Mika Goto*
G. Andrew Karolyi**

Understanding Electricity Price Volatility Within and Across Markets

Abstract

This study analyzes how electricity price volatility evolves over time for different electricity trading hubs in several deregulated markets around the world. The goal is to uncover common features across hubs within each market in the daily spot price volatility processes related to seasonality, mean reversion, conditionally autoregressive heteroskedasticity (ARCH) and possibly time-dependent jumps. We apply our analysis to markets in U.S., Nord Pool, and Australia. We show that ARCH and time-dependent jumps are important statistical features of price volatility across all hubs in each market but with different levels of intensity. We also find that inferences about the role of seasonality components are sensitive to modeling of the ARCH and jump features.

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* Research Economist, Socio-economic Research Center, Central Research Institute of Electric Power Industry, Ohtemachi, Chiyoda-ku, Tokyo 100-8126, Japan, Phone: +81 (3) 3201-6601, Fax: +81 (3) 3287-2805, Email: mika@criepi.denken.or.jp.

** Charles R. Webb Professor of Finance in the Fisher College of Business, Ohio State University, Columbus, Ohio 43210-1144, U.S.A. Phone: (614) 292-0229, Fax: (614) 292-2418, E-mail karolyi@cob.osu.edu.

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1. Introduction

Markets for electric power in many countries around the world are rapidly deregulating the processes for power generation and distribution. What regulators had previously controlled by fixing prices as a function of supply costs now represents a competitive interaction of complex supply and demand forces, resulting in dynamic and uncertain electricity prices. Factors that influence aggregate demand among local-market distributors by electricity spot market include weather, season, and the regional concentration and location of retail customers; while aggregate supply is influenced by the location of generators, their market concentration, the transmission structure and the bidding and auction process of the market. As a result, deregulated prices in these markets are characterized by volatility that varies over time and occasionally reaches extremely high levels, commonly known as "price spikes." Understanding the volatility process is critically important to distributors, generators and market regulators as it influences the pricing of derivative contracts traded on electric power prices that allow them to better manage their financial risks.

How different factors influence the volatility process is complex and still represents an important research challenge in spite of dozens of studies that have been devoted to this question in the fields of economics, statistics, mathematics, and engineering. Our study contributes to this literature by focusing on uncovering common features in the electricity price volatility processes not only across markets but also across different electricity-trading hubs within these markets. Specifically, we adopt general and flexible econometric models that allow for the possibility of seasonality, mean reversion, conditionally autoregressive heteroskedasticity (ARCH) behavior and time-dependent jumps and apply it to daily spot (on-peak) prices for multiple trading hubs and areas in the U.S., Nord Pool, and Australia. These markets are worthy of study, not only because they represent among the largest competitive markets for wholesale electric power in the world, but also because they offer interesting institutional features among the different markets. This is useful because what differentiates electricity is its non-storability as a commodity and the low price elasticity of demand, which exacerbates the impact of supply and demand shocks, and the complex physical constraints, which govern the flow of power within transmission networks. Our central hypothesis is that factors unique to specific markets, such as weather, the size and concentration of local generators, distributors, and the retail market, lead to locational price differences. However, we also postulate that common physical features of electricity, combined with basic technologies of transmission network systems, should also lead to commonalities of volatility behavior of the prices, even though the markets are geographically diverse.

We uncover several interesting findings. We show that the ARCH and time-dependent jumps are very important statistical features of price volatility across all hubs and areas in each of the three markets. However, the magnitude and persistence of the volatility process and the magnitude and intensity of the jumps are varied. It appears that institutional features of these different markets play an important role in explaining these cross-market variations. Finally, we find that inferences about the role of seasonality components are sensitive to the modeling of ARCH and jump features.

The rest of the paper is organized as follows. Section 2 outlines the related literature on electricity price behavior to clearly distinguish our contribution. Section 3 then describes briefly the institutional features of the U.S., Nord Pool and Australian power markets. The data and a preliminary statistical analysis follow in Section 4. Our models and the main estimation results are provided in Section 5, and finally, Section 6 summarizes the study's findings and outlines potential future research initiatives.

2. Background Literature on Electricity Price Behavior

The literature on electricity pricing is vast. Some studies focus on statistical and mathematical modeling of the stochastic properties of prices, while others employ economic equilibrium models of the supply and demand functions for pricing. Many consider agency-based modeling of the different players and their objective functions to examine strategic bidding. Market power among suppliers and even distributors (less than perfectly elastic demand curves) is used to explain price behavior. Finally, there are large numbers of studies of transmission pricing, efficiency gains from deregulation, valuation of generation and transmission facilities. In this section, we focus our attention on those studies that relate to the causes of electric price volatility.

2.1. Statistical and Mathematical Models of Spot Price Dynamics

Electricity demand is heavily influenced by economic and business activities and the weather. However, demand is usually characterized as highly inelastic because electricity is a necessary commodity (Stoft, 2002, Part 1). When there are low levels of demand, generators supply electricity using base-load units with low marginal costs. But during summer and winter seasons, certain days of the week, and even within the day itself (on-peak versus off-peak hours), higher quantities are needed and generators with higher marginal costs enter into the system. Such seasonal factors have been studied in McMenamin and Monforte (1997), Knittel and Roberts (2001), Lucia and Schwartz (2002), Escribano, Pena and Villaplana (2002) and Guthrie and Videbeck (2002). For example, consider Lucia and Schwartz (2002) who analyze Nord Pool's spot, futures and forward prices and conclude that seasonal systematic patterns are of crucial importance in explaining the shape of the futures/forward curve and show that a simple sinusoidal function is adequate to characterize the pattern. This paper utilizes average daily prices and so focuses the investigation on weekly and monthly seasonal patterns.

Since increases in demand push up prices, there are increasing incentives for the more expensive generators to enter the supply side, so that some degree of mean-reversion is expected in prices that makes the price return back to the former level. Most studies employ mean-reverting models (Deng, 2000, Robinson, 2000, Knittel and Roberts, 2001, Escribano et al., 2002), although some allow for non-mean-reverting behavior (De Vany and Walls, 1999). Some show that there are interesting interactions on the degree of mean-reversion in the price process with other features such as time-varying conditional volatility and price spikes. Deng, specifically, incorporates multiple jumps, regime-switching and stochastic volatility into a number of mean-reversion models and show how sensitive real-option-based models of physical assets in generation and transmission can be.

Volatility in electricity prices varies over time with weather-related and other demand and supply forces and it is likely to be mean-reverting itself for similar reasons outlined above. Bodily and De Buono (2002) propose a mean-reverting proportional volatility model and find empirical support with intraday prices over constant volatility, geometric Brownian motion models.[1] Robinson and Baniak (2002) employ nonparametric techniques to test for changes in volatility around key supply-driven events in the U.K. (most notably, the expiry of Northern England coal contracts in 1993). Duffie and Gray (1998) propose ARCH models for heating oil, natural gas, crude oil and electricity prices but show the limitations of the functional model for electricity, which show results close to integrated (non-mean-reverting, or "explosive") processes for volatility. Knittel and Roberts (2001), Escribano et al. (2002) use generalized ARCH (GARCH) models for electricity prices and ensure stationarity in volatility when price spikes are captured by separate jump-diffusion processes. Deng (2000) also emphasizes the importance of modeling jump processes in electricity prices, especially as they relate to monthly seasonal factors.

2.2. Equilibrium Models of Spot and Derivative Prices

Futures, forward and options contracts exist in a number of electricity markets and spot price dynamics are important for pricing these contracts. Most studies in this literature seek equilibrium prices of the derivative prices, though some evaluate the volatility, volume and maturity effects of these contracts for the underlying spot prices and volatility. Examples of equilibrium models of pricing and hedging in forward markets include Kellerhals (2001), Bessembinder and Lemmon (2002), Lucia and Schwartz (2002) and Longstaff and Wang (2003). Longstaff and Wang show that the forward premia for day-ahead prices in the Pennsylvania-New Jersey-Maryland (PJM)

[1] This is a meaningful alternative specification, since a number of mathematical models of electricity prices propose one-factor diffusion models with constant volatility. See, for example, Skantze, Gubina and Ilic (2000) and Barlow (2002). Another mathematical approach dispenses with time-series dynamics and sets up the pricing as a linear-programming algorithm (Hogan, Read and Ring, 1996).

hub in the U.S. is related to price uncertainty, which they model as a GARCH process, as well as demand uncertainty and price shocks, which they model from load dynamics. Kellerhals employs a stochastic-volatility model, which he operationalizes with a Kalman-filtering algorithm.

