What moves wholesale electricity prices in the Pacific Northwest?

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ABSTRACT

Wholesale electricity has the most volatile prices when compared to other energy commodities like crude oil, natural gas and gasoline, primarily because electricity cannot be economically stored and its market demand is price-insensitive. Market price responds to fluctuations in temperature that drive daily demand. It also reacts to variations in hydro availability, fuel price, and capacity available that drive supply. This paper explores how electricity price can vary with its fundamentals via regressions with alternative stochastic specifications. Using ETS in SAS V.9, we estimate these regressions whose results are useful to understand wholesale electricity price movements and to make forecast of future prices.

INTRODUCTION

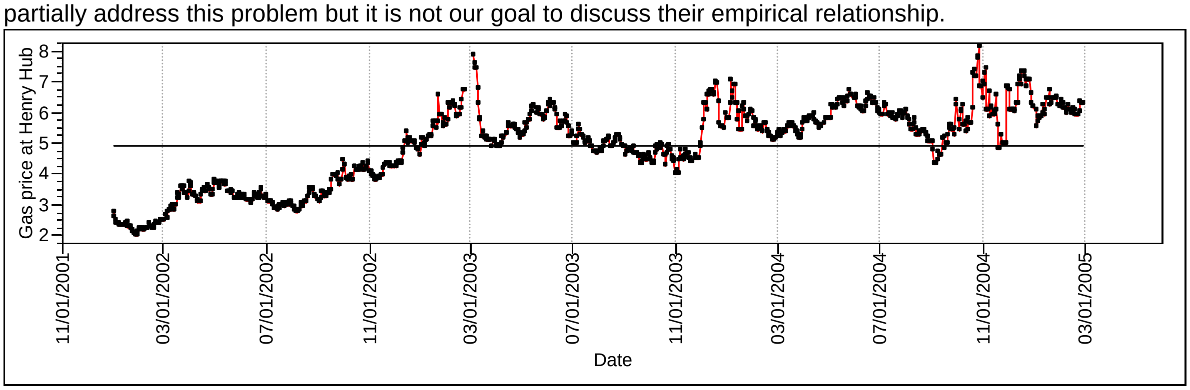
As Californians, we understand the importance of electricity, especially the astronomical electricity price during our energy crisis that led to rolling blackout. Electricity is one of the most interesting commodities — it is highly volatile though non-storable. Even though NYMEX (New York Mercantile Exchange) has offered electricity futures that could be used for hedging, the only geographical region is PJM (Pennsylvania, New Jersey, and Maryland) regional grid.[1] Therefore, it may not be that useful to those electricity wholesalers in the West coast. Our research is aimed to answer a simple question: what factors are contributed to the movement of the wholesale electricity price in the Pacific Northwest? If we could answer that question, then we may be able to develop a strategy to hedge away the price risk. In this paper, we have focused our attention on the Mid-Columbia (Mid-C) market (physically located along Columbia River in central Washington), a major wholesale electricity-trading hub located in the Pacific Northwest of the United States. All graphs are generated using SAS JMP.

MARKET STRUCTURE

To fully understand the situation, we need to have some knowledge of the electricity market. Here is a brief description of the wholesale electricity market.

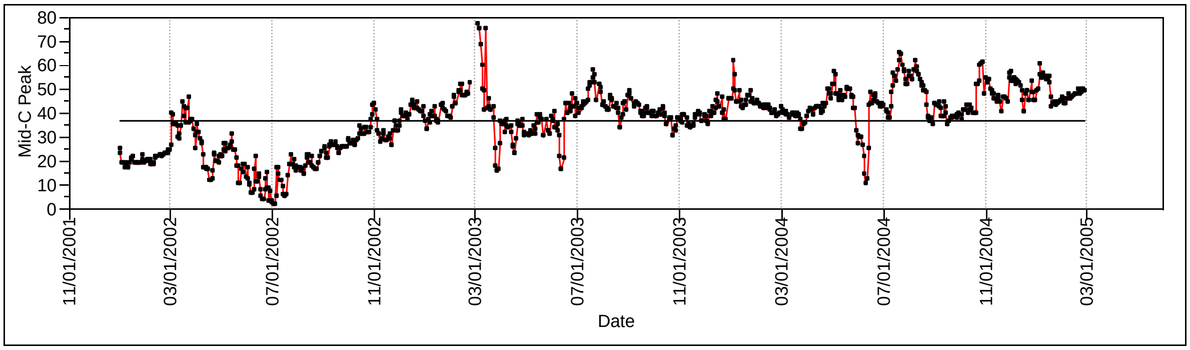
Electricity price is measured in price per megawatt hour (MWh) and divided into peak vs. non-peak, firm vs. non-firm. Peak hours are from 7:00 AM to 11:00 PM (the hour ending 0800 to the hour ending 2300) prevailing local time. Peak days are Mondays through Fridays, excluding North American Electric Reliability Council (NERC) holidays. Firm price reflects an obligation (to the seller) to deliver while non-firm deliver is subjected to curtailment or cessation of delivery by the supplier or purchases in accordance with prior agreements or under predefined conditions. Thus, non-firm sales are sometimes called economy or interruptible sales. In the eastern region of the United States, electricity is mostly generated from coal, nuclear, or natural gas. Since the on-peak electricity price movements tend to coincide with those of the natural gas, the on-peak marginal demand is most likely served by natural gas generators with the highest per MWh fuel cost. As a result, the volatility of gas price further amplifies the volatility of electricity.

