Evaluating Market Risk of Coal

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Abstract

We use daily price of spot, futures and swap contracts to study the market risk of coal. The Value at Risk (VaR), GARCH (1, 1), diagonal-VECH, diagonal-BEKK and CCC models are applied in this paper. The empirical results demonstrate that both variance-covariance method and GARCH model pass Basle's back-test at 99% confidence level, which outperforms the historical simulation method. Meanwhile, although variance-covariance and GARCH models also have good performance at 95% confidence levels, most contracts pass back-test except RFM, which falls into yellow zone in variance-covariance method and RSQ, which falls into yellow zone in GARCH method. Historical simulation method is the poorest of three methods to calculate VaR of coal return series. The empirical result of MGARCH shows that cross volatility of RS/RFQ is higher than other combinations in diagonal VECH, CCC and diagonal BEKK model. However, the degree of closeness of the three MGARCH models in explaining all combinations shows no high cross volatility.

Keywords: constant conditional correlation, CCC, coal, diagonal-BEKK, diagonal-VECH, GARCH, VaR

1. Introduction

Coal generates 42% of the world's electricity, and coal-fired thermal power plants make major efforts to target smooth electricity generation, cost control, safety and commitment to environmental protection. This study aims to investigate coal price fluctuation because coal accounts for over 70% of electricity generating costs. Kat and Oomen (2006) point out that commodity markets have been developed for centuries, but coal still lacks investor's interests. Like other commodities, coal price experienced greater volatility than ever in 2008 due to global monetary easing policy and rapid economic growth in emerging markets. Lucarelli (2011) observes that the coal price entered into the volatile phase since the year 2004. From the lack of investor's interest, to a booming interest now, more investors have jumped into the coal market and this exacerbates coal price movements. The higher price volatility causes higher pressure on costs control for a coal-fired thermal power plant. In Asia, Japan, Korea and Taiwan have suffered the most from fluctuations in coal prices, as coal is one of their major power fuels and these three countries heavily rely on coal imports due to a severe lack of natural resources. Coal price from 2003 has entered into a volatile phase, which forces sellers, buyers, traders and speculators to hedge their positions against the possibility of adverse price volatility. In contrast to other commodities such as oil and natural gas, the coal market is relatively less known and coal prices are opaque. With the slow development of a reliable coal price index in the 21th century, the market becomes more translucent. With more transparency and increasing interests from other parties, except for the buyers and sellers in the coal market, it is worthwhile to analyze the volatility of coal prices.

Furthermore, the price volatility increases with time and there is a lack of literature in investigating the volatility. This research is conducted from a coal-fired power plant operation point of view to investigate the appropriate model for evaluating coal price volatility. We apply three methods to calculate and compare the result of VaR, including incorporating GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model to capture coal price volatility, and to quantify the price risk that coal-fired power plants may experience. MGARCH (Multiply Generalized Autoregressive Conditional Heteroscedasticity) is applied to investigate cross correlation among spot, futures and swap contracts with different maturity.

2. Literature Review

Jorion (1996) defines VaR in that it summarizes the worst expected loss over a target horizon within a given confidence interval. VaR simply means risk measuring in dollars. It tells the investor, given a probability, what will be the worst expected loss for a specific period. VaR simply explains downside risk. For example, a bank with a daily VaR of $30 million at 99% confidence level implies that this bank will face a 1% chance of loss greater than $30 million loss within one day.

Risk managers or shareholders might refer to VaR to decide if they feel comfortable of this risk or warn them to trim it. Basle Committee requested banks based on 99% confidence level to maintain three (3) times VaR as minimum capital requirement at ten (10) days holding period of portfolios. Linsmeier and Pearson (2000) define VaR as a combination of a single number, a measure of possible losses under normal market condition. Rahl and Lee (2000) illustrate VaR as the maximum losses of portfolios within holding periods under a specified probability. Giot and Laurent (2002) define VaR as a quantitative tool to assess risk over a given period. Under normal market conditions, when measuring VaR one needs to choose holding period and confidence level. Those who use VaR will see the degree of risk aversion and the cost of exceeding expected risk to decide confidence level. The 99% and 95% levels are the most common choices.