Cross-hedging between electricity and other energy derivatives markets is the focus in a number of studies because of the limited liquidity of the electricity forward markets. Woo, Horowitz and Hoang (2001) demonstrate the effectiveness of cross-hedging electricity prices in one hub using "strip" contracts to purchase power in other hubs; Emery and Wilson (2002) do the same for cross-hedging with natural gas futures. Pirrong and Jermakyan (2001) show that forward premia embedded in day-ahead PJM prices are related to weather derivatives.[2] Deng, Johnson and Sogomonian (2001) examine how traded exotic electricity options can be used to value generation and transmission assets. Finally, Walls (1999) shows that there is strong evidence of increasing volatility in spot and forward prices as futures contract maturity dates approach, even after controlling for the volume of trade.

2.3. Market Design, Market Power and Pricing

Numerous studies in industrial economics show how the design of markets can influence price behavior.[3] The attributes of markets that these studies focus on include the price elasticity of demand, concentration of ownership and capacity of generators, generation technology, organization of electricity pools (whether participation is

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[2] Routledge, Seppi and Spatt (1999) develop equilibrium forward curves for commodities and apply it to the "spark spread" in electricity markets.

[3] Parts 3, 4 and 5 of Stoft's (2002) book on designing markets for electricity features detailed discussion of market architecture, market power and locational pricing, including power transmission, and transmission rights. Borenstein (2000) delineates carefully the arguments for and against market power and the importance of understanding market structure, in general.

voluntary or mandatory), transmission market structure and pricing, types of auctions (uniform versus discriminatory) and supply-curve bidding rules. With some exceptions, careful time-series modeling of spot prices is not emphasized in these studies. Wolak (2000), one such exception, examines the design of electricity markets in England and Wales, Nord Pool, Australia and New Zealand and confirms that industries with a larger component of private participation in the generation market are associated with higher volatility of prices. He also shows that markets with mandatory participation in pools have higher price volatility. Johnsen, Verma and Wolfram (1999) examine different pools in the Nord Pool market and show that prices are sensitive to periods with and without binding transmission constraints. Mount (2001) shows that the U.K. experienced an unusual pattern of price spikes associated with the use of market power by the two dominant generators; he develops a model of a uniform versus discriminatory price auction and shows that the former exacerbates price volatility.[4]

Mansur (2001), Vucetic, Tomsovic and Obradovic (2001), and Puller (2002) offer clinical studies of the PJM market during the summer of 1999, California during the summer of 1999, and the California power crisis in 2000, respectively, in which they relate price spikes to non-cooperative oligopoly behavior. In the same vein, Bernard, Gordon and Tremblay (1997) present evidence that electricity prices in Quebec were manipulated during elections for partisan gain by the incumbent nationalist government.

These studies emphasize the important differences in the institutional features of the electricity markets around the world and their impact on pricing and volatility. We address some of these features in our comparative analysis.

[4] Rassenti, Smith and Wilson (2001a, 2001b) provide experimental evidence on demand-side bidding and discriminatory price auctions.

3. The Electricity Supply Industry in the U.S., Nord Pool and Australia

3.1. United States

The 1978 Public Utilities Regulatory Policies Act (PURPA) and Energy Policy Act (EPAct) enacted in 1992 initiated U.S. deregulation from a collection of regulated, regional monopolies to a competitive market of independent power producers and distributors. There are over 3,000 electric utilities in the U.S. that deliver power to customers. Most utilities ("wired companies") are exclusively distribution utilities that are owned by municipals, purchasing wholesale power from those that generate power and distribute it over transmission lines owned by the larger "merchant power" utilities to customers.[5] About 50 percent of net electricity generation is thermal (coal-fired) followed by nuclear (20 percent), natural gas (18 percent) and hydropower (7 percent).[6]

The U.S. bulk power system has evolved into three major networks, or power grids: Eastern Interconnected System, Western Interconnected System and the Texas Interconnected system. Utilities within each power grid coordinate operations and buy and sell power among themselves. Reliability planning and coordination is conducted by the North American Electric Reliability Council (NERC) and its ten regional councils. Electricity flows over all available paths of the transmission system to reach customers. The major trading hubs (with acronyms in parentheses) are Cinergy (CIN, Ohio, Indiana), California North-Path 15 (NP15), California and Oregon Border (COB), Four Corners (FC, for Utah, Colorado, New Mexico, Arizona), Palo Verde (PV, Arizona), Mead

[5] *The Restructuring of the Electric Power Industry*, Energy Information Administration (http://www.eia.doe.gov/).
[6] *Annual Energy Review*, Energy Information Administration (http://www.eia.doe.gov/).

(MEAD, Nevada), Mid Columbia (MID, Washington), Entergy (Missouri), New York, New England and PJM.

For the majority of hubs, an independent system operator (ISO)[7] and three-tiered market, i.e., day-ahead, hour-ahead and real time markets, have failed to develop; rather, a combination of traditional tariff-based utility pricing, wholesale price matching, bilateral purchases, and sales contracts is used to commit, schedule, and dispatch power (DOE/EIA, 2000). In contrast, in New England, New York, the PJM Interconnection, and California, a three-tiered trading structure consisting of a "day-ahead" market, an "hour-ahead" market, and a "real-time" market was designed in order to ensure that market performance would match the grid's reliability requirements. Although the volume of the wholesale electricity trading has been growing rapidly in the US, the majority of the volume is traded via bilateral contracts with and without brokerage.

3.2. Nord Pool

The Nordic Power Exchange, or "Nord Pool," is one of the oldest spot and futures electricity markets in the world. It is a voluntary market for electric power contracting that has its roots in the liberalization of the electricity sectors in the Nordic countries (Norway, Sweden, Denmark, and Finland) starting in Norway with the Electricity Act of 1991. About 99 percent of Norway's and 46 percent of Sweden's electricity generation comes from installed hydroelectric capacity; 55 percent of Finland's and 87 percent of Denmark's power is generated by thermally (coal-fired).[8] While generation ownership is a mix between public and private sectors, it is highly concentrated (Wolak, 2000). For

[7] Independent System Operators (ISOs) are regionally-based non-profit entities created by state regulators to manage the transmission grid in their area and maintain reliability by making a real-time spot and day-ahead forward market.
[8] *Nordel Annual Report 2002*, Nordel (http://www.nordel.org/).

example, Norway's state-owned Statkraft supplies over 50 percent of the Norwegian electricity market.

Nord Pool organizes a physical market, called "Elspot," and a financial market, "Eltermin" which also provides clearing services. Elspot is a spot market where electric power contracts for day-ahead physical delivery are traded for each of the 24 hours of the day. A liquidity grows firmly in the Nord Pool, which results in about 32% of the total electricity consumption is traded at Nord Pool in 2002. A system price for each hour is defined as the market-clearing price for the entire exchange area when no transmission constraints apply. A balancing or regulation market operates in each Nord Pool member country to manage transmission bottlenecks resulting from trade (e.g. Sweden's Svenska Kraftnät and Finland's Fingrid); the costs of balancing trade is recouped with a capacity fee in market settlement. Nord Pool's Eltermin financial market allows trading in forward and futures with delivery periods up to three years in advance.[9]

3.3. Australia

Prior to 1997, electricity supply in Australia was provided by vertically-integrated publicly-owned state utilities with little interstate grid connections or trade. The Australian National Electricity Market (NEM) was created in 1997 from the merger of the Victoria pool and the New South Wales (NSW) pool and the NEM Management Company (NEMMCO), a self-funding company owned by participant states, jointly manages system operations. There are now five trading areas (Australian Capital Territory, NSW, Queensland, South Australia and Victoria), all of which are interconnected. Australia runs about 80 percent coal-fired generation (15 percent

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[9] *The Nordic Power Market: Electricity Power Exchange across National Borders*, Nord Pool (http://www.nordpool.no/).

renewable, hydro) and most of the consumption is in the eastern states of NSW, Victoria and Queensland. Generation capacity exceeds 43 gigawatts (GW).[10]

Generation of power is highly concentrated: in Victoria, there are five generators and five distribution companies, whereas in NSW, there are two generation and six distribution companies. In 2003, all electricity consumers were able to choose between electricity retailers. Bids are used to construct a "merit order" and generation is scheduled according to this merit order and regional spot prices are calculated for each five-minute period from actual supply and demand. Hourly and half-hourly prices are constructed as the average price of these five-minute prices. Supply curve bidding by generators can be in price-quantity pairs and 10 such pairs can be submitted each day. Re-bids and default-bids can be issued under certain restrictions.[11] NEM is a mandatory auction market in which generators of 30 MW or larger compete. NEMMCO manages the wholesale electricity market and settles the short-term forward market.

4. Data and Preliminary Statistical Analysis

4.1. Data

Table 1 presents a data description of the electricity price series in our study.