The situation is more complicated for the Pacific Northwest because of thermal and hydro generation. Weather, or hydro condition, is notoriously difficult to forecast or predict. The output of a hydro system is mainly determined by the precipitation, which is usually random and not related to electricity demand. A system with reservoir storage can partially address this problem but it is not our goal to discuss their empirical relationship.

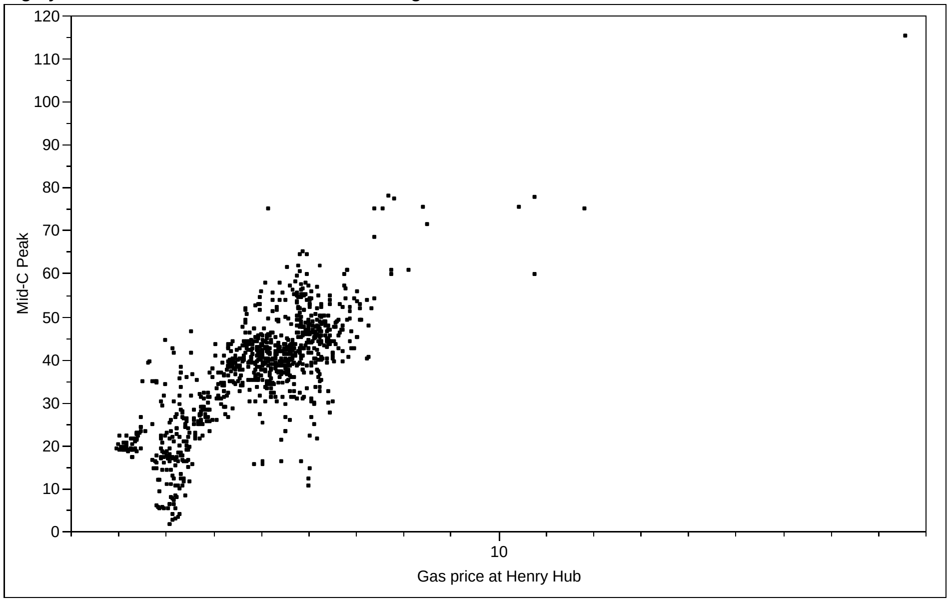


For the gas price, we use the Henry Hub gas price, which is the major natural gas exchange located in Louisiana.

[1] In fact PJM serves more than 44 million customers in Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia, and Washington, D.C.



As we can see from the graphs above, both electricity and gas price exhibit high volatility and seasonality pattern. They are also highly correlated as shown in the follow diagram.



We have also calculated the Heating Degree Day (HDD) and Cooling Degree Day (CDD) according to the definition of the Chicago Mercantile Exchange (CME). We incorporated both CDD and HDD to model the demand of electricity from heating and cooling. Another benefit of this model specification is that the electricity wholesalers could trade weather derivatives from CME. HDD and CDD futures and options on futures are the first exchange-traded, temperature-related weather derivatives. These contracts are designed to help businesses protect their revenues during times of depressed demand or excessive costs because of unexpected or unfavorable weather conditions.

ESTIMATION

We have adopted a partial-adjustment equilibrium-price model that yields a parsimonious specification for an electricity spot price regression. Let $\boldsymbol{\beta}$, $\boldsymbol{\eta}$, and $\boldsymbol{\delta}$ denote column vectors of parameters, let λ denote a parameter, and let μ_t denote a random-error term. In the present context the spot price regression translates into the following model:

$$y_t = \mathbf{x_t\beta} + \mathbf{M\eta} + \mathbf{D\delta} + \lambda y_{t-1} + \mu_t \text{ —— (1)}$$

The vectors of parameter estimates are denoted **b**, **m**, and **d**, respectively; *l* is the estimate of λ. Thus, for example, b_0 is the estimate of the intercept, b_1' is the estimated coefficient attached to $x_{1t}' = x_{1t}^2$, m_3 is the estimated coefficient attached to $M_3 = 1$ in March, and d_4 is the estimated coefficient attached to $D_4 = 1$ on Thursday.

