REGIME JUMPS IN ELECTRICITY PRICES

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Abstract	Electricity prices are known to be very volatile and subject to frequent jumps due to system breakdown, demand shocks, and inelastic supply. As many international electricity markets are in some state of deregulation, more and more participants in these markets are exposed to these stylised facts. Appropriate pricing, portfolio, and risk management models should incorporate these facts. Authors have introduced stochastic jump processes to deal with the jumps, but we argue and show that this specification might lead to problems with identifying the true mean-reversion within the process. Instead, we propose using a regime jump model that disentangles mean-reversion from jump behaviour. This model resembles more closely the true price path of electricity prices.	
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Regime Jumps in Electricity Prices

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Electricity prices are known to be very volatile and subject to frequent jumps due to system breakdown, demand shocks, and inelastic supply. As many international electricity markets are in some state of deregulation, more and more participants in these markets are exposed to these stylised facts. Appropriate pricing, portfolio, and risk management models should incorporate these facts. Authors have introduced stochastic jump processes to deal with the jumps, but we argue and show that this specification might lead to problems with identifying the true mean-reversion within the process. Instead, we propose using a regime jump model that disentangles mean-reversion from jump behaviour. This model resembles more closely the true price path of electricity prices.

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1: INTRODUCTION

Worldwide, electricity markets are being reformed from a highly regulated government controlled system into deregulated markets. Following EU directions, EU electricity markets need to be fully deregulated before 2007, whereas the US, UK, and several Nordic countries have started this process earlier. In all cases, the reliability of the total electricity system for an economy are at stake and people need to get used to operating in an environment with very volatile prices instead of more or less fixed prices as in the past. Frictions occur due to this liberalisation process (think of the California power struggle in the first half of 2001) and it is still uncertain what the near future will bring.

Participants in electricity markets will face enormous market risks due to the highly volatile electricity markets. Daily volatilities of 29% are common; for comparison international stock indices have volatilities close to 20%, but on a yearly basis. Good risk- and portfolio management is absolutely crucial to survive in these markets as well as a broad understanding of financial instruments that can be used to hedge risks, such as forwards/futures and options. In most of the markets that are being liberalised, options and futures are not commonly traded yet and most of these exchanges are developing electricity derivatives markets.

For risk management, portfolio management, and option pricing issues it is crucial to have a good insight in the dynamics of electricity prices. For example, electricity is not storable which makes spot option valuation using the Black-Scholes model or future valuation while assuming risk neutrality inapplicable; all valuations are dependent on a model that properly describes the dynamics of electricity prices. Research has been conducted to these dynamics and has indicated various stylised facts of electricity prices: high volatility, mean-reversion (prices tend to fluctuate around a long term equilibrium mean), seasonality (for example high summer prices in Arizona due to huge demand for power from air conditioning usage), and frequent extreme jumps in prices that die out rapidly (result of fluctuations in demand and low elasticity of supply, due to system breakdown and limited inventory capacities)[1].

In this paper, we also focus on modelling electricity prices and concentrate on estimating the extreme jumps. Jumps in electricity prices are characterized by their short existence; prices fall back to a normal level sometimes after even one day (for example in case of system

[1] See Pilipović (1998) and Clewlow and Strickland (2000) for results on stylised facts of electricity price dynamics.

breakdown). The motivation for our study comes from past studies that have applied a stochastic jump model in combination with mean-reversion to model the jumps. The mean-reversion component is used to force the price of electricity to fall back to a normal level after a shock or jump has occurred; mean-reversion is directly associated with the jump process. However, it might well be that mean-reversion exists only in the “normal” price process; the normal mean reverting process is then not specified correctly in traditional jump models. We argue that a stochastic jump process with mean-reversion might lead to an erroneous specification of the true mean-reversion process. In this paper, we show the existence of such a normal mean reverting process that is not directly associated with jumps. Furthermore, our results indicate that the estimates for the mean-reversion parameters change dramatically when a stochastic jump component is added. For the jump model with mean reversion the results appear to be completely counterintuitive, suggesting that mean reversion and jumps are hard to identify separately. We then introduce a regime jump process that is capable of modelling the jumps separately from the mean-reversion process. In the regime jump model, we assume that the electricity price is in one out of three different regimes at each point in time. We identify a normal regime that can contain a mean-reversion component. In addition, we identify two extra regimes: the first regime models a price jump and a second regime models the way the process falls back to the normal process. Markov transition matrices specify the probabilities that the electricity prices move from one regime to another from one time point to the next.