Insert Table 1 here

For the U.S., price data are based on Dow Jones Electricity Price Indexes and are drawn from Datastream International. These are volume-weighted price indexes based on Dow Jones Firm, On-Peak, daily, one-day-ahead spot price indexes, and are

[10] See http://www.esaa.com.au/ for details on history, system conditions, market structure, ownership, concentration and types of bidding systems.

denominated in U.S. dollars per MWh. We have price data for eight different trading hubs (CIN, COB, FC, MEAD, MID, NP15, PV and PJM) from May 19, 1997 to the end of 2002. The trading volume data measured in MWh is also provided by Dow Jones Electricity Price Indexes for those eight hubs.[12]

The Nord Pool data is also from Datastream International and constitutes daily average spot prices obtained from wholesale price transactions at each area and are denominated in Norwegian Kroner (NOK) per MWh. The nine different trading areas are Aarhus (ARH, Denmark), Bergen (BER, Norway), Copenhagen (COP, Denmark), Helsinki (HEL), Kristiansand (KRI, Norway), Oslo (OSL, Norway), Stockholm (STO, Sweden), Tromso (TRM, Norway) and Trondheim (TRN, Norway). The daily data extend as far back as January 1993 and up till February 2003.

The Australian data (December 1998 to January 2003) is obtained from NEMMCO (www.nemmco.com.au) and represents both hourly prices and total demand data. We compute demand-weighted daily electricity prices from on-peak hourly prices (7 am to 10pm, weekdays) and the prices are denominated in Australian dollars per MWh. The five trading areas in the transmission network for which we obtain data are New South Wales (NSW), Queensland (QLD), South Australia (SA), Snowy (SNO, Australian Capital Territory) and Victoria (VIC).

4.2. Unit Root Tests and Summary Statistics

Figure 1 Panels A to C present the time series for daily prices for three representative series in each of the three markets.

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[11] Demand-side bidding is basically not allowed and wholesale customers cannot bid into the pool, except some special cases for the purpose of the demand side management.

[12] The volume data are obtained from the Central Research Institute of the Electric Power Industry (CRIEPI) of Japan.

Insert Figure 1 here

Comparisons across the price level figures show notable differences in volatility overall. For example, Nord Pool prices exhibit clear cyclical variability compared with either the U.S. or Australian prices. In all three sets of price figures, the volatility is dominated by episodes of extremely high prices. For example, NP15 in the U.S. averages prices around $25 to $50 per MWh, but during California power crisis in 2000 and 2001, prices had been much higher, in the hundreds of dollars, sometimes spiking above $500 per MWh during peak demand periods. The Australian prices for NSW and QLD show a greater frequency of extreme price spikes than any of the other series.

Table 2 presents the Augmented Dickey Fuller (ADF) and the Phillips-Perron (PP) tests for unit roots using prices series.

Insert Table 2 here

The statistics are reported for each series in each of the panels associated with the U.S., Nord Pool and Australia. The ADF and PP tests are based on τ statistics or Dickey Fuller t statistics, and its variation, z statistics, respectively. Those statistics follow the empirical distribution obtained from the experiment, because it is known to be difficult to derive the complex distribution analytically. The null hypothesis is a unit root process. Moreover, we compute the statistics for each of three different cases (Hamilton, 1997). In Case 1, we estimate a model without a constant or a time trend. Case 2 estimates a model with a constant, and finally, Case 3 estimates a model with a constant and a time trend. We use the asymptotic critical values for each test and case computed by methods similar to those of MacKinnon (1991) (see page 708 in Davidson and

MacKinnon, 1993). We denote significance levels at the 1 percent, 5 percent and 10 percent levels.

In most cases for all the markets, we are able to reject the null hypothesis of a unit root in price series at the 1 percent significance level. Some exceptions are for the Case 1 tests in the Nord Pool market, which we cannot reject the null hypothesis for the Case 1 even at the 5 percent level in BER, COP and KRI by both statistics, and in OSL and TRN by ADF τ statistics. However, we can reject the null for all the other cases in the Nord Pool. Although we find that some of the price data do not indicate robust stationarity near their respective critical values of test statistics, we determine to use the original price data series in this study without any data conversion such as log difference aiming to mitigate possible unit root biases. The treatment seems to be reasonable if we consider the risk for masking the important features of the price series of electricity by using log difference data transformations.

Table 3 presents summary statistics for the daily price series for each hub in each of the three markets.

Insert Table 3 here

We report the mean, coefficient of variation (*CV*) or relative standard deviation, minimum, maximum, skewness, kurtosis and Ljung-Box statistics based on the autocorrelations up to three lags for both the prices and squared prices series. Average levels of the daily prices series vary in each market, from the lowest 37 $/MWh for PJM to the highest 89 $/MWh for MEAD and NP15 in the U.S., from 155 NOK/MWh for OSL to 217 NOK/MWh for COP, and from 41 for NSW to 68 for SA in Australia. The daily coefficient of variation statistics of the prices are, on average, very high and widely dispersed across trading hubs in the U.S. and Australia, while they are relatively low and uniform in the Nord Pool. For example, in the U.S. the coefficient of variation ranges from 68% at PJM to 225% at CIN, from 126% at SNO to 230% at SA in Australia, and yet from well within a range of 45% (ARH) to 56% (BER, HEL) in Nord Pool. It is worthwhile to recall Figure 1 for NP15 which clearly shows that the 2000-2001 price spike outliers greatly influence this average coefficient of variation (119%) for the period of analysis.

All of the series exhibit positive excess skewness with coefficients higher than 0.5, and they all display high positive excess kurtosis, with coefficients sometimes over a 100 in the U.S. and Australia. These are again likely to signify fat-tailedness due to very large price spike outliers. The magnitude of the kurtosis statistic is aligned with the magnitude of the range defined by the maximum and minimum in each series. Finally, these series do exhibit some serial correlation in the prices. The Ljung-Box statistics are distributed as a chi-squared with n degrees of freedom according to the number of lags. The critical values for 1, 2 and 3 lags at the five percent level are 3.84, 5.99 and 7.81, respectively. The null of no autocorrelation is strongly rejected at this level of significance for all of the prices series and squared prices series. One concern is that this autocorrelation in the series is induced by the presence of price spikes and higher order autoregressive dependence in the prices that stems from GARCH-like effects.

5. Model Specification and Estimation

5.1. Model Specification

In section 2, our survey of the existing literature on electricity prices suggests that for a reasonable model of electricity prices, we should include some kind of seasonality, the possibility of mean-reversion, time-dependent jumps and time-varying volatility. To simultaneously introduce the GARCH and the jump component for our electricity price analysis, this study applies the procedures of Das (2002) to electricity prices data.[13] We propose to introduce a mean-reversion specified in a deterministic term using a seasonal factor of monthly dummies, a lagged dependent variable and a volume variable,[14] which describes a central tendency of the price development over time. The time-varying volatility with a GARCH specification and jumps are included in a stochastic term of our model. The jump effects are examined for both the time-independent case and the time-dependent case. These models will be applied commonly across all the series. Our objective is not to search for the optimally specified model for each series, but to choose a particular specification that can reveal interesting differences and commonalities across electricity prices over all trading hubs/areas within a country and across countries.

Our general model contains three specifications. The first specification (R1) includes no jump process, the second specification (R2) includes a jump process but without time-dependent intensity and the third specification (R3) includes a jump process for which the jump intensities are seasonally dependent. Specifically, our models for the prices series P_t are described as follows.

Model R1: No jump, but include seasonals in the mean, GARCH (1,1). Let,

$$P_t = d(t) + e_t, \tag{1.}$$

$$d(t) = b_0 + b_1 \cdot P_{t-1} + c_1 \cdot Volume + \sum_{r=2}^{12} M_r D_r^M \tag{2.}$$

[13] Das (2002) enhanced the Gaussian model to include jump and ARCH-type process and applied it to the analysis of the interest rate behavior, while Escribano et al. (2002) applied the same type of models to various wholesale electricity prices around the world. Our general discrete model is based on an "ARCH Poisson-Gaussian" model originally proposed by Das.

[14] Because we do have volume series only for the U.S. electricity prices, we condition the prices on volume for the estimation of the U.S. It is dropped for the other markets in our sample.

where D_r^M are monthly dummy variables (February, March, etc.), and

$$e_t = \sigma_t \varepsilon_t , \tag{3.}$$

$$\sigma_t^2 = h_t = \omega + \alpha \cdot e_{t-1}^2 + \beta \cdot h_{t-1} , \tag{4.}$$

$$\varepsilon_t \sim \text{i.i.d. } N(0,1) . \tag{5.}$$

Model R2: With jump but no time-dependent intensity, GARCH (1,1). Let,

$$P_t = d(t) + S_t , \tag{6.}$$

where *d(t)* is defined as (2) to be a deterministic mean for the data. Here we assume that jumps occur with the arrival intensity λ_t which is governed by the Poisson distribution, and the jump size is determined by the normal distribution with mean, μ_J, and variance, σ_J^2. Then, S_t represents a stochastic term of the prices that is described as,

$$S_t = \begin{cases} h_t^{1/2} \cdot \varepsilon_t , & \text{With prob.} 1 - \lambda_t , \\ h_t^{1/2} \cdot \varepsilon_t + \mu_J + \sigma_J \cdot \varepsilon_{Jt} , & \text{With prob.} \lambda_t , \end{cases} \tag{7.}$$

where ε_{Jt} distributes with is i.i.d. $N(0,1)$.