After some investigation we hypothesize the disturbance term to follow an AR(1) process:

$$\mu_t = \rho\mu_{t-1} + \varepsilon_t \text{ —— (2a)}$$

The estimate of ρ is denoted r, and the disturbance term in the AR(1) process, ε_t, is hypothesized to be normally distributed about a zero mean and to have a GARCH (1, 1) time-dependent variance, σ_t^2, that is also a linear function of the vector z_t, a subset of x_t. Any such time dependency for the variance of ε_t will carry over to that of μ_t, and subsequently plague the spot-market price y_t, too.

Let γ denote a column vector of parameters whose estimate will be denoted g, and let α_j (j = 0, 1, 2) denote a parameter estimated by a_j. The expanded GARCH(1, 1) specification is:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\sigma_{t-1}^2 + z_t\gamma \text{ —— (2b)}$$

The final regression model to be fitted is written as:

$$y_t = \mathbf{x_t\beta} + \mathbf{M\eta} + \mathbf{D\delta} + \lambda y_{t-1} + \rho\mu_{t-1} + \varepsilon_t \text{ —— (3)}$$

with ε_t being a normally distributed disturbance term that has a zero mean and a conditional variance given by equation (2b).

RESULT

We have used the GARCH options provided in SAS/ETS' PROC AUTOREG to obtain the following results.

Variable	**AR(1) / GARCH (1, 1)**	**AR(1)**	**OLS**
MSE	12.53	11.39	11.40
AIC	4468.92	5043.09	5042.57
Total R-Square	0.9275	0.9348	0.9347
Log Likelihood	-2205.46	-2496.54	-2497.28
x_{0t} = Intercept	6.0711 (5.75)*	6.9221 (4.65)*	7.4580 (4.88)*
x_{1t} = Henry Hub Price	0.8514 (3.49)*	0.6338 (2.25)	0.7120 (2.56)
$x_{1t}^2 = x_{1t}$' = (Henry Hub Price)^2	0.0643 (4.95)*	0.0981 (5.40)*	0.1003 (5.47)*
x_{2t} = Washington Hydro Index	-0.5833 (-4.40)*	-0.5931 (-3.24)*	-0.6353 (-3.35)*
x_{3t} = Columbia River Flow	-0.1644 (-4.65)*	-0.2305 (-5.60)*	-0.2407 (-5.71)*
x_{4t} = Portland CDD	0.0608 (3.51)*	0.1095 (5.19)*	0.1074 (4.96)*
x_{5t} = Portland HDD	0.0152 (0.87)	0.0434 (1.84)	0.0378 (1.58)
M_1 =1 if Jan; else 0	-0.0870 (-0.23)	0.1974 (0.40)	0.2417 (0.46)
M_2 =1 if Feb; else 0	0.1862 (0.43)	0.1781 (0.35)	0.2143 (0.41)
M_3 =1 if Mar; else 0	3.5113 (8.36)*	0.5138 (0.94)	0.5597 (0.98)
M_4 =1 if Apr; else 0	-0.1193 (-0.21)	0.7397 (1.27)	0.7313 (1.20)
M_5 =1 if May; else 0	0.4823 (0.81)	1.0075 (1.42)	0.9887 (1.34)
M_6 =1 if Jun; else 0	-0.8744 (-1.21)	-0.4347 (-0.51)	-0.5442 (-0.62)
M_7 =1 if Jul; else 0	0.2906 (0.45)	-0.0164 (-0.02)	-0.0527 (-0.06)
M_8 =1 if Aug; else 0	-0.6443 (-1.10)	-0.5547 (-0.74)	-0.5948 (-0.77)
M_9 =1 if Sep; else 0	-0.6955 (-1.24)	-0.4868 (-0.73)	-0.5259 (-0.76)
M_{10} =1 if Oct; else 0	-0.6640 (-1.70)	-0.2311 (-0.40)	-0.2905 (-0.48)
M_{11} =1 if Nov; else 0	-0.3090 (-0.72)	0.1290 (0.24)	0.1434 (0.26)
D_1 =1 if Mon; else 0	1.4801 (5.91)*	1.5496 (3.93)*	1.5599 (4.05)*
D_2 =1 if Tue; else 0	0.1595 (0.63)	0.3931 (1.03)	0.4178 (1.10)
D_3 =1 if Wed; else 0	0.7879 (2.66)*	1.0265 (2.67)*	1.0446 (2.72)*
D_4 =1 if Thu; else 0	0.5497 (1.87)	0.3245 (0.84)	0.3583 (0.93)
D_5 =1 if Fri; else 0	-1.0178 (-3.70)*	-1.2941 (-3.29)*	-1.2703 (-3.31)*
y_{t-1} = Lag(Mid-C Price)	0.7864 (50.28)*	0.7707 (40.72)*	0.7559 (42.94)*
μ_{t-1} = Lagged error in the AR(1) process	0.1713 (3.86)*	0.0510 (1.37)	
α_0 = Intercept of the GARCH (1,1) process	0 (5294)*		
ε_{t-1}^2 = Lagged error squared in the GARCH (1,1) process	0.3411 (6.89)*		
σ_{t-1}^2 = Lagged conditional variance in the GARCH (1,1) process	0.6063 (16.16)*		
x_{1t} = Henry Hub Price in the GARCH(1, 1) process	0.0973 (3.02)*		
x_{3t} = Columbia River Flow in the GARCH(1, 1) process	0.0222 (1.76)		