Our results indicate that the electricity prices process exhibits significant mean-reversion in its normal process and we show that the regime jump process performs better in modelling the jumps in combination with mean-reversion than a stochastic jump model. We therefore conclude that the regime jump model is a much richer specification of the electricity price dynamics than the other models used. Like other models, the regime jump process can be used to simulate different scenarios and is therefore an important tool for both modelling future price expectations and risk management purposes.

This paper is organized as follows. We explain the methodology in section 2. In section 3, we present summary statistics of the data we use. Section 4 shows empirical estimates from application of the model to electricity prices from several international markets. Section 5 concludes.

2: ELECTRICITY PRICE MODELLING

In this section, we present the models that we use to examine the dynamics of electricity prices. We start from a basic random walk model and we sequentially add mean-reversion and jump components to this model. We leave seasonality out of our analysis given our focus on mean-reversion and jumps. We present two ways of modelling electricity price jumps. First, we apply a stochastic jump model that has been used in various studies. Secondly, we present a new approach based on regime switching models in order to account for price jumps. The advantage of the latter model is, as we argue below, that jumps are modelled separately from mean-reversion, which reduces a potential identification problem. The empirical results in section 4 indicate that this is indeed the case and that the latter model is a richer description of electricity price dynamics.

2.1: BASIC MODEL

We start our analyses by examining a basic price model for electricity. From this model we extend by adding mean-reversion and jump components in order to examine the importance of each. The basic model that we use is a standard random walk model with drift parameter:

(1) $$dx_t = \mu + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma^2)$$

where x_t is the logarithm of the daily electricity price, μ and σ are the drift and volatility of the spot price respectively.

2.2: MEAN-REVERSION

An important characteristic of energy price dynamics is mean-reversion. Previous studies[2] have indicated that energy prices tend to behave around a long-term mean referred to by β. The rate of mean-reversion α forces prices to move back to their long-term equilibrium value after the actual price has deviated from this equilibrium. Following Pilipović (1997), we extend the basic model (1) with mean-reversion in the log-price of electricity resulting in equation (2):

[2] Pilipović (1998) and Clewlow and Strickland (2000) provide evidence about mean-reversion in energy price series such as electricity, gas, and oil.

(2) $$dx_t = \alpha(\beta - x_t) + \varepsilon_t, \quad \varepsilon_t \sim N(0,\sigma^2)$$

For estimation purposes, we rewrite equation (2) into the following equation:

(3) $$dx_t = \tilde{\mu} + \rho x_t + \varepsilon_t, \quad \varepsilon_t \sim N(0,\sigma^2).$$

From (3) it is easy to see that α and β can be calculated from the estimates of $\tilde{\mu}$ and ρ. Note that the interpretation of $\tilde{\mu}$ is different from the drift rate μ in the basic model (1).

2.3: Standard Jump Processes

The existence of large jumps in the price of electricity is another stylised fact. Depending on the elasticity of supply and conditions of demand, jumps have an important influence on the risks faced by participants in the electricity markets. If these jumps are not modelled correctly, then risk measures will likely underestimate the amount of risk that is taken.

Price jumps are traditionally modelled by adding a Poisson error component to a time series description. In our analysis we add the stochastic jump component to our basic random walk model (1) and the model with mean-reversion (3). Furthermore, we assume that the size of the jump Z is log normally distributed with mean μ_Z and variance σ_Z^2: $\ln Z \sim N\left(\mu_Z, \sigma_Z^2\right)$. The basic random walk model with Poisson jumps is given in equation (4):

(4) $$dx_t = \mu + \varepsilon_t + \sum_{i=1}^{n} \ln Z_i, \quad \varepsilon_t \sim N(0,\sigma^2),$$

where n is the actual number of jumps during the time interval under consideration.

The parameters are estimated by maximizing the following logarithmic likelihood function:

(5) $$l = -T\lambda - \frac{T}{2}\ln(2\pi) + \sum_{t=1}^{T} \ln\left[\sum_{j=0}^{\infty} \frac{\lambda^j}{j!} \frac{1}{\sqrt{\sigma^2 + j\sigma_Z^2}} \exp\left(\frac{-(dx_t - \mu - j\mu_Z)^2}{2(\sigma^2 + j\sigma_Z^2)}\right)\right],$$

where λ is the mean number of times that a jump occurs and T is equal to the number of observations. When computing the likelihood the infinite sum between brackets is truncated. In our application to electricity price series we set the number to 10 after some experimentation. The likelihood function for the model with mean-reversion can be constructed similarly.