Model R3: With time-dependent jumps, GARCH (1,1). Let,

$$P_t = d(t) + S_t , \tag{8.}$$

where *d(t)* is defined as (2) and S_t is defined as (7), but the jump arrival intensity is specified to be seasonal dependent as follows,

$$\lambda_t = l_1 \cdot \text{Winter}_t + l_2 \cdot \text{Fall}_t + l_3 \cdot \text{Spring}_t + l_4 \cdot \text{Summer}_t , \tag{9.}$$

where:

$Winter_t$, = 1 in December, January and February, and 0 otherwise,
$Fall_t$ = 1 in September, October and November, and 0 otherwise,
$Spring_t$ = 1 in March, April and May, and 0 otherwise,
$Summer_t$ =1 in June, July and August, and 0 otherwise.

The mean prices function, *d(t)*, allows for a constant, lagged prices series over one period, a contemporaneous sensitivity to volume and eleven monthly dummies in each of the three models (R1, R2 and R3). Models R2 and R3 introduce a Poisson-distributed random variable, λ_t, which corresponds to the likelihood that a jump occurs, and a measure of the jump size that corresponds to a random variable normally distributed with mean μ_J and standard deviation σ_J. We assume that all variables of prices, jump intensity and jump-size are independently distributed with each other. Essentially, the volatility process for the residuals from the mean prices function, S_t, has two regimes (basic low regime and jump added high regime) and our specification has the flexibility to shift between the regimes stochastically. The difference between R2 and R3 derives from a deterministic specification that the Poisson-distributed random variable of jump intensity will vary across seasons (Eq. 9). The basic volatility process itself follows a GARCH(1,1) process and is governed by (non-negative) parameters ω, α, and β. The positivity restriction is needed to guarantee positive conditional variances. If $\alpha + \beta < 1$, the variance is mean-reverting, where its unconditional mean equals $\sigma^2 = \omega/(1 - \alpha - \beta)$.

The models are estimated by maximum likelihood. Estimation of the parameter vector involves the following maximization in respect of the transitional probability $f(\cdot)$:

$$Max \sum_{t=1}^{T} \left[\log(f[P_t | P_{t-1}])\right] \qquad (10.)$$

where,

$$f[P_t | P_{t-1}] = \lambda_t \exp\left[\frac{-(P_t - f(t) - \mu_J)^2}{2(h_t + \sigma_J^2)}\right]\frac{1}{\sqrt{2\pi(h_t + \sigma_J^2)}} + (1-\lambda_t)\exp\left[\frac{-(P_t - f(t))^2}{2(h_t)}\right]\frac{1}{\sqrt{2\pi(h_t)}}. \qquad (11.)$$

This process approximates the true Poisson-Gaussian density using a Bernoulli mixture of the normal distributions (Das, 2000).

5.2. Estimation Results

Table 4 presents the summary of the models and main estimation results for the various markets in the United States (Panel A), Nord Pool (Panel B) and Australia (Panel C).[15]

Insert Table 4 here

Coefficient estimates are presented for each of the three different specifications with the log-likelihood function value (LL) and Schwarz-Bayes Information Criterion (SBIC). Statistically significant coefficients are denoted by superscript "*" and "**" at the 5 percent and 1 percent significance levels.

Panel A for the U.S. markets provides several interesting findings. First, the dependence on trading volume is weak for some hubs such as MEAD, MID and NP15, and often insignificantly different from zero. For the other hubs, however, the parameter is positive and significant, which implies a tendency that the prices increase when the traded volumes increase related to the demand-supply relations. Second, the deterministic seasonal dummies in the mean prices equation (not reported) are almost never significant except a few months for some hubs, in which the prices peaks (positive coefficients) are often obtained in summer months (CIN, FC and PJM), but the inferences are sensitive to the model used. For MID, all monthly dummies are significant with minus signs, but the results seem to be distorted by the influence of the excess positive

[15] For FC in the U.S. the volume data is not available and the parameter is omitted. We also drop the parameter estimates for the monthly dummy variables to conserve space. These are available from the authors upon request.

constant term, and when jump processes are allowed, the significance of the dummies disappears. Third, the GARCH parameters are reliably different from zero. Moreover, the autoregressive component, β, is large and averages around 0.70, except models R2 and R3 in CIN and PJM where the parameter values are around 0.25. While that of the lagged squared residual, α, shows adverse tendency, which is large in both (R2 and R3) models of CIN and PJM with values around 0.65. The parameter is also over 0.7 in the model R1 for CIN, COB, MID and PJM. For the other hubs, the averages are around 0.25.

The sum, $\alpha + \beta$, is close to one, so that shocks to the conditional volatility process are highly persistent. If the sum exceeds one, this result implies that the volatility forecast is explosive. This is a very unappealing result since the predictions of the model will be meaningless for any risk management applications. Fortunately, these explosive volatility circumstances occur only when no jump component is allowed, i.e., R1 models only. For example, in the case of PJM, the sum equals 0.71 + 0.62 or 1.33 for the R1 model, but, for R2, the autoregressive coefficient declines to 0.62 + 0.23, and for R3 with seasonal-dependent jump intensities, it declines even more so to 0.58 + 0.22. This change of volatility parameters across models are generally observed in all hubs. Finally, likelihood ratio tests and the Schwarz-Bayes Information Criterion uniformly imply that the models with jump components dominate. Whereas the specification of constant jump process (R2) and one with seasonal-dependent jump intensity (R3) is not nested and the comparison is not straightforward, the likelihood for the R3 is greater, suggesting that the specification with seasonal-dependent jump intensity provides a better fit than that of constant jump process. This is supported by the fact that almost all the seasonal jump parameters are significantly estimated.

There are strong common features to the jump and GARCH-like features of prices in the different trading hubs. The conditional volatility dynamics are remarkably similar and the series only differ in terms of the unconditional volatility and that is captured by the constant, ω. Typically, the jump probability, λ, is statistically significant and ranges from 0.0134 (MID) to as high as 0.1005 (PJM). The jump-size mean, μ_J, and standard deviation, σ_J, vary across models but are estimated with statistical significance in all models and hubs. In the most general models, R3, the time-dependent jump probability coefficients are almost all significantly different from zero, and show a much higher coefficient in the summer (l_4) for CIN and PJM which accords with intuition on the regions with the highest seasonal volatility in temperatures.

Panel B presents results for the nine Nord Pool series. There is no volume series, so the results are not directly comparable to the U.S. series, but given the economically and statistical weakness of those results we proceed. The deterministic seasonal function for the mean prices is not unusual (again, not reported), except for strange results that we obtain in model R1 for ARH, HEL, STO, TRM and TRN. In each of these cases, all of the monthly dummies are significantly different from zero, most likely because of an unusual price spike that occurs in January, which yields an unusually high or unusually low constant, b_0. This is confirmed by the fact that these unusual results abate when the jump processes are explicitly modeled in R2 and R3. Such excess constant term and over-estimated seasonal dummies are also observed in the model R1 for MID in the U.S. The GARCH processes for the Nord Pool series imply that the volatility processes are all close to integrated for the simplest model R1, i.e., the sum $\alpha + \beta$ exceeds one in the model R1 for all areas. Again, however, when the jump processes are accounted for, the volatility process is not close to a unit root, decreasing to around 0.80 to 0.85, but it still has persistence. For example, for STO, the volatility series has $\alpha + \beta$ equal to 1.42 (1.00 + 0.42) without the jump process (R1) and 0.76 (0.40 + 0.36) with the jump process (R2). Actually, the degree of persistence is much smaller than for the U.S. series; the β coefficients range from 0.34 to 0.49 in model R2 and from 0.34 to 0.48 in R3.[16]

The jump probability coefficient, λ, is always statistically significant and ranges from 0.044 (HEL) to 0.183 (COP), which is higher than the results for the U.S. The jump-size coefficients on the mean, μ_J, and standard deviation, σ_J, are all statistically significant, but the levels vary depending on the areas. The highest value of σ_J is 133.24 in the model R3 for HEL. The other areas with high σ_J are ARH and STO, which are over 100. For the other areas, it ranges from around 27 to 73. For model R3, the seasonal dependence of the jump probability is reliably significant across Nord Pool series, and it clearly indicates the seasonal pattern of much higher l_1 (winter), and also l_4 (summer) coefficient values in ARH and COP. Again, the likelihood function as well as Schwartz-Bayes values for the R3 is greater, suggesting that the specification with seasonal-dependent jump intensity provides a better fit than that of constant jump process. This is again supported by the fact that almost all the seasonal jump parameters are significantly estimated.

