



Retailer Value-at-risk in Interconnected Power Markets: An Australian Empirical Analysis

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ABSTRACT

This paper investigates value-at-risk in the Australian interconnected power markets. We model the price change using seven different volatility models and perform the back testing from both investors' (sellers' side) and retailers' (buyers' side) perspectives. From investors' perspective, we find that GARCH (1,1) model outperforms moving average (MA) and exponentially weighted MA models. On the other hand, the MA outperforms various GARCH (1,1) models from retailers' perspective. Our findings lead to a new insight to analyze carefully the position of modeling risk in power market since different position generates different result.

Keywords: Back-testing, Power Markets, Value-at-risk, Volatility

JEL Classifications: G17, G32, Q40

1. INTRODUCTION

Research works on risk measurement using value-at-risk (VaR) in power market are limited. The possible explanation is that VaR method historically came from industry practice and is normally used for standard financial instruments (like stocks and bonds). At that time, VaR in power market had not been applied yet. However, as financialization of commodity markets occurs, it is likely that power market will be treated like other financial instruments. Therefore, the use of VaR in power market will emerge and this will explore new financial research area.

Another issue is that most papers investigating VaR in power market tend to take the position from generators', the sellers', perspective (for instance Chan and Gray, 2006; Walls and Zhang, 2006; Frauendorfer and Vinarski, 2007; Herrera and González, 2012; Andriosopoulos and Nomikos, 2012). This paper argues that analyzing VaR in power market from retailers', the buyers', perspective is also essential since the price spike, a stylized fact of power price, indeed generates market risks that must be managed carefully. Therefore, a dramatic increase (i.e. huge positive "return") is unfavorable while a dramatic decrease (i.e. huge

negative "return") is favorable for the retailers in power market. This new perspective changes the common VaR perspective by investigating right-tail side instead of left-tail side.

2. AUSTRALIAN POWER MARKET

The Australian power market has transformed over the last two decades. The market participants of Australia were owned by government and monopolies before 1997. Then, in the late 1990s, the Australian government commenced significant structural reform by separating between power generation and power transmission. Nowadays, the Australian power market (National Electricity Market [NEM]) is an interconnected power market among several regional networks between power suppliers and retailers.

The price mechanism in the NEM can be explained as follows. As the generators submit offers every 5 min, the submitted offers then become the basis in determining the number of generators that are required to produce electricity. Then, the final price is constructed every half-hour for each of the regions by averaging the 5 min spot prices. Therefore, there are 48 different half-hourly spot prices in a day for each region in the NEM.

3. LITERATURE REVIEW

There are a number of studies examining VaR in power market. The works tend to extend the standard VaR model, but cover only from the sellers' perspective. Chan and Gray (2006) develop a model that incorporates autoregression and weekly seasonality in their EGARCH specification. Walls and Zhang (2006) use EVT in their modified VaR model and demonstrate that the modified VaR is more accurate in the Alberta power market. Another extension of VaR in power market by adopting EVT is proposed by Herrera and González (2012). Frauendorfer and Vinarski (2007) propose a quasi-sensitivity analysis of the VaR with respect to the risk factors price and volatility. Andriosopoulos and Nomikos (2012) extend a set of VaR models to capture the dynamics of energy prices. However, none of them performs VaR analysis from buyers' side. The analysis from buyers' side offers new insight to the retailer about how much the market risk exposure in the power market.

4. METHOD

Instead of analyzing VaR from seller side, this paper offers new perspective by analyzing VaR from buyer side in the power market. We calculate common analytical VaR as explained in financial risk literature (such as Hull, 2007; Danielsson, 2011). However, we calculate the VaR value of the retailer by looking at the right-tail instead of the left-tail. In contrast to the previous research about VaR in power market, we propose various models of forecasting volatility so that the dynamic price change in the power market is captured by the dynamic volatility. We use seven different volatility models:

1. Moving average (MA)

The MA model is formulated (Danielsson, 2011):

$$\sigma_t^2 = \frac{1}{n_w} \sum_{k=1}^{n_w} y_{t-k}^2 - k \quad (1)$$

where σ_t denotes the volatility forecast for time t , y_t denotes the realized return at time t , and n_w denotes the number of estimation window.

2. Exponentially weighted MA (EWMA)

EWMA extends the MA by putting weight (λ) on recent observation. This paper formulates the EWMA model that is close to Hull (2007) and Danielsson (2011):

$$\sigma_t^2 = (1 - \lambda)y_{t-1}^2 + \lambda\sigma_{t-1}^2 \quad (2)$$

where σ_t denotes the volatility forecast for time t and y_t is the realized return at time t .