2.4: Regime Jumps

The stochastic jump process from the previous section allows for sudden jumps in the price level and the probability that a jump will occur in a certain period is variable. This jump process is commonly used to model, for instance, stock prices, but it does not incorporate an important characteristic of jumps in electricity prices: electricity price jumps die out rather quickly and do not lead to sustainable higher price levels. For example, a sharp price increase in one day due to system breakdown might lead directly to a jump down in prices on the following day when the system is repaired or when alternative supply is being generated. An up-jump is thus directly followed by a down-jump. The stochastic jump process introduced above only models a sustainable price increase, not explicitly the fast die-out property of electricity price jumps. Only the stochastic jump process (4) with a mean-reversion component is capable of modelling the die-out property; mean-reversion forces extreme high or low prices to revert back to the long-term equilibrium price. However, this specification might lead to identification problems. If the normal price process exhibits mean-reversion, which is not unlikely, then the 'normal' mean-reverting process is calibrated with data from the jumps. For this reason, we introduce a regime jump model that is capable of modelling jumps apart from the 'normal' mean-reverting process.

The regime jump model that we introduce in this paper is closely related to the regime switching models that were originally introduced by Hamilton (1989). Hamilton observed large swings in the value of the dollar relative to other currencies; long periods of dollar appreciation are followed with long periods of dollar depreciation. Obviously, the dynamics of the value of the dollar are different in each swing and Hamilton therefore introduced the regime model. In this model, the dollar is in one out of two regimes at each time period, representing an appreciation or a depreciation swing, and with a certain probability the dollar switches between both regimes from one period to another. Practically, regime models allow for distinct time series behaviour in each of the regimes.

We apply the technique introduced by Hamilton (1989) to model jumps in electricity prices. We identify three possible regimes: a normal regime that describes the 'normal' electricity price dynamics, an initial jump regime that models the process when the price of electricity suddenly increased or decreases, and a third regime that describes the process how price move back to the normal regime after a jump has occurred. Starting from our basic model (1) for the log price of electricity, the basic regime jump model can be written as follows:

$$(6) \qquad dx_t = \mu_{r_t} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_{r_t}^2).$$

where r_t is a latent variable representing the regime or state the process is in at time t. In our application to electricity markets we have $r_t \in \{-1,0,1\}$, with $r_t = 0$ representing the normal state, $r_t = 1$ being the initial jump, and $r_t = -1$ being the subsequent reversal to normal levels. Note that prices are modelled by a random walk in each of the regimes but with different values for the mean and the variance of changes for each regime.

Note that when we condition on the regimes, the parameters of the model can easily be estimated by maximum likelihood. In order to estimate the latent regime dynamics we need to specify the mechanism that describes how we can jump from one regime to another. In regime switching models this is accomplished through a Markov transition matrix, which contains probabilities of jumping from one state to another. Maximum likelihood estimates of the parameters and the regimes can be found by applying the Kalman filter methodology (see for example Harvey (1989)) with the regimes as latent variables.

2.4.1: The Markov Transition Probabilities

We need to make assumptions about the way the process alternates between the different regimes. The switches between the regimes are controlled by one-period transition probabilities. Let $\pi_{i,j}$ be the probability that the electricity price process switches from regime j in period t to regime i in period t+1. Our definition of regimes implies that the process cannot stay in one of the jump processes but moves sequentially from the initial jump process (regime +1) to the reversing process (regime -1) and then back to the normal process (regime 0). Therefore, if a jump occurs, the process will follow the next sequence of regimes: from the normal regime 0, it jumps into regime 1, then it reverts to regime –1, and it ends in the normal regime 0. This implies restrictions on the transition probabilities; $\pi_{-1,0}$ is zero, because from the normal regime the process can either stay in the normal regime or it can move into the initial jump regime. Being in the jump regime, the process can only go to the reverting regime ($\pi_{-1,1}=1$) and from the reverting regime the process can only go to regime 0 ($\pi_{0,-1} = 1$). More specifically, we specify the following (3x3) Markov transition matrix Π (note that the columns sum to one):

$$(7) \qquad \Pi = \begin{bmatrix} 0 & 0 & 1 \\ 1 & \pi_{0,0} & 0 \\ 0 & 1-\pi_{0,0} & 0 \end{bmatrix}$$