The estimation results for Australia are shown in Panel C. There is little robustness of the monthly seasonal dummies in the mean prices function across

[16] β is much smaller in the models R2 and R3 for COP, but they are statistically insignificant.

specifications (again, not reported), as we saw with the U.S. and Nord Pool results. That is, the monthly dummies are almost significant in model R1, but the significance disappears except a few months in R2 and R3, and the signs of parameters are not consistent across models and areas. Also, an excess constant term and over-estimated seasonal dummies are clearly observed in model R1 for NSW and SA, and QLD to some extent. The volatility processes are also integrated and explosive in R1 specifications. For example, in NSW, $\alpha + \beta$ equals 5.01 + 0.28 or 5.29. As with the other countries/regions, this misspecification of the volatility process is mitigated by the inclusion of jump components. The jump probability coefficients are lower for the Australian series compared with those for Nord Pool, but slightly higher than those in the U.S., λ averages between 0.049 (SNO) and 0.125 (QLD). While the mean and the standard deviation coefficients for jump size are relatively larger than those for the other two markets, and they are statistically significant. For QLD, the mean, μ_J, exceeds 118 and the standard deviation coefficient, σ_J, is over 192 in R2 and R3 models. The jump size parameters are even larger for SA: they are over 120 for the mean and over 225 for the standard deviation in both models (R2 and R3).

Seasonal dependence in the jump probability is significant, and we can recognize seasonal differences among dummies. For NSW, l_1 (which is summer in Australia) is 0.09 and it is about two to three times as large as the coefficients for the other three seasons. These distinctions are important in all five trading areas in the Australian market, the more general model with seasonal-dependent jump probabilities provides higher log-likelihood in our estimation than more restrictive model with constant jump probabilities.

For all hubs/areas, the jump seasonality is clearly captured by the seasonal difference of the probabilities. These findings suggest that the statistically significant jump is commonly observed in all markets, but the jump features are different among the U.S., Nord Pool and Australia. In Australia, relatively large jumps occur, but the jump arrival rate is not as great as that of Nord Pool. In the Nord Pool markets, relatively small jumps occur but with greater frequency. The U.S. markets lie in the middle of the two extremes in Nord Pool and Australia, but the standardized jump mean is comparably high in MID and COB. Jump seasonality is important for all price series. It is implied that some of these features are closely related to the institutional structure of markets. This offers support for previous studies that suggest that compulsory participation in pools, such as in Australia, tends to cause large price spikes (Wolak, 2000).

5.3. Residual Diagnostics

Table 5 presents summary statistics for the standardized residuals for each of the three models for each price series by hubs/areas.

<u>Insert Table 5 here</u>

Overall, the standardized residuals still retain large positive skewness and excess positive kurtosis. Compared to those reported in Table 3, there are both larger and smaller cases for the skewness and kurtosis depending on markets and hubs/areas. This suggests that what appears to have been successful modeling of jump processes and time-varying conditional volatility still leaves large clusters of extreme outliers unexplained, which are likely significantly affected by price jumps that our jump-volatility models fail to capture. That is, there remain important unexplained systematic components in the series across all data series, which likely represent important sources of model misspecification bias. Another feature of the residual diagnostics is that there is still a strong autoregressive component in the residuals for many of the series in the R1 specification. However, the autocorrelation evidence almost disappears in the R2 and R3 specifications. Exceptions include COB, PV and NP15 in the U.S. at all lags, and COP and OSL in Nord Pool at all lags. For all the other series, the Ljung-Box statistics cannot reject the null of white noise for up to three lags.

It is important to note that one of the purposes of the models specified in R2 and R3 is to estimate the arrival probability of jumps, not to exactly forecast when the jumps occur. This basic structure of the models is related to the biased residuals shown in Table 6. It may be an empirical limitation of the models to meet white noise residuals conditions when we combine the GARCH process with a jump process in an integrated model, but this issue is beyond the scope of this study.[17]

6. Conclusions and Future Research

Deregulation in markets for electricity has introduced uncertainty in the competitive prices set in different trading hubs and areas within those markets. In this paper, we have shown that there is considerable volatility in electricity prices and that this volatility varies over time and at times can reach extremely high levels, especially during peak-load seasons, like summers. We have presented models of electricity price volatility that incorporate these features of seasonality, time-varying conditional volatility

[17] For the purpose of forecasting electricity price behaviors, some simulation-type modeling such as a multi-agent modeling and a large-scale optimization modeling may be useful (see Bunn, 2004).

and jumps that fits price series in the U.S., Nord Pool and Australia reasonably well. Moreover, they accord well with economic intuition for each of these markets.

The most important contribution of our study, however, is the finding that these various features have strong common elements across the different trading hubs and areas within and across countries/regions of the world. In addition to the mean-reversion with seasonal changes, for example, there are GARCH attributes in all of the volatility processes that we examine, but we also find that the degree of persistence is remarkably similar even though there are important institutional differences in the markets around the world. Similarly, the importance of modeling jump dynamics with a seasonal dependency is common to all series in the three regions we study, although the degree of the jump size and the jump arrival intensity are different among markets and hubs/areas, which may be reflecting some influence of different conditions of markets in respect of institutional structure, weather, composition of generator and distributors, and demand and supply balance, etc.

We caution our readers that our modeling exercise in not complete. The residual diagnostic analysis clearly shows that there are important systematic patterns that our current modeling effort has ignored or misspecified. A logical extension, for example, is to consider asymmetric shocks to the volatility process, as in Knittel and Roberts (2001), while based on the flexible specification that we have introduced. The idea is that large positive shocks are likely to have larger and most persistent impact on future conditional volatility than negative shocks due to convexity or nonlinearity in the supply process from generators.

An even more important extension is to develop multivariate models that capture the joint simultaneous dynamics in the conditional volatility and jump processes across markets or the joint dynamics with the other energy commodities. Some early investigations along this line include DeVany and Walls (1999), but, even more recently, Worthington, Kay-Spratley and Higgs (2003) and Davies and Minton (2003). One advantage is parsimonious specifications in which the price dynamics in any one trading hub in a network is proportional to a common factor (e.g. factor ARCH model of Engle, Ng and Rothschild, 1992; Kroner and Ng, 1998). Another advantage is that there may exist cross-correlations or "lead-lag" effects in electricity prices and volatilities across trading hubs that can possibly reveal the economic importance of physical constraints in the flows associated with transmission grids in networks.

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Table 1. Data Description

The table describes the data collected for the three countries/regions studied in this paper – U.S., Nord Pool and Australia. We present the sources, from which the data is collected, the construction of the daily price series for the empirical analysis, when needed, as well as the data period. For the U.S. data, there are eight price indexes. For Nord Pool, there are nine price series, and there are five price series for the Australian data.

Country	Sources	Construction	Data Period
U.S.	Price data are based on Dow Jones Electricity Price Indexes obtained on Datastream. Proprietary volume from Central Research Institute of Electric Power Industry (CRIEPI).	Volume-weighted price indexes are based on Dow Jones firm, on-peak, daily one-day forward electricity Indexes. Units are in $/MWh.	Cinergy, *CIN*: Sep./8/98 – Dec./19/02 California & Oregon Border, *COB*: May/19/97 – Dec./19/02 Four Corners, *FC*: Sep./14/98 – Dec./19/02 Mead Marketplace, *MEAD*: Aug./8/00 – Dec./19/02 Mid-Columbia, *MID*: June/1/98 – Dec./19/02 North Path 15, *NP15*: Dec./18/00 – Dec./19/02 Palo Verde, *PV*: Aug./27/96 – Dec./19/02 Pennsylvania, New Jersey & Maryland, *PJM*: Apr./24/98 – Dec./19/02
Nord Pool	Datastream	Daily average spot prices are obtained from Datastream. Units are in Norwegian Kroner per megawatt hour (NOK/MWh).	Aarhus, *ARH*: July/1/99 – Feb./3/03 Bergen, *BER*: Jan./1/96 – Feb./3/03 Copenhagen, *COP*: Oct./2/00 – Feb./3/03 Helsinki, *HEL*: Dec./29/97 – Feb./3/03 Kristiansand, *KRI*, Jan./1/96 – Feb./3/03 Oslo, *OSL*: Jan./1/93 – Feb./3/03 Stockholm, *STO*: Jan./1/96 – Feb./3/03 Tromso, *TRM*: Jan./2/95 – Feb./3/03 Trondheim, *TRN*: Jan./1/96 – Feb./3/03
Australia	Both hourly prices and demand data are obtained from the National Electricity Market Management Company Ltd website: www.nemmco.com.au	Demand-weighted daily electricity prices are constructed from on-peak hourly prices. On-Peak hours are defined as 7a.m. – 10p.m., weekdays. Units are in A$/MWh.	New South Wales, *NSW*: Dec./7/98 – Jan./31/03 Queensland, *QLD*: Dec./7/98 – Jan./31/03 South Australia, *SA*: Dec./7/98 – Jan./31/03 Snowy, *SNO*: Dec./7/98 – Jan./31/03 Victoria, *VIC*: Dec./7/98 – Jan./31/03