3. ARCH (1)

ARCH (1) model formulates that the conditional variance depends on the recent squared return. According to Engle (1982), ARCH (1) model can be written as follow:

$$\sigma_t^2 = \omega + \alpha y_{t-1}^2 \quad (3)$$

where σ_t denotes the volatility forecast for time t and y_t is the realized return at time t .

4. GARCH (1,1)

GARCH (1,1) generalizes the ARCH (1) model by also capturing previous conditional variance variable in the model. According to Bollerslev (1986), GARCH (1,1) model can be written as follow:

$$\sigma_t^2 = \omega + \alpha y_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (4)$$

where σ_t denotes the volatility forecast for time t and y_t is the realized return at time t .

5. GARCH (1,1) – student t

The model is similar with Equation (4) but the conditional normal distribution is replaced with the Student-t distribution.

6. EGARCH

Nelson (1991) modifies the GARCH model by designing exponential relationship. The model can be written as follow:

$$LN(\sigma_t^2) = \omega + \alpha \left[\frac{|y_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right]^2 + \beta LN(\sigma_{t-1}^2) + \gamma \frac{y_{t-1}}{\sqrt{\sigma_{t-1}^2}} \quad (5)$$

where σ_t denotes the volatility forecast for time t and y_t is the realized return at time t .

7. GJR

Glosten et al. (1993) extends the GARCH model by adding an additional term for considering asymmetric response of volatility to recent positive and negative return. It is the GJR model and the model can be written as follow:

$$\sigma_t^2 = \omega + \alpha y_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma y_{t-1} I_{t-1} \quad (6)$$

$I_{t-1}=1$ if $y_{t-1}<0$ and $I_{t-1}=0$ otherwise

where σ_t denotes the volatility forecast for time t and y_t is the realized return at time t .

The estimated VaR is obtained from the value of estimated volatility from those seven different models.

5. DATA AND EMPIRICAL ANALYSIS

We obtained the daily series of Australian power market prices in four interconnected markets (NSW, QLD, SA and VIC) from the AEMO website. Then, we calculated the daily price for each region by averaging 48 half-hour power prices. We decomposed the sample period into in-sample and out-of-sample periods. The in-sample period is from 1 January 2000 to 31 December 2009 while the out-of-sample period is from 1 January 2010 to 31 December 2014. Our choice about in-sample period is motivated by our focus on financialized commodity markets. Commodity markets have entered financialization era and been identified to possess special properties since 2000s (Rossi, 2012; Tang and Xiong, 2012). Therefore, we start our in-sample period at January 1 2000. Many finance empirical works use 10 years (Ledoit and Wolf, 2008). Therefore, we decide to use 10 years data (until the end of 2009) for modeling basis (in-sample period). Then, we forecasted various volatility models from in-sample period and used the estimated

volatility model to obtain VaR value. Finally, we performed back-testing during out of sample period.

Table 1 reports the descriptive statistics of power price change in the four regions. We use “price change” instead of “return” because we emphasize the price risk from the retailers instead from the investors’ perspective. The descriptive statistics include the mean, standard deviation, minimum, maximum and the number of observation in the each region. Panel A reports the descriptive statistics from January 1, 2000 to December 31, 2014 (all periods), Panel B reports the descriptive statistics from January 1, 2000 to December 31, 2009 (in-sample period) and Panel C reports the descriptive statistics from January 1, 2010 to December 31, 2014 (out-of-sample period).

We find that average daily power price changes range from negative 0.07% in SA to 0.07% in VIC during all sample period, range from negative 0.01% in QLD to 0.13% in SA during in-sample period and range from negative 0.48% in SA to 0.03% in QLD during out-of-sample period. Overall, SA region tends to show the smallest price change while QLD and VIC regions tend to show the highest price change.

We also find that the volatilities of power price change range from 35.2% in VIC to 46.90% in SA during all sample period, range from 38.01% in VIC to 48.15% in SA during in-sample period and range from 24.42% in NSW to 44.31% in SA during out-of-

sample period. Overall, SA region tends to be the most volatile of price change while NSW and VIC regions tend to be the least volatile of price change.

Table 2 Panel A reports the results of back-testing VaR in the four regions using seven different volatility models from investors’ perspective at 99%, 95%, and 90% confidence levels. The reported numbers are the number of VaR violations. A VaR violation from investors’ perspective occurs when a negative return is worse than VaR limit in the designated confidence level. The best volatility model implies the least VaR violation.

We find that the power price volatilities are best captured by GARCH (1,1) model in four regions at 99% confidence level, by GACRH (1,1) model in NSW and QLD regions and by ARCH (1) model in SA and VIC regions at 95% confidence level, and by ARCH (1) model in NSW and SA regions, by EGARCH model in QLD region and by MA model in VIC region at 90% confidence level. Overall, we can observe that GARCH (1,1) method tends to perform best in modeling power price change volatility from investors’ perspective.