Many methods of calculating VaR have been developed nowadays since the advent of VaR. This study applies two major methods including historical simulation approach (nonparametric approach, unconditional volatility) and variance-covariance approach (also named delta-normal or parametric approach, conditional volatility). In addition, we use GARCH (1, 1) model to incorporate time-varied volatility to see if it improves VaR estimation. Each approach has its own assumptions, advantages and features. After the calculation of VaR, it is necessary to check if the model has a goodness fit. Since there are many methodologies of calculating VaR, there have naturally developed many methods to evaluate the performance of VaR. From a statistic point of view, there are maximum likelihood and root mean squared error (RMSE), mean absolute error, (MAE) among other models. Kupiec (1995) presents likelihood ratio test (LR test) and records a failure (or exception) if actual loss is larger than VaR, and a success when actual loss is less than VaR over the sample period. After many banks adopted their own internal risk measurement, different types of back tests have been developed. Basle Committee (1996) incorporates back test in conjunction with measuring internal market risk to meet capital requirements. The core of back test methods is to compare the actual outcome with internal model measure. If the difference is small enough, the internal risk measures are fine. In some respects, if comparison comes with big differences, there is something wrong with the models or assumptions of the back test. Jorion (2001) indicates that back test is a statistical method to verify the conformity between actual trading losses and projected losses.

Since the onset of VaR in 1993, it has become a vital tool to manage risk and is widely applied in economic and financial areas, such as setting risk limits, developing hedging strategy, managing cash flows and overall portfolio selection and allocation. This section reviews some empirical results of VaR. Mahoney (1996) examines the performance of VaR calculated by the historical simulation method versus two parametric models with normality distribution for portfolios of currency exchange rates and foreign equity. The findings yield that the historical simulation method outperforms the two parametric methods under higher levels of confidence (greater than 95%). Danielsson and Vries (1997) develop a new semi-parametric method, which is the mixture of non-parametric historical simulation and J.P. Morgan Risk Metrics, for VaR evaluation on SP500 index. Their empirical results exhibit semi-parametric method, which is superior to historical simulation and J.P. Morgan Risk Metrics on the VaR prediction. Hull, White (1998) adopt the GARCH and associate with historical simulation method to incorporate volatility for estimating VaR for different exchange rates and stock indices. Their finding shows that adding GARCH model does generate better results than traditional historical simulation method. Manfredo and Leuthold (1998) use VaR in different industry firms, such as energy and agricultural economics. With VaR estimation, academia helps to make decisions of pre-harvest for corn, wheat, and soybeans.

Jackson, Maude and Perraudin (1998) estimate VaR of actual fixed income, equity security and foreign exchange of a large bank with different methodologies, and illustrate simulation-based VaR methods explain tail probability better than parametric VaR methods. In the prospects of volatility forecast, parametric VaR get better accuracy than non-parametric and simulation-based methods. Giotand Laurent (2004) examine the performance of Risk Metrics, skewed student ARCH models and skewed Student APARCH on commodity portfolios with aluminum, nickel, copper, WTI and Brent crude oil and cocoa. The skewed Student APARCH model is regarded as the best in all cases. Hsieh (2004) applies GARCH and extreme value model on investigating VaR for grain portfolios of wheat, corn and soybean, and his results illustrate extreme value models can adequately deal with fat tail problem. Kuester, Mittnik, Paolella (2005) apply a fat tail GARCH and an extreme value theory approach on NASDAQ and produce the best VaR prediction result. Hsu (2007) applies various GARCH-type model to estimate VaR for Natural Gas. Lu, Marlow & Wang (2008) applies the EGARCH and GARCH to examine volatility in different bulk shipping sectors to capture the volatile and asymmetric characters. Janabi (2008) attempts to improve asset allocation decisions by including risk of commodity with long and short selling trading position in VaR calculation. He then re-engineers VaR model and develops liquidity-adjusted VaR (L-VaR) with taking illiquid markets and adverse markets into his assessment. Hung, Lee and Liu (2008) apply normal distribution (GARCH-N), t distribution (GARCH-t) and heavy tail distribution (GARCH-HT) into VaR calculation of energy commodities to deal with kurtosis and fat tail event. They find GARCH-HT has better accuracy than others. Fuss, Adams and Kaiser (2009) compare the performance of dynamic VaR and traditional VaR of the S&P GSCI of agricultural, energy, industrial metals, livestock and precious metals and conclude that incorporating time-varying volatility such as CAVaR and GARCH type model generate better performance on VaR.