Even though most of the estimated parameters are relatively similar in all three equations, the above result shows that both OLS and AR(1) specifications have resulted in spurious result due to the misspecification of error variance.

SAS 8 VS. SAS 9?

One of the unexpected finding of our research is the discrepancy between the GARCH estimation from SAS 8 and SAS 9. We have used identical program in the same machine but received similar but different results.

GARCH Estimates (SAS 8)				GARCH Estimates (SAS 9)			
SSE	11772.4938	Observations	938	SSE	11754.1106	Observations	938
MSE	12.55063	Uncond Var	1.99719E-7	MSE	12.53103	Uncond Var	2.00065E-7
Log Likelihood	-2205.4641	Total R-Square	0.9274	Log Likelihood	-2205.4605	Total R-Square	0.9275
SBC	4609.39694	AIC	4468.92819	SBC	4609.38979	AIC	4468.92104
Normality Test	477.4423	Pr > ChiSq	<.0001	Normality Test	494.0636	Pr > ChiSq	<.0001

The estimated parameters are also different.

	SAS 8		SAS 9	
	Value	SE	Value	SE
Intercept	6.1092	1.052	6.0711	1.0562
WA_INDEX	-0.5815	0.1322	-0.5833	0.1325
columbia	-0.165	0.0353	-0.1644	0.0354
henry	0.8405	0.243	0.8514	0.244
henry_sq	0.065	0.0129	0.0643	0.013
port_cdd	0.0605	0.0173	0.0608	0.0173
port_hdd	0.0144	0.0175	0.0152	0.0175
m_1	-0.0717	0.379	-0.087	0.3797
m_2	0.1848	0.4301	0.1862	0.4307
m_3	3.5533	0.4203	3.5113	0.4202
m_4	-0.1025	0.5645	-0.1193	0.5648
m_5	0.4975	0.5942	0.4823	0.5953
m_6	-0.8898	0.7225	-0.8744	0.7241
m_7	0.3022	0.6436	0.2906	0.6448
m_8	-0.6567	0.5828	-0.6443	0.584
m_9	-0.6901	0.5596	-0.6955	0.561
m_10	-0.7049	0.3923	-0.664	0.3913
m_11	-0.3291	0.4299	-0.309	0.4292
w_1	1.471	0.2501	1.4801	0.2507
w_2	0.1576	0.2527	0.1595	0.2533
w_3	0.7735	0.2959	0.7879	0.2964
w_4	0.5291	0.2938	0.5497	0.2938
w_5	-1.0204	0.2744	-1.0178	0.275
lag_midc	0.7871	0.0156	0.7864	0.0156
AR1	-0.1716	0.0442	-0.1713	0.0444
ARCH0	1.05E-08	3.72E-12	1.05E-08	1.99E-12
ARCH1	0.3416	0.0494	0.3411	0.0495
GARCH1	0.6057	0.0375	0.6063	0.0375
HET1	0.0221	0.0126	0.0222	0.0126
HET2	0.0978	0.0322	0.0973	0.0322

CONCLUSION

Using SAS/ETS, we have investigated the underlying factors of the movement of the wholesale electricity prices in the Pacific Northwest. Our result will be very useful to the market practitioners as they could actually hedge the electricity price risk using CME weather derivatives and NYMEX gas futures.

ENDNOTE

Both authors are advisors to InfoAtlas.
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