Table 2. Unit Root Tests

The table presents the hypothesis that the prices of the 22 data series used in this study have unit root processes. Descriptions of the data are presented in Table 1. Stationarity is tested using the Augmented Dickey-Fuller (ADF) τ-test and Phillips-Perron (PP) z-test. The ADF τ-test and the PP z-test are based on the following specifications:

Case 1: $\Delta p_t=\zeta_1\Delta p_{t-1}+ \zeta_2\Delta p_{t-2}+ \zeta_3\Delta p_{t-3}+ \rho p_{t-1}+\varepsilon_t$;

Case 2: $\Delta p_t=\zeta_1\Delta p_{t-1}+ \zeta_2\Delta p_{t-2}+ \zeta_3\Delta p_{t-3}+\alpha+\rho p_{t-1}+\varepsilon_t$;

Case 3: $\Delta p_t=\zeta_1\Delta p_{t-1}+ \zeta_2\Delta p_{t-2}+ \zeta_3\Delta p_{t-3}+ \alpha+\rho p_{t-1}+\delta t+\varepsilon_t$.

p_t is the electricity price or return at time t. The error terms $\{\varepsilon_t\}$ are assumed to be Gaussian white noise processes for the ADF statistics, but the assumptions on no autocorrelation and invariant variance are not required for the PP statistics. *, [a], [b], *denotes significance at the 1%, 5% and 10% level respectively.*

Panel A: U.S.

Statistics	Case	CIN	COB	FC	MEAD	MID	NP15	PV	PJM
ADF τ Statistics	1	-8.83*	-5.88*	-4.48*	-2.55[a]	-5.69*	-2.95*	-4.71*	-4.12*
	2	-10.64*	-7.10*	-6.03*	-3.52*	-6.88*	-3.39[a]	-6.21*	-9.92*
	3	-10.67*	-7.25*	-6.13*	-4.82*	-6.90*	-4.07*	-6.52*	-9.98*
PP z Statistics	1	-13.64[a]	-12.52[a]	-5.38	-3.27	-11.51[a]	-3.38	-5.92[b]	-6.39[b]
	2	-15.30[a]	-15.37[a]	-7.26	-4.68	-14.18[a]	-4.02	-7.86	-13.86[b]
	3	-15.31	-15.75	-7.39	-6.45	-14.23	-5.01	-8.28	-13.92

Panel B: Nord Pool

Statistics	Case	ARH	BER	COP	HEL	KRI	OSL	STO	TRM	TRN
ADF τ Statistics	1	-2.27[a]	-1.66[b]	-1.34	-2.20[a]	-1.63[b]	-1.88[b]	-1,84[b]	-1.84[b]	-1.72[b]
	2	-7.29*	-3.86*	-3.63*	-5.16*	-3.82*	-4.46*	-4.43*	-4.38*	-4.09*
	3	-9.14*	-3.87[a]	-4.07*	-6.44*	-3.83[a]	-4.59*	-4.48*	-4.49*	-4.12*
PP z Statistics	1	-3.52	-1.75	-1.49	-2.86	-1.83	-1.99	-2.50	-2.23	-2.11
	2	-12.82[b]	-4.03	-4.11	-7.33	-3.99	-4.66	-6.72	-5.46	-5.13
	3	-15.28	-4.04	-4.60	-9.20	-4.00	-4.80	-6.78	-5.57	-5.16

Panel C: Australia

Statistics	Case	NSW	QLD	SA	SNO	VIC
ADF τ Statistics	1	-5.24*	-7.43*	-10.74*	-5.45*	-7.86*
	2	-9.29*	-10.48*	-14.29*	-8.90*	-11.82*
	3	-9.67*	-10.55*	-14.61*	-9.04*	-11.88*
PP z Statistics	1	-16.62*	-19.61*	-26.91*	-16.49*	-19.04*
	2	-22.82*	-23.13*	-30.83*	-23.21*	-22.89*
	3	-23.00[a]	-23.17[a]	-30.83*	-23.30[a]	-22.89[a]

Table 3. Summary Statistics

The table presents summary statistics for the daily prices of the 22 data series used in this study. Descriptions of the data are presented in Table 1. Coef. Of Var. (%) is the coefficient of variation that measures the ratio of the standard deviation of prices to mean price in percent. LB(*n*) and $LB^2(n)$ denote the Ljung-Box test of significance of autocorrelations of *n* lags for the daily prices and daily squared prices series, respectively. The critical values for 1, 2 and 3 lags are 3.84, 5.99 and 7.81 at the five percent level, respectively.

Panel A: U.S.

	CIN	COB	FC	MEAD	MID	NP15	PV	PJM
Mean (US$/MWh)	38	68	63	89	75	89	56	37
Coef. of Var. (%)	225	180	121	99	178	119	127	68
Min.	14	8	11	15	1	18	9	17
Max.	1900	3200	547	498	3322	513	537	348
Skew.	19	11	3	2	11	2	3	6
Kurt.	388	256	9	3	230	2	11	48
LB(1)	466	935	1620	672	872	550	1910	583
LB(2)	565	1750	3050	1280	1620	1040	3600	756
LB(3)	644	2360	4290	1810	2210	1470	5040	827
$LB^2(1)$	307	31	1280	543	37	477	1500	283
$LB^2(2)$	312	50	2190	979	58	821	2550	314
$LB^2(3)$	318	54	2760	1260	66	1070	3190	318
No. of Obs	1111	1706	1831	766	1542	600	2177	1167

Panel B: Nord Pool

	ARH	BER	COP	HEL	KRI	OSL	STO	TRM	TRN
Mean (NOK/MWh)	180	166	217	160	166	155	169	161	166
Coef. of Var. (%)	45	56	50	56	55	55	53	53	54
Min.	44	26	87	53	29	17	43	24	23
Max.	987	831	831	991	831	831	991	831	831
Skew.	4	3	3	4	3	3	3	3	3
Kurt.	24	12	11	24	13	13	17	15	13
LB(1)	460	1780	537	1070	1780	2540	1580	1930	1690
LB(2)	820	3480	1030	2030	3490	4980	3050	3760	3300
LB(3)	1080	5120	1470	2900	5130	7320	4460	5520	4830
$LB^2(1)$	302	1740	543	859	1740	2480	1280	1820	1600
$LB^2(2)$	506	3350	1030	1600	3360	4780	2430	3490	3050
$LB^2(3)$	620	4830	1440	2240	4840	6890	3470	4990	4370
No. of Obs	936	1849	609	1329	1849	2630	1849	2109	1849

Panel C: Australia

	NSW	QLD	SA	SNO	VIC
Mean (A$/MWh)	41	60	68	40	42
Coef. of Var. (%)	128	184	230	126	170
Min.	13	14	11	10	4
Max.	685	2113	2359	776	1644
Skew.	7	11	10	7	13
Kurt.	58	165	111	72	249
LB(1)	138	134	190	147	130
LB(2)	181	176	205	272	142
LB(3)	185	187	205	292	144
$LB^2(1)$	39	10	192	16	25
$LB^2(2)$	42	11	194	42	25
$LB^2(3)$	42	11	194	42	25
No. of Obs	1082	1082	1082	1082	1082

Table 4: Estimation Results

The table presents the results of fitting the following 3 models to the 22 prices series. Descriptions of the data are presented in Table 1. LL denotes the Log-Likelihood statistic and SBIC denotes the Schwarz-Bayes Information Criterion. In the below models, P_t denotes prices at time *t*. Statistically significant coefficients are denoted by superscripts ** and * at the one percent and five percent significance levels, respectively.

Model R1: No jump, but include seasonals in the mean, GARCH (1,1).

$$P_t = d(t) + e_t,$$

$$d(t) = b_0 + b_1 \cdot P_{t-1} + c_1 \cdot Volume + \sum_{r=2}^{12} M_r D_r^M$$, where D_r^M are monthly dummy variables where $e_t = \sigma_t \varepsilon_t$,

$$\sigma_t^2 = h_t = \omega + \alpha \cdot e_{t-1}^2 + \beta \cdot h_{t-1},$$

$$\varepsilon_t \sim \text{i.i.d.} N(0,1)$$

Model R2: With jump but no time-dependent intensity, GARCH (1,1).

$P_t = d(t) + S_t$, where *f(t)* is defined as (2).

$$S_t = \begin{cases} h_t^{1/2} \cdot \varepsilon_t & \text{With prob.} 1-\lambda_t \\ h_t^{1/2} \cdot \varepsilon_t + \mu_J + \sigma_J \cdot \varepsilon_{Jt} & \text{With prob. } \lambda_t \end{cases}$$

$$\varepsilon_J \sim \text{i.i.d.} N(0,1)$$

Model R3: With time-dependent jumps, GARCH (1,1).