3. Data and Methodologies

The prices of coal, globalCOAL NEWC Index, are obtained from globalCOAL. This index is the leading price benchmark for seaborne thermal coal in the Asia-Pacific region. Sample covers the period from Dec. 5, 2008 to Dec. 31, 2011 and has 756 daily observations which consist of settlement prices of nearby monthly, quarterly and yearly futures contracts, sourced from Intercontinental Exchange (ICE). Spot price and mid- price of nearby monthly, quarterly and yearly swap contracts are from globalCOAL coal trading platform. Variables hereafter are defined as below. S: spot price

FM, FQ and FY: nearby futures price for monthly, quarterly and yearly maturity contract respectively.
SM, SQ and SY: nearby swap price for monthly, quarterly and yearly maturity contract respectively.
RS, RFM, RFQ, RSM, RSQ and RSY: return for S, FM, RQ, SM, SQ and SY respectively.

Utilized models in our analysis are as follows: VaR, Historical Simulation method, Variance-Covariance method, ARCH (Autoregressive Conditional Heteroscedasticity), GARCH (Generalized Autoregressive Conditional Heteroscedasticity), diagonal VECH, CCC, diagonal BEKK, and back test. Jorion (1996) expresses that "VaR summarizes the worst expected loss over a target horizon within a given confidence interval". We apply standard historical simulation and variance-covariance method to estimate VaR. For ARCH model, we adopt the equation from Yang (2009). GARCH combines autoregressive (AR) and moving average (MA) to evaluate conditional variance. It is similar to ARMA models but applies to residuals instead of variables. We also use the equations from Yang (2009). The VECH model is proposed by Bollerslev, *et. al* (1988) and aims to reduce the number of parameters to be calculated and restrict matrices to be diagonalized for positive definite matrix. It means that the conditional covariance between residuals depends only on its own lagged value and lagged cross-products of residuals. We us the VECH model in Ding and Engle (2001). To simplify the computational complexity of MGARCH (Multivariate GARCH), Bollerslev (1990) assumes that the conditional correlations are constant in his CCC GARCH model where CCC is the abbreviation of Constant Conditional Correlation. The assumption of constant conditional correlation is always challenged just like the assumption of constant variance in conventional regression. Back test is used to test how good the market risk measurements are. We adopt the back test procedure required by Basle (1996) for financial institutions. The framework of back test are that banks with their own internal risk measure under a 99% confidence level for one day holding period and requires banks to review both presumed and actual trading outcomes by means of back test. By recording the trading outcomes exceeds presumed results ("exceptions"), banks can know how accurate model-generated is.

4. Empirical Results

4.1 VaR Calculation

VaR calculation simply follows Basle committee's requirement to set 250 days of historical data as window period. Given 250 days of returns from 2010/12/21 to 2011/12/30, we lag 250 days back from 2010/12/21 to get 250 days' historical data (2009/12/18 - 2010/12/20). The VaR calculations for each individual returns are presented below. In addition, GARCH (1,1) is applied for volatility to see if incorporating time-varying volatility could improve VaR calculation. All methods are applied and compared on the basis of 99% and 95% confidence levels respectively.

4.2 Historical Simulation Method

A window period is from 2010/12/21 - 2011/12/30 with total 250-day sample for historical simulation. VaR measure is the 4th largest loss at 99% confidence level and the 14th largest loss under 95% confidence level in the sample of 250 days. Table 1 shows that, under 99% confidence level, the returns of futures yearly contract (RFY) have the highest loss of -3.12% and returns of swap quarterly and yearly contracts (RSQ & RSY) have the least loss of -2.46%. With the respect of 95% confidence level, returns of futures yearly contract (RFY) have the highest loss of -1.73% and returns of futures monthly contract (RFM) have the least loss of 1.29%.