Note that we define an initial jump (regime +1) and a reversal jump (-1). The sign of the initial jump is not specified; it might either be an upward or a downward jump. Regarding the jumps, we make two additional restrictions being that the size of the reversal jump is exactly opposite to the size of the initial jump (i.e. $\mu_{+1}=-\mu_{-1}$) and that the volatilities are equal ($\sigma_{+1}=\sigma_{-1}$). These restrictions correspond with a short one-day jump in the market, in which the price jumps and falls back to a normal level the day after. For other jump behaviour, one could put different restrictions on the model.

3: DATA

The electricity price data that we use in this study were taken from several electricity markets around the world:

- California Power Exchange;
- Telerate UK Day Ahead Index (Base);
- DJ German Power Index (Base);
- Dutch APX Index.

All series were sampled at a daily frequency. The sample lengths differ, however, depending on market existence and on the general availability of the data. All data were taken from Bridge™. For comparison reasons we have also included three data series on energy products:

- Brent Crude Spot;
- Crude Oil Light Sweet (Nymex);
- Natural Gas (Nymex).

Table 1: Summary statistics electricity price returns.

	CalPow	UKPow	GerPow	APX	Brent	OilLS	NatGas
Start	1/4/98	17/8/99	5/10/00	01/01/01	13/5/96	13/5/96	13/5/96
End	25/12/00	10/5/01	10/5/01	10/5/01	10/5/01	10/5/01	10/5/01
Mean	66.90	-34.20	14.86	-2.512	9.065	7.310	13.30
Stddev	442.7	453.2	343.0	662.1	33.88	36.52	53.28
Min	-201.0	-121.7	-85.42	-237.2	-11.61	-18.35	-15.69
Max	268.5	120.2	97.44	174.1	12.65	19.58	15.11
Skew	0.740	0.819	0.361	-0.801	-0.059	0.049	-0.320
Kurt	17.65	3.576	3.327	11.19	2.591	8.977	2.283

Note: *Start/End* are the start and end dates of the series, respectively. Date format: dd/mm/yy. *Mean* and standard deviation (*Stddev*) are annualized. *Kurt* is excess kurtosis. CalPow: California Power Exchange; UKPow: Telerate UK Day Ahead Index (Base); GerPow: DJ German Power Index (Base); APX: Dutch APX Index; Brent: Brent Crude Spot; OilLS: Crude Oil Light Sweet (Nymex); NatGas: Natural Gas (Nymex).

Strikingly, electricity price return series are very volatile. This phenomenon is less predominant in the other three energy series. As can also be seen from the figures a major reason for the excess volatilities is the fact that electricity prices exhibit jumps regularly.

4: EMPIRICAL RESULTS

In this section, we compare the results of applying the various models introduced in section 2 to the energy price processes from which the data was presented in the previous section. We examine whether the mean-reversion unrelated to jumps exists in the normal price process by examining the results from the random walk model with and without mean reversion and the stochastic jump model. We then show the parameter estimates of the regime jump model presented in section 2.4. The results indicate that the regime jump model provides a richer specification of the true electricity price process.

First we apply a simple random walk price process with drift to the price processes indicated above; i.e. being equation (1). Table 2 shows the parameter estimates with the log-likelihood for the different price processes. We clearly observe the high volatility characteristics of electricity prices, when compared with Natural Gas or the oil price series. Daily volatility equals more than 20% for California, the UK, and Germany, and even 40% for the APX, whereas these numbers are equal to 2% for the oil and 3% for the Natural Gas series. The high volatility for the APX data is due to the fact that the APX market opened in January 2001, resulting in only a short range of data. None of the estimates for the mean price change are significant.

Table 2: Estimation results: basic model (1).

	CalPow	UKPow	GerPow	APX	Brent	OilLS	NatGas
μ	0.003	-0.001	0.001	-0.000	0.000	0.000	0.001
	(0.009)	(0.012)	(0.014)	(0.036)	(0.001)	(0.001)	(0.001)
σ	0.273	0.279	0.211	0.408	0.021	0.023	0.033
	(0.006)	(0.009)	(0.010)	(0.025)	(0.000)	(0.000)	(0.001)
LogLik	-117.50	-74.57	29.77	-67.22	3109.1	2980.6	2508.0

Table 3 shows the parameter estimates for an extension of the previous model with mean-reversion; i.e. equation (3). The mean-reversion parameter ρ is significant and negative for all power series, but not for the gas and oil series. This is consistent with evidence from previous studies, indicating the importance of mean-reversion in electricity price processes. The negative values for ρ imply that the rate of mean reversion α as defined in equation (2) is positive. From (2) it can be seen that the price process is forced to move back to a long-term mean after it has deviated when α is positive.