The situation is completely different when we perform similar analysis but from retailer perspective. As reported in the Table 2 Panel B, however, we find that the power price changes are best captured by MA model in NSW, QLD and VIC regions and by EGARCH model in SA region at 99%, 95% and 90% confidence

Table 1: The descriptive statistics of power price change in the four regions

Statistics descriptive	Panel A: All-sample period				Panel B: In-sample period				Panel C: Out-of-sample period			
	NSW %	QLD %	SA %	VIC %	NSW %	QLD %	SA %	VIC %	NSW %	QLD %	SA %	VIC %
Mean	0.0183	0.0023	-0.0716	0.0692	0.0183	-0.0091	0.1334	0.1137	0.0183	0.0253	-0.4817	-0.0198
Standard deviation	39.40	45.30	46.90	35.22	45.06	47.95	48.15	38.01	24.42	39.49	44.31	28.87%
Minimum	-403.28	-415.47	-398.58	-399.29	-403.28	-414.45	-395.46	-368.41	-248.50	-415.47	-398.58	-399.29
Maximum	406.45	426.88	439.62	381.15	406.45	426.88	439.62	381.15	239.78	415.77	352.82	361.77
Number of observation	5479	5479	5479	5479	3653	3653	3653	3653	1826	1826	1826	1826

Table 2: Back-testing VaR results in the four regions using seven different volatility models from investors’ perspective (sellers’ side) in the Panel A and from retailers’ perspective (buyers’ side) in the Panel B

CL	Panel A								Panel B							
	Moving average (MA)				GARCH (1,1) - normal				Moving average (MA)				GARCH (1,1) - normal			
	NSW	QLD	SA	VIC	NSW	QLD	SA	VIC	NSW	QLD	SA	VIC	NSW	QLD	SA	VIC
n-99	15	22	28	17	1	6	13	4	12	19	30	16	17	31	39	16
n-95	16	34	55	25	9	16	47	26	16	39	50	20	32	48	59	33
n-90	18	56	77	35	26	34	85	51	19	52	74	28	44	62	96	56
	EWMA				GARCH (1,1) - t Student				EWMA				GARCH (1,1) - t Student			
n-99	32	41	43	30	1	8	13	3	50	48	54	44	22	38	30	16
n-95	71	70	86	75	11	16	37	20	95	77	89	87	38	52	54	35
n-90	117	101	122	124	30	41	57	47	143	119	131	128	73	72	83	57
	ARCH (1)				E-GARCH				ARCH (1)				E-GARCH			
n-99	3	10	15	7	14	12	43	25	15	24	31	16	15	10	38	18
n-95	6	19	35	14	18	21	64	34	22	41	55	25	17	19	65	25
n-90	10	31	53	40	18	30	91	49	26	61	76	41	25	28	92	46
	GJR-GARCH								GJR-GARCH							
n-99					19	49	65	26					25	55	57	21
n-95					31	69	86	41					43	87	90	41
n-90					54	93	118	62					60	111	120	62

CL: Confidence level, n: Number of VaR violations (a VaR violation occurs when a negative return is worse than VaR limit in the designated confidence level).” Thus, “n-99” refers to the number of VaR violation during out-of-sample period at 99% confidence level, “n-95” refers to the number of VaR violation during out-of-sample period at 95% confidence level and “n-90” refers to the number of VaR violations during out-of-sample period at 90% confidence level

levels. Overall, we can observe that MA method tends to perform best in modeling power price change volatility from retailers' perspective.

Therefore, we should be careful when modeling risk in the power market. First, we have to understand our position whether we are from the buyer or seller side. Different side will generate different result of which volatility model tends to be the best. Second, we should note that price spike risk is indeed the risk faced by the retailers in the power markets. Thus, an unexpected high positive return seems good in financial market (stocks) but is highly unfavorable in the power market, especially from the retailers' perspective. While GARCH (1,1) model performs better than MA and EWMA models from investors' perspective, the MA performs better than various GARCH (1,1) models from retailers' perspective in the power market. GARCH (1,1) model is expected to perform better for high frequency data (Bollerslev, 1986; Andersen and Bollerslev, 1997). This theory works in power market when we discuss from the sellers' side. From the buyers' side, however, we provide an evidence that the theory does not work.

6. CONCLUSION

This paper investigates VaR in the power market using seven different volatility models from the retailers' perspective. We model the volatility and perform the back testing VaR of price changes. We compare the back testing results from both investors' (sellers' side) and retailers' (buyers' side) perspectives.

We find that the back testing results are substantially different from both sides in the power markets. GARCH (1,1) model tends to perform better than MA and EWMA models from investors' perspective. On the other hand, the MA performs better than various GARCH (1,1) models from retailers' perspective. This implies a new perspective to consider our position (seller or buyer side) when we model the price change risk in the power market.

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