Table 1: Historical Simulation method –VaR

Period	99% CONFIDENCE LEVEL							95% CONFIDENCE LEVEL						
	RS	RFM	RFQ	RFY	RSM	RSQ	RSY	RS	RFM	RFQ	RFY	RSM	RSQ	RSY
2010/12/21~ 2012/12/30	-2.66%	-2.86%	-2.74%	-3.12%	-2.66%	-2.46%	-2.46%	-1.44%	-1.29%	-1.44%	-1.73%	-1.70%	-1.58%	- 1.39%

4.3 Variance-Covariance Method

Table 2 demonstrates that the spot contract (RS) has the largest loss of -3.16768%, and yearly swap contract (RSY) has the least loss of -2.37793% under scenario of 99% confidence level. Interestingly, returns of spot contract (RS) and swap yearly contract (RSY) have the largest loss of -2.67146% and least loss of -2.00542% respectively under confidence level of 95%. This method is relatively easy by monitoring variance or standard deviation to interpret expected risk.

Table 2: Variance-Covariance method – VaR

	Mean	Max	Min	SD	Z Value		VaR%	
						5%	99%	95%
RS	-0.0269	8.3766	-5.1144	1.3595	-2.33	-1.965	-3.16768	-2.67146
RFM	-0.0140	11.2834	-4.9646	1.3128	-2.33	-1.965	-3.05887	-2.57969
RFQ	-0.0391	4.8971	-4.6799	1.0981	-2.33	-1.965	-2.55860	-2.15779
RFY	-0.0232	3.8532	-4.3870	1.2473	-2.33	-1.965	-2.90632	-2.45104
RSM	-0.0190	12.4415	-3.9094	1.3339	-2.33	-1.965	-3.10789	-2.62103
RSQ	-0.0408	5.2085	-4.7417	1.1397	-2.33	-1.965	-2.65552	-2.23953
RSY	-0.0240	3.9678	-3.8979	1.0206	-2.33	-1.965	-2.37793	-2.00542

4.4 GARCH

It is well-documented in the literature that GARCH (1, 1) could adequately fit most economic and financial time series as a parsimonious representation to model conditional volatility. This section applies GARCH (1, 1) to model volatility of each individual return. At beginning of process GARCH, ARMA is used to find adequate mean equation for each variable. The adequate ARMA model is found by over fitting method to focus on white noise instead of significance of coefficient. Based on the criteria of no white noise and minimizing AIC, the best ARMA model for each return is shown below.

Table 3: ARMA model estimates

	RS	RFM	RFQ	RFY	RSM	RSQ	RSY
ARMA model	AR(7)	AR(3,20)	AR(5,8,14,22,30,36)	ARMA[(1,19,34),(1)]	AR(0,20)	ARMA[(16,19,22,30),(1)]	AR(20,30)
AIC	3.53613	3.572435	3.47095	3.802071	3.661651	3.616393	3.45188
Log Likelihood	-1315.513	-1310.87	-1241.806	-1366.464	-1344.657	-1306.943	-1249.307
Sum of coefficient	0.276916	0.218129	0.224549	0.045082	0.150186	-0.08653	-0.0230284
JB	7595.294	22171.28	4919.973	15438.97	62981.88	2818.369	1752.387
JB p value	0	0	0	0	0	0	0

The sum of coefficient of each variable is less than 1, which indicates a convergence at the end. This implies there is equilibrium in the long term. Similar to the findings of descriptive statistics, all variables are not normally distributed.