Note that the inclusion of mean-reversion leads to a richer specification of the electricity price process indicated by the higher log-likelihood values for the electricity series. Furthermore, imposing mean-reversion lead to slightly lower parameter estimates for volatility for the series that exhibit significant mean-reversion.

Table 3: Estimation results: basic model *with* mean-reversion (3).

	CalPow	UKPow	GerPow	APX	Brent	OilLS	NatGas
$\tilde{\mu}$	0.208	1.156	1.501	2.348	0.006	0.009	0.004
	(0.040)	(0.107)	(0.179)	(0.280)	(0.006)	(0.007)	(0.003)
σ	0.270	0.252	0.183	0.327	0.021	0.023	0.033
	(0.006)	(0.008)	(0.009)	(0.020)	(0.000)	(0.000)	(0.001)
ρ	-0.057	-0.374	-0.490	-0.711	-0.002	-0.003	-0.004
	(0.011)	(0.034)	(0.058)	(0.084)	(0.002)	(0.002)	(0.003)
α^*	0.057	0.374	0.490	0.711	0.002	0.003	0.004
β^*	3.649	3.091	3.063	3.302	3.000	3.000	1.000
Eq. price*	38.441	21.997	21.397	27.178	20.086	20.086	2.718
LogLik	-104.10	-20.94	60.32	-38.89	3109.5	2981.3	2509.0

* *These values are calculated based on the parameter estimates for ρ_0 and μ_0.*

From the previous tables we observe the importance of mean-reversion in electricity prices. This is a well-known result and corresponds with the results found by many previous studies. In the following tables we present the effects of including a stochastic jump process as in equation (4). Table 4 contains the parameter estimates for the basic jump model (4) without mean-reversion. The estimates for the parameter λ are high, signifying that jump behaviour is an important feature in electricity price data. For the electricity series we see that the mean size of the jump μ_Z is positive, as would be expected from these series, indicating the existence of large upward jumps in prices. The standard deviations σ_Z of the jumps are all higher than the standard deviations on the normally distributed error term. For the oil and gas series we find that, although significant jump behaviour is detected, the jumps are small. Note the decrease in the value of the volatility estimates for all series. Jumps determine for an important part the volatility estimates in standard models like (1).

Table 4: Estimation results: stochastic jump model *without* mean reversion (4).

	CalPow	UKPow	GerPow	APX	Brent	OilLS	NatGas
μ	-0.013	-0.036	-0.005	-0.013	0.001	0.000	0.003
	(0.004)	(0.006)	(0.004)	(0.024)	(0.001)	(0.001)	(0.001)
σ	0.064	0.059	0.029	0.234	0.016	0.020	0.022
	(0.006)	(0.007)	(0.005)	(0.020)	(0.002)	(0.001)	(0.002)
$\sqrt{\lambda}$	0.770	0.905	0.926	0.342	0.591	0.143	0.640
	(0.045)	(0.049)	(0.068)	(0.080)	(0.233)	(0.037)	(0.134)
μ_Z	0.026	0.043	0.006	0.110	-0.002	0.000	-0.006
	(0.015)	(0.017)	(0.017)	(0.270)	(0.002)	(0.017)	(0.003)
σ_Z	0.316	0.294	0.226	0.974	0.023	0.075	0.037
	(0.022)	(0.020)	(0.021)	(0.261)	(0.006)	(0.018)	(0.006)
LogLik	209.6	35.77	92.07	-36.58	3144.9	3060.2	2557.5

In table 5 we have collected results for the stochastic jump model (4) with a mean reversion component added like in equation (3). Mean reversion seems to be less important than shown in table 2; although the mean reversion parameter is significant for all series, the values of the log likelihood increase only for two series: *UKPow* and *APX*. The model with mean reversion does not improve much upon the version without mean reversion for *Brent*, *OilLS*, *NatGas* and, interestingly, *CalPow*. Another striking result is observable. The mean-reversion parameter estimates are all positive, whereas they were negative in the basic model (3). This is counterintuitive since a positive value for ρ implies a negative value for α in equation (2) and this implies that when prices are above their long-term average, they will tend to move more upwards. This may signify that jump behaviour and mean reversion may be hard to disentangle when modelled by a Poisson process.

