), time to expiration (x_5) and dividend yield (x_6). In our application, the underlying asset has volatility given by $(\sigma_i^2) = \sigma_{E,i}^2 + \gamma^2\sigma_{G,i}^2 - 2\rho\gamma\sigma_{E,i}\sigma_{G,i}$, where ρ is the correlation between the electricity and gas prices. In the previous section we have shown alternative estimates and properties for price volatility of electricity futures (forwards) and the relationships among them. For example, it is possible to derive alternative estimates for $\sigma_{E,i}$ over the plant's planning horizon i using time to maturity for certain types of markets.

We also note that, since all power-generating plants operate when electricity prices are high, the value of a peak-load plant lies in its capacity to shut down when the prices are low. This is seen by rewriting the above V using the put-call parity as follows:

$$V = \sum_{i=1}^{n} \mathrm{e}^{-ri}(F_{E,i} - \gamma F_{G,I}) + \sum_{i=1}^{n} EPut(F_{E,i}, \gamma F_{G,i}, \sigma_i, r, i, r) \tag{16}$$

or

$$V = \text{NPV(operate all the time)} + \text{option value (shut down when electricity prices low)}, \tag{17}$$

where the first NPV represents net present value of the plant operating all the time and the second term represents value of the put option to stop operation when the prices are low. If we include costs other than the cost of natural gas, such as the costs of production and maintenance, then the first term (NPV) above becomes $\sum_{i=1}^{n}\mathrm{e}^{-ri}(F_{E,i} - \gamma F_{G,I} - \text{additional costs})$ and the NPV term as a result will likely to be negative most of the time.[17] Under such conditions a peak-load plant only generates positive value by shutting down its generating capacity.

7. Concluding remarks

As the deregulation of electric power generation and delivery proceeds, more and more electric-power-intensive firms will face the on-going decision problem of how to meet their future needs for electricity. The firms decide on the delivery type and time, and the price of electricity. Hedging is to some extent possible by combining various types of financial derivatives written on electricity. The volatility of spot and futures electricity prices for various types of delivery plays an important role in these risk management decisions undertaken by the firms.

In this paper we have presented some limited empirical evidence first showing that the observed electricity prices exhibit certain volatility properties, which are known to hold for many other commodities for which futures markets exist. The results are interesting because electricity, unlike other commodities, cannot be stored. We have also shown that price volatility of electricity varies systematically depending on delivery type (e.g. firm vs. non-firm). This needs to be taken into account in firms' risk management in which price volatility is an important input. For example, a firm without self-generating capacity must decide how

[16]In practice a peak-load plant may be operated on an hourly basis (e.g. on during the day and off at night). If so, the options mature hourly.

[17]Strictly speaking the Black-Scholes formula gives only an approximate solution when these costs (which are not lognormally distributed) are included in the model (McDonald (2003)). Numerical methods are available for this type of problems.

much of its electric power needs should be met by electricity purchased from non-firm versus firm sources while taking into account carefully the risks of both delivery types. Such risks would include the possibility of not being able to operate the firm's factories and the excessive cost the firm must pay to secure firm delivery of its electricity needs.

We have also shown that electricity futures prices tend to approach spot prices as their expiry dates approach and that there are systematic relationships between futures and spot prices over time. The relationship between electricity futures and spot prices depends on the cost of carry, convenience yield and other factors, which in turn, depend on region-specific technical and transmission conditions.

Acknowledgements

The authors thank the Editor and an anonymous reviewer of this journal for helpful comments on the earlier version of the paper.

Data Appendix A

The daily electricity prices we have used in this paper are briefly explained in the following.

California– Oregon Border (Dow Jones, COB) Data, June 1999– May 2000

Spot market prices

There are 4 types of Dow Jones spot market prices for COB: (i) non-firm on-peak, (ii) non firm off-peak, (iii) firm on-peak and (iv) firm off-peak prices. We have data on these prices for Monday through Saturday for non-firm on-peak, firm on-peak and firm off-peak types. Non-firm off-peak data that exist for Monday through Sunday. Firm electricity and peak periods of delivery are defined as follows.

Firm electricity: electricity that meets the minimum criteria for secure supply and for being financially firm and backed by liquidating damages.

Non-firm electricity: electricity whose supply may be interrupted for any reason at any time.

On-peak hours: 6:00 a.m.–10:00 p.m., every day, prevailing time.

Off-peak hours: 10:00 p.m.–6:00 a.m., every day, prevailing time.

The DJ spot firm and non-firm electricity prices for COB and PJM markets used in our paper are calculated as indexes using the day-ahead prices in the respective markets. The specific procedure used by Dow Jones is given in the following (see Dow Jones (1998) for details).

Firm Daily Price Indexes: The firm daily indexes average together blocks of power sold on a one-day forward pre-scheduled basis. No real-time power is included in these indexes. Transactions are limited to power traded in 16-hour blocks during on-peak hours and 8-hour blocks for off-peak. Transactions, which call for delivery for more than 1 day are not included in calculations for these indexes. Volume should be reported as total megawatts (MW) transacted per hour.