Model R3 is similar to Model R2, except jump intensities are seasonally dependent i.e.
$\lambda_t = l_1 Winter_t + l_2 Fall_t + l_3 Spring_t + l_4 Summer_t$
where $Winter_t$ = 1 in December, January and February, and 0 otherwise,
$Fall_t$ = 1 in September, October and November, and 0 otherwise,
$Spring_t$ = 1 in March, April and May, and 0 otherwise,
$Summer_t$ =1 in June, July and August, and 0 otherwise.

Table 4 (continued)

Panel A: U.S.

Parameters	CIN			COB			FC			MEAD		
	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3
b_1	0.7886 **	0.7871 **	0.7789 **	0.8937 **	0.9576 **	0.9570 **	0.8982 **	0.9071 **	0.9054 **	0.9081 **	0.9267 **	0.9265 **
c_1	0.0002	0.0010 *	0.0011 *	0.0048 **	0.0022 *	0.0022 *				0.0070	0.0070	0.0072
λ		0.0644 **			0.0190 **			0.0466 **			0.0535 **	
l_1			0.0368 **			0.0251 **			0.0224 **			0.0806 **
l_2			0.0401 **			0.0091			0.0353 **			0.0129
l_3			0.0740 **			0.0218 *			0.0518 **			0.0990 **
l_4			0.1834 **			0.0235 *			0.0980 **			0.0592 *
ω	0.2389 *	2.1691 **	2.4498 **	0.5265 **	0.5270 **	0.5334 **	0.3646 **	0.8456 **	0.8965 **	0.1857	0.3948 *	0.4061 **
α	0.7238 **	0.6992 **	0.6829 **	0.7534 **	0.2899 **	0.2879 **	0.3178 **	0.2451 **	0.2466 **	0.2694 **	0.1504 **	0.1470 **
β	0.6304 **	0.2815 **	0.2440 **	0.5886 **	0.6719 **	0.6710 **	0.7843 **	0.6642 **	0.6537 **	0.7887 **	0.7823 **	0.7830 **
μ_J		29.2324 **	25.8569 **		146.8540 **	102.3870 **		35.2429 **	32.3907 **		45.3894 **	45.8164 **
σ_J		33.7430 **	32.0252 **		371.5680 **	377.1560 **		43.6759 **	42.3869 **		50.9138 **	51.9925 **
LL	-2865.81	-3711.68	-3700.65	-3966.63	-5353.63	-5351.86	-4744.57	-6020.87	-6013.02	-2064.00	-2735.27	-2730.11
SBIC	2925.42	3781.81	3781.30	4029.88	5428.05	5437.44	4804.67	6092.24	6095.66	2120.45	2801.68	2806.49

Parameters	MID			NP15			PV			PJM		
	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3
b_1	0.8952 **	0.9473 **	0.9458 **	0.9322 **	0.9299 **	0.9293 **	0.9044 **	0.9052 **	0.9049 **	0.8843 **	0.8041 **	0.7955 **
c_1	-0.0010	0.0000	0.0000	0.0051	0.0033 *	0.0031	0.0037 **	0.0040 **	0.0040 **	0.0024 **	0.0015 **	0.0015 **
λ		0.0134 **			0.0453 **			0.0262 **			0.1005 **	
l_1			0.0191			0.0569 *			0.0126			0.0584 **
l_2			0.0035			0.0057			0.0194 *			0.0526 **
l_3			0.0153 *			0.1130 **			0.0268 **			0.0678 **
l_4			0.0186 *			0.0507 **			0.0573 **			0.2728 **
ω	0.4870 **	0.5429 **	0.5585 **	0.1994 *	0.4656 **	0.5432 **	0.3782 **	0.7506 **	0.8100 **	0.4183 **	1.6197 **	1.9619 **
α	1.0782 **	0.3860 **	0.3865 **	0.1916 **	0.1763 **	0.1562 **	0.2667 **	0.2443 **	0.2504 **	0.7147 **	0.6187 **	0.5759 **
β	0.5239 **	0.6446 **	0.6426 **	0.8193 **	0.7181 **	0.7182 **	0.7805 **	0.7017 **	0.6899 **	0.6207 **	0.2287 **	0.2194 **
μ_J		190.1460 *	137.2040 **		44.7203 **	43.3729 **		43.7683 **	41.9822 **		18.4335 **	17.7186 **
σ_J		518.2510 **	506.3740 **		48.5724 **	52.4872 **		43.0797 **	44.6597 **		23.0836 **	22.8554 **
LL	-4126.67	-5174.02	-5171.84	-1399.47	-1925.45	-1919.55	-5013.51	-6927.67	-6922.19	-2821.50	-3704.28	-3682.88
SBIC	4189.07	5247.43	5256.26	1453.84	1989.41	1993.11	5078.84	7004.53	7010.58	2881.53	3774.90	3764.09

Table 4 (continued)

Panel B: Nordic Pool

	ARH			BER			COP			HEL			KRI		
Parameters	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3
b_1	0.7065 **	0.8633 **	0.8660 **	1.0216 **	0.9915 **	0.9916 **	0.8830 **	0.9649 **	0.9627 **	0.9266**	0.9709 **	0.9714 **	0.6385 **	0.9921 **	0.9924 **
λ		0.0973 **			0.0657 **			0.1828 **			0.0439 **			0.0650 **	
l_1			0.1248 **			0.1132 **			0.2909 **			0.0791 **			0.1163 **
l_2			0.0658 **			0.0464 **			0.1272 *			0.0250 *			0.0379 **
l_3			0.0934 **			0.0695 **			0.1071 **			0.0345 **			0.0712 **
l_4			0.1204 **			0.0318 *			0.1651 *			0.0356 *			0.0320
ω	11.6820	34.3738 **	34.5311 **	6.4135 **	7.2832 **	7.8822 **	216.7430 **	100.4750 **	110.3250 **	6.6973 **	19.4363 **	19.9008 **	5.7769 **	5.9781 **	6.6248 **
α	0.9298 **	0.4054 **	0.4050 **	0.6840 **	0.3132 **	0.3113 **	0.8756 **	0.3681 **	0.3506 **	0.7294 **	0.4937 **	0.4897 **	0.5289 **	0.3595 **	0.3576 **
β	0.5732 **	0.4333 **	0.4280 **	0.5597 **	0.4866 **	0.4775 **	0.2761 **	0.0062	0.0050	0.6036 **	0.3363 **	0.3369 **	0.6189 **	0.4801 **	0.4685 **
μ_J		59.2375 **	56.5818 **		15.0014 **	15.4166 **		21.0925 **	22.1378 **		41.2425 *	41.3320 *		12.1198 **	12.7161 **
σ_J		121.9850 **	121.6990 **		34.249 **	34.9484 **		58.3613 **	59.4532 **		132.6590 **	133.2400 **		30.8178 **	31.8023 **
LL	-3969.52	-4553.52	-4551.69	-5344.97	-6700.31	-6693.71	-2363.12	-2788.99	-2783.83	-4631.90	-5368.35	-5363.98	-5207.26	-6630.33	-6622.94
SBIC	4024.25	4618.52	4626.95	5405.15	6771.77	6776.45	2414.41	2849.91	2854.36	4689.43	5436.68	5443.09	5267.44	6701.79	6705.69

	OSL			STO			TRM			TRN		
Parameters	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3
b_1	0.9911 **	0.9890 **	0.9891 **	0.9808 **	0.9793 **	0.9792 **	0.9847 **	0.9861 **	0.9860 **	0.9912**	0.9896 **	0.9900 **
λ		0.0729 **			0.0519 **			0.0546 **			0.0539 **	
l_1			0.1136 **			0.0794 **			0.0966 **			0.0945 **
l_2			0.0405 **			0.0316 **			0.0293 **			0.0348 **
l_3			0.0872 **			0.0473 **			0.0645 **			0.0537 **
l_4			0.0429 **			0.0582 **			0.0448 **			0.0423 **
ω	7.2770 **	6.2338 **	6.9957 **	25.0757 **	20.8334 **	20.6254 **	7.9248 **	14.0760 **	14.4332 **	11.1867 **	12.1841 **	12.6084 **
α	0.4369 **	0.3194 **	0.3144 **	1.0021 **	0.4030 **	0.3931 **	0.7017 **	0.3820 **	0.3725 **	0.9028 **	0.4078 **	0.4054 **
β	0.6382 **	0.4817 **	0.4705 **	0.4156 **	0.3568 **	0.3594 **	0.5664 **	0.3570 **	0.3469 **	0.4905 **	0.3712 **	0.3610 **
μ_J		10.3578 **	10.9383 **		31.1423 **	30.6337 **		17.5635 **	16.8098 **		19.2993 **	19.1331 *
σ_J		26.9351 **	27.9171 **		101.4910 **	99.7826 **		68.8447 **	67.1076 **		73.0745 **	72.1015 **
LL	-7277.26	-9294.03	-9285.59	-6278.71	-7411.64	-7407.92	-6586.30	-7936.71	-7929.38	-5823.21	-6994.69	-6989.53
SBIC	7340.26	9368.84	9372.22	6338.89	7483.10	7490.66	6647.53	8009.42	8013.57	5883.39	7066.15	7072.28