The following tables present the parameter estimates from the regime jump model with and without mean-reversion. Since we have seen before that jumps and mean reversion are most important in electricity price series we only present the results of those series. Table 6 presents the parameter estimates for the basic model (6) without mean-reversion using the transition matrix given by (7).

Table 5: Estimation results: jump model *with* mean reversion (4).

	CalPow	UKPow	GerPow	APX	Brent	OilLS	NatGas
μ	-0.009	0.143	0.009	0.578	0.001	0.002	0.002
	(0.005)	(0.016)	(0.025)	(0.080)	(0.001)	(0.002)	(0.002)
σ	0.064	0.065	0.029	0.221	0.016	0.020	0.022
	(0.006)	(0.007)	(0.005)	(0.017)	(0.002)	(0.001)	(0.002)
$\sqrt{\lambda}$	0	-0.009	-0.001	-0.021	0	0.000	0.000
		(0.001)	(0.001)	(0.003)		(0.000)	(0.001)
μ_Z	0.769	0.872	0.923	0.253	0.591	0.141	0.643
	(0.044)	(0.055)	(0.066)	(0.074)	(0.233)	(0.037)	(0.133)
σ_Z	0.027	0.092	0.006	0.135	-0.002	0.000	-0.006
	(0.015)	(0.019)	(0.017)	(0.392)	(0.002)	(0.017)	(0.003)
ρ	0.315	0.269	0.225	1.062	0.023	0.076	0.037
	(0.022)	(0.020)	(0.021)	(0.362)	(0.006)	(0.019)	(0.006)
α^*	-0.315	-0.269	-0.225	-1.062	-0.023	-0.076	-0.037
β^*	0.029	-0.532	-0.040	-0.544	-0.043	-0.026	-0.054
Eq. price[*]	1.029	0.588	0.961	0.580	0.957	0.974	0.947
LogLik	210.5	70.93	92.24	-16.06	3144.9	3060.5	2557.5

[*] *These values are calculated based on the parameter estimates for ρ_0 and μ_0.*

We find that the transition dynamics can be quite different among the electricity price series that we study. The probability of staying in the normal regime ranges from 69.1% (*CalPow*) indicating frequent jumps to 99.5% (*GerPow*). For CalPow and UKPow, we observe initial downward jumps. For GerPow, we observe low probability of a jump (0.5%), but if they occur they are large in size (0.914) on average.

Table 6: Estimation results;
regime jump model *without* mean reversion (6).

	CalPow	UKPow	GerPow	APX	Brent	OilLS	NatGas
μ_0	0.007	-0.093	0.000	0.006	0.000	0.000	0.001
	(0.014)	(0.008)	(0.013)	(0.051)	(0.001)	(0.001)	(0.001)
σ_0	0.345	0.132	0.193	0.480	0.019	0.020	0.028
	(0.011)	(0.007)	(0.009)	(0.038)	(0.001)	(0.001)	(0.001)
$\mu_{+1}=-\mu_{-1}$	-0.002	-0.159	0.914	0.026	0.029	0.007	0.027
	(0.006)	(0.042)	(0.043)	(0.027)	(0.014)	(0.022)	(0.013)
$\sigma_{+1}=\sigma_{-1}$	0.059	0.430	0.060	0.081	0.042	0.086	0.058
	(0.006)	(0.028)	(0.030)	(0.022)	(0.007)	(0.019)	(0.007)
$\pi_{0,0}$	0.691	0.777	0.995	0.794	0.983	0.993	0.953
	(0.032)	(0.034)	(0.005)	(0.062)	(0.011)	(0.004)	(0.020)
LogLik	104.98	13.43	44.35	-50.78	3149.9	3064.9	2549.8

When estimating the regime jump model with a mean reversion component in the neutral regime we find significant values for the mean-reversion parameter for the electricity series.

Furthermore, the log likelihood values increase when compared with the results in table 6. The values for the mean-reversion parameters are consistent with mean-reverting behaviour as we found in table 3. From the stochastic jump model in table 5, we observed completely different values indicating even non mean-reverting behaviour. Examining the values for the long term equilibrium prices (β), the values in table 7 are close to the values of table 3 and more what we would have expected a priori than what we found from the stochastic jump model in table 5. For example, the long-term equilibrium price for the German series equals approximately EUR 21 in table 3 and table 7, whereas it equals EUR 0.96 in table 5.