Non-firm Daily Price Indexes: The non-firm indexes combine one day ahead pre-scheduled transactions with real-time transactions. The non-firm indexes follow the same convention as the firm indexes with respect to single day delivery. Volumes reported should reflect the total number of MWh transacted during the on- or off-peak reporting period.

Futures prices

The New York Mercantile Exchange (NYMEX) futures market trades electricity futures for 1-month ahead, 2-months ahead and 3-months ahead products. Our prices exist for Monday through Friday since June 1st, 1999. NYMEX COB electricity futures expire on the last day prior to the month of delivery. If that day of expiry is Saturday or Sunday, then the futures expire on the last business day prior to the day of expiry. For example, three-month October futures for the month of July actually expire on September 30th.

Pennsylvania, New Jersey, Maryland Western Hub (Dow Jones, PJM, firm on-peak), June 1999– May 2000

The type of data that exists for the PJM spot market are for firm on-peak electricity which are given for Monday through Friday. (See above for the specific procedure used by Dow Jones for generating PJM spot price indexes.) Data on NYMEX 1-month ahead, 2-month ahead and 3-month ahead electricity futures exist for the PJM market, as for the COB market. NYMEX futures for the PJM market expire on the 28th of a relevant month. If the 28th day of the month is Saturday or Sunday, then the futures expire on the last business day prior to the 28th day of the month.

References

Anderson, R., Danthine, J., 1983. The time pattern of hedging and the volatility of futures prices. Review of Economic Studies 50, 249–266.

Barkovich, B., Hawk, D., 1996. Charting a new course. IEEE Spectrum, 26–31.

Bellalah, M., 1999. Valuation of futures and commodity options with informational costs. Journal of Futures Markets 19, 645–664.

Bjorgan, R., Liu, C.-C., Lawarree, J., 1999. Financial risk management in a competitive risk market. IEEE Transactions on Power Systems 4, 1285–1291.

Chang, E., 1985. Returns to speculators and the theory of normal backwardation. Journal of Finance 40, 193–208.

Gedra, T., 1994. Optional forward contracts for electric power markets. IEEE Transactions on Power Systems 9, 1766–1773.

Gedra, T., Varaiya, P., 1993. Markets and pricing for interruptible electric power. IEEE Transactions on Power Systems 8, 122–128.

Gray, R., 1961. The search for a risk premium. Journal of Political Economy 69, 250–260.

Heinkel, R., Howe, M., Hughes, J., 1990. Commodity convenience yields as an option profit. Journal of Futures Markets 10, 519–533.

Hennessy, D., Wahl, T., 1996. The effects of decision making on future price volatility. American Journal of Agricultural Economics 78, 591–603.

Heneault, M., Galoana, F., Gross, G., 1999. A review of restructuring in the electricity business, Paper Presented in the 13th PSCC Conference, Trondheim, June 28–July 2.

Hogan, W., 1998. Getting the prices right in PJM: what the data teaches us. Electricity Journal 11, 61–67.

Houthakker, H., 1957. Can speculators forecast prices? Review of Economics and Statistics 39, 143–151.

Hudson, D., Coble, K., 1999. Harvest contract price volatility for cotton. Journal of Futures Markets 19, 717–733.

Hull, J., 2003. Options, Futures, and Other Derivatives, fifth ed. Prentice-Hall, NJ.

Jones, D., 1998. Wholesale Electricity Price Indexes: Palo Verde. Dow Jones, New York.

Jessome, D., El-Hawary, M., 1999. A simulated deregulated electric market for Atlantic Canada, Paper Presented at the Canadian Electrical Association (Generation Operations Management Section), Vancouver, Canada, March.

Kenyon, D., Jones, E., MaGuirk, A., 1993. Forecasting performance of corn and soybean harvest futures contracts. American Journal of Agricultural Economics 75, 399–407.

Kaye, R., Outhred, H., Bannister, C., 1990. Forward contracts for the operation of an electricity industry under spot pricing. IEEE Transactions on Power Systems 5.

McDonald, R.L., 2003. Derivatives Markets. Addison-Wesley, Boston.

Moschini, G., Lapan, H., 1995. The hedging role of opinions and futures under joint price, basis, and production risk. International Economic Review 36, 1025–1049.

Nakashima, T., 2000. Coordination and decision making of regulation, operation, and market activities in power systems. Ph.D. Thesis, Department of Electrical and Computer Engineering, University of British Columbia, Vancouver, Canada.

Samuelson, P., 1965. Proof that properly anticipated prices fluctuate randomly. Industrial Management Review 6, 41–49.

Silvapulle, P., Moosa, I., 1999. The relationship between spot and futures prices: evidence from the crude oil markets. Journal of Futures Markets 19, 175–193.

Susmel, P., Thompson, A., 1997. Volatility, storage and convenience: evidence from natural gas markets. Journal of Futures Markets 17, 17–43.

Sweeney, J.L., 2002. The California Electricity Crisis, Publication No. 513. Hoover Institution Press, Stanford, CA.

Telser, L., 1958. Futures trading and the storage of cotton and wheat. Journal of Political Economy 66, 233–255.