Table 4 (continued)

Panel C: Australia

	NSW			QLD			SA			SNO			VIC		
Parameters	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3
b_1	0.4020 **	0.7035 **	0.7027 **	0.2996 **	0.5105 **	0.5113 **	0.5138 **	0.7058 **	0.7064 **	0.8422 **	0.7437 **	0.7422 **	0.8857 **	0.7163 **	0.7156 **
λ		0.0520 **			0.1246 **			0.1050 **			0.0488 **			0.0477 **	
l_1			0.0942 **			0.1707 **			0.1330 **			0.0861 **			0.0859 **
l_2			0.0319 **			0.1060 **			0.0764 **			0.0211 *			0.0260 *
l_3			0.0302 **			0.1141 **			0.1010 **			0.0342 **			0.0341 **
l_4			0.0562 **			0.1016 **			0.1116 **			0.0625 **			0.0517 **
ω	-0.8887 *	13.8560 **	13.9986 **	4.6595	25.4785 **	25.5391 **	9.2797	19.5648 **	19.5729 **	-0.1802	11.1797 **	11.9809 **	22.1854 **	13.6713 **	13.5785 **
α	5.0098 **	0.3099 **	0.3076 **	5.4183 **	0.2428 **	0.2441 **	2.9287 **	0.5230 **	0.5186 **	5.8381 **	0.3410 **	0.3596 **	5.1688 **	0.4446 **	0.4373 **
β	0.2796 **	0.2394 **	0.2313 **	0.2269 **	0.1568 **	0.1573 **	0.2472 **	0.0520 **	0.0511 **	0.2188 **	0.2636 **	0.2222 **	0.1296 **	0.1964 **	0.1940 **
μ_J		118.3870 **	114.0420 **		118.6500 **	118.6600 **		124.8430 **	123.9040 **		101.3350 **	96.5565 **		122.0620 **	117.6200 **
σ_J		142.2720 **	140.8300 **		192.7390 **	192.8960 **		225.7360 **	225.0870 **		136.1040 **	133.4220 **		158.5460 **	156.4830 **
LL	-4138.00	-4041.05	-4035.42	-4482.73	-4770.09	-4767.02	-5000.19	-4721.98	-4720.06	-3946.97	-3992.41	-3986.58	-4171.43	-4087.51	-4082.87
SBIC	4193.89	4107.42	4112.27	4538.62	4836.46	4843.87	5056.08	4788.35	4796.91	4002.86	4058.79	4063.43	4227.32	4153.89	4159.72

Table 5. Residual Diagnostics

The table presents summary statistics for the standardized residuals of the 3 models presented in Table 4, for each of the 22 data series. Descriptions of the data are presented in Table 1. LB(*n*) denotes the Ljung-Box test of significance of autocorrelations of *n* lags. The critical values for 1, 2 and 3 lags are 6.63, 9.21 and 11.34 at the one percent level, 3.84, 5.99 and 7.81 at the five percent level, respectively.

Panel A: U.S.

	CIN			COB			FC			MEAD		
Parameters	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3
Mean	0.14	0.39	0.46	0.19	0.13	0.14	0.06	0.18	0.19	0.11	0.21	0.21
Std. Dev.	0.99	2.05	2.36	0.98	1.35	1.35	1.00	1.99	2.00	1.00	1.28	1.29
Skew.	1.81	6.07	7.14	1.83	2.70	2.70	2.14	17.91	17.66	0.94	1.34	1.35
Kurt.	9.56	60.34	77.56	11.68	26.50	26.41	21.48	555.03	543.33	3.09	4.98	4.98
LB(1)	20.70	0.62	0.29	31.80	17.80	17.90	2.38	0.91	0.87	0.92	0.01	0.01
LB(2)	21.30	6.41	5.02	31.90	18.70	18.80	15.60	1.78	1.82	2.20	0.58	0.59
LB(3)	21.30	7.70	6.15	32.60	19.40	19.40	17.70	1.84	1.86	2.45	1.73	1.78

	MID			NP15			PV			PJM		
Parameters	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3
Mean	0.09	0.16	0.16	0.06	0.20	0.21	0.09	0.11	0.12	0.07	0.55	0.55
Std. Dev.	0.99	2.32	2.33	1.00	1.32	1.35	0.99	1.18	1.19	1.00	2.32	2.31
Skew.	2.60	24.27	24.39	0.80	1.38	1.39	0.88	1.11	1.16	1.95	6.60	6.32
Kurt.	22.57	794.06	799.40	2.64	5.01	4.97	3.63	4.96	5.37	9.98	71.75	64.91
LB(1)	10.90	0.06	0.06	14.90	12.00	13.30	2.15	3.98	4.22	10.10	1.87	2.65
LB(2)	25.70	0.07	0.07	14.90	12.00	13.40	2.29	3.98	4.22	18.60	4.53	5.05
LB(3)	29.80	0.20	0.20	16.10	12.60	14.00	12.80	12.90	12.90	30.90	8.27	8.37

Table 5. (continued)

Panel B: Nordic Pool

	ARH			BER			COP			HEL			KRI		
Parameters	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3
Mean	0.06	0.35	0.35	-0.07	0.11	0.11	-0.01	0.23	0.22	0.05	0.22	0.21	-0.01	0.09	0.08
Std. Dev.	1.00	3.59	3.63	1.00	1.58	1.57	1.00	2.17	2.12	1.00	4.54	4.50	1.00	1.50	1.50
Skew.	2.13	20.65	20.74	1.60	3.30	3.29	1.63	1.82	1.75	2.05	29.16	29.07	1.52	2.87	2.86
Kurt.	13.45	542.97	546.38	11.10	31.61	31.41	7.01	13.43	13.24	17.41	974.35	969.87	11.50	30.35	30.08
LB(1)	0.10	2.01	1.98	1.50	0.02	0.02	1.85	3.43	3.57	6.43	0.20	0.20	5.96	2.52	2.42
LB(2)	8.94	2.24	2.20	4.56	0.09	0.09	6.59	5.11	5.47	18.80	0.21	0.21	6.27	2.61	2.48
LB(3)	19.20	2.24	2.20	5.08	1.99	1.96	7.48	7.47	7.65	25.10	0.21	0.21	6.68	3.81	3.66

	OSL			STO			TRM			TRN		
Parameters	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3
Mean	-0.01	0.11	0.10	-0.01	0.18	0.19	0.16	0.14	0.14	0.05	0.15	0.16
Std. Dev.	1.00	1.50	1.49	1.00	3.72	3.74	0.99	2.95	2.96	1.00	3.20	3.20
Skew.	1.61	2.68	2.64	1.89	32.78	32.72	1.84	29.49	29.21	2.25	29.42	29.23
Kurt.	12.38	28.54	27.87	18.51	1279.95	1276.80	22.28	1153.13	1138.22	23.42	1100.45	1090.22
LB(1)	8.06	5.33	5.20	3.45	0.38	0.39	9.30	0.29	0.30	4.32	0.27	0.28
LB(2)	8.91	5.58	5.50	9.27	0.41	0.42	18.90	0.36	0.37	8.43	0.29	0.30
LB(3)	8.92	5.79	5.68	13.20	0.41	0.42	26.80	0.44	0.45	12.40	0.36	0.36

Panel C: Australia

	NSW			QLD			SA			SNO			VIC		
Parameters	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3	R1	R2	R3
Mean	0.08	0.74	0.75	0.25	1.12	1.11	-0.14	1.36	1.36	0.06	0.62	0.63	-0.07	0.83	0.84
Std. Dev.	1.00	4.97	4.99	0.97	4.79	4.78	0.99	7.55	7.57	1.00	4.28	4.28	1.00	7.16	7.20
Skew.	4.66	10.48	10.43	3.07	8.40	8.41	3.85	11.53	11.52	5.03	10.45	10.15	4.27	18.47	18.42
Kurt.	38.04	136.85	135.68	14.64	102.04	102.32	23.61	180.65	180.55	40.07	137.09	129.01	34.58	428.86	426.69
LB(1)	6.88	0.59	0.59	4.17	0.18	0.18	5.45	0.61	0.61	0.27	0.71	0.71	0.59	0.34	0.35
LB(2)	15.20	0.66	0.65	7.30	0.18	0.18	28.10	1.03	1.03	3.83	0.74	0.75	2.15	0.41	0.41
LB(3)	19.30	1.21	1.21	8.68	0.18	0.19	48.50	1.11	1.11	4.01	1.75	1.71	2.16	0.68	0.68

Figure 1. Prices of Selected Electricity Price Series Across Markets