Table 7: Estimation results;
regime jump model *with* mean reversion (6).

	CalPow	UKPow	GerPow	APX	Brent	OilLS	NatGas
μ_0	0.303	0.600	1.311	2.593	0.012	0.005	0.002
	(0.062)	(0.093)	(0.172)	(0.329)	(0.010)	(0.007	(0.003
σ_0	0.338	0.143	0.171	0.362	0.025	0.020	0.028
	(0.011)	(0.009)	(0.008)	(0.028)	(0.001)	(0.001)	(0.001)
$\mu_{+1}=-\mu_{-1}$	-0.002	-0.207	0.914	0.025	-0.001	0.007	0.027
	(0.006)	(0.058)	(0.043)	(0.025)	(0.002)	(0.022)	(0.013)
$\sigma_{+1}=\sigma_{-1}$	0.060	0.472	0.060	0.066	0.013	0.087	0.058
	(0.006)	(0.039)	(0.030)	(0.018)	(0.001)	(0.019)	(0.007)
ρ_0	-0.083	-0.204	-0.429	-0.792	-0.004	-0.002	-0.000
	(0.017)	(0.030)	(0.056)	(0.100)	(0.003)	(0.002)	(0.003)
$\pi_{0,0}$	0.687	0.860	0.995	0.843	0.642	0.993	0.953
	(0.033)	(0.029)	(0.005)	(0.057)	(0.084)	(0.004)	(0.020)
α^*	0.083	0.204	0.429	0.792	0.004	0.002	-
β^*	3.651	2.941	3.056	3.274	3.000	2.500	-
*Eq. price**	38.498	18.938	21.241	26.417	20.086	12.182	-
LogLik	117.51	40.06	70.16	-26.92	3185.8	3065.2	2549.8

* *These values are calculated based on the parameter estimates for ρ_0 and μ_0.*

The analysis above clearly demonstrated the importance of jumps and mean-reversion in electricity price dynamics. For pricing, risk management, and portfolio management issues it is important to model these stylised facts correctly. A wrong assessment might lead to a false indication of the true risk faced. From this perspective, we observed that the stochastic jump model leads to strange effects on the mean-reversion estimates. We argue that this is due to the fact that mean-reversion in jump models is used to reverse prices back to normal levels after a jump. This specification might lead to identification problems if mean-reversion also exists in data from normal (no jump) periods. The regime jump model disentangles mean-reversion and jump behaviour. Results drawn from this model prove the existence of mean-reversion in the normal price process and highlight the importance of separate modelling of jumps and mean-reversion. The regime jump model seems to be a first attempt to come to a richer specification of electricity price dynamics.

4: CONCLUDING REMARKS AND PRACTICAL IMPLICATIONS

In this paper we examine the performance of different models in order to describe the behaviour of electricity prices. It is well known that electricity prices exhibit mean-reversion and that large jumps occur frequently. However, stochastic jump models that have been applied in previous studies suffer from a potential identification problem. In these models, mean-reversion is used to control jumps. Identification problems might occur when mean-reversion also exists in normal trading periods.

Using data from various electricity markets, natural gas and oil markets we show that mean-reversion parameter estimates change from negative to positive after adding a stochastic jump process. Positive signs are not consistent with the nature of mean-reversion; they imply a further move away from the long-term mean. Therefore, we conclude that stochastic jump models indeed lead to misspecification of the true mean-reverting behaviour.

In an attempt to disentangle the jump modelling from mean-reversion, we introduce a regime jump model in this paper. This model identifies three different regimes, a normal one and two that control for a jump and a reversal back to the normal process. Our results indicate the existence of mean-reversion in the normal process with consistent parameter estimates. This result implies that the regime jump model is a better specification of electricity price dynamics.

From our results, we conclude that stochastic jump processes are not a proper way to model electricity price jumps as lead to problems with identifying the true mean-reverting process in the data. From that perspective, the regime jump model is a first attempt to disentangle mean reversion from jump modelling. These results lead to differences in results when implemented in forward pricing and risk management frameworks.[3]

[3] Huisman and Mahieu (2001a and b) use the regime jump framework to model foreward price curves and for risk management issues.

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