4.5 GARCH (1,1)

The maximum likelihood method is used in estimating the parameters in GARCH (*p, q*). The best ARMA model is selected previously, and GARCH model is proceeding with rectifying mean equation until residuals have no autocorrelation and no ARCH effect is found. Autocorrelation and ARCH effect are diagnosed by Q-test and Lung-Box Q^2 test respectively. Table 4 shows us the results of GARCH (1,1) which is used to examine the volatility of coal returns where α (ARCH term) reflects external and expected shocks in short term. Higherαexplains higher volatility in short term. β (GARCH term) explains the memory of volatility. When 0<β<1, the greaterβ, the slower and longer fluctuation. α+β can examine the persistence of volatility and response to time-varying variance. If (α+β) <1, the greater the (α+β) the longer persistence of volatility. Despite this volatility, variables eventually converge to equilibrium in long run after shocks. If (α+β)>1, it implies non-stationary of GARCH process and shocks would not result in convergence. From the empirical findings in Table 3, the value of α ranked from large to small respectively are RSM 0.27983, RFM 0.26785, RFQ 0.146633, RSY 0.144493, RFY 0.090094, RS 0.075437 and RSQ 0.054688. These numbers mean that RSM and RFM response to external shocks is more intensive than others and RS and RSQ are relatively less impacted by external and short term shocks. This is because returns of RSM and RFM are major financial settlement instruments with higher liquidity. On the other hand, the change in RS contract is subject to fundamental aspects of economy, which features less drastic fluctuation in short term. As for RSQ, we might attribute to its long risk management instrumental and less liquid characteristics.

The value ofβfrom large to small respectively are RSQ 0.938326, RFY 0.923961, RS 0.900453, RSY 0.860101, RFQ 0.848553, RSM 0.718424 and RFM 0.48147. RSM and RFM have the smallestβand the reasons are similar to the reason for α, as two contracts with higher liquidity. The results also show that the value of (α+β) for both RFY and RSY are greater than unity ((α+β)>1), which means the shocks would not decrease and fail to converge even in the long run. This implies that RFY and RSY might not be an adequate risk management instrument. Instead, quarterly and monthly contracts might be a better choice.

Table 4: GARCH (1,1) model

	RS	RFM	RFQ	RFY	RSM	RSQ	RSY
	AR(9)	AR(1,2,3,19,34)	AR(1,2,4,5,16)	AR[(1,2,19,21,34]	AR(0,20)	ARMA[(16,19,22,30),(1)]	AR(20,30)
	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)
ARCH term	0.075437	0.26785	0.146633	0.090094	0.27983	0.054688	0.144493
GARCH term	0.900453	0.48147	0.848553	0.923961	0.718424	0.938326	0.860101
ARCH+GARCH term	0.97589	0.74932	0.995186	1.014055	0.998254	0.993014	1.004594
Kurtosis	16.58325	28.97176	23.53764	24.59282	51.464	17.28436	17.62476
AIC	3.418483	3.405401	2.937199	3.517612	3.65619	3.385853	3.226343
Log Likelihood	-1263.094	-1219.647	-735.5171	-1260.099	-1339.65	-1219.372	-1164.549
JB	6011.691	20967.77	9364.062	14720.36	72006.65	6453.166	6774.062
JB p value	0	0	0	0	0	0	0

Table 5 illustrates VaR with incorporating volatility by GARCH model. RSM has the largest loss of -3.70043% at 99% confidence level and RFQ has least loss of -2.36259%. Similar to 99% confidence level, the scenario of 95% confidence level demonstrates that RSM has the largest loss of -3.12373% and RFQ has least loss of -1.99861%.

Table 5: GARCH – VaR

Return	Mean	Max	Min	Variance σ^2	SD	Z statistics 1%	Z statistics 5%	VaR%-GARCH (1,1) 99%	VaR%-GARCH (1,1) 95%
RS	-0.0269	8.3766	-5.1144	1.2049	1.0709	-2.33	-1.965	-2.49520	-2.10432
RFM	-0.0140	11.2834	-4.9646	1.5200	1.2000	-2.33	-1.965	-2.79600	-2.37201
RFQ	-0.0391	4.8971	-4.6799	1.0487	0.9972	-2.33	-1.965	-2.36259	-1.99861
RFY	-0.0232	3.8532	-4.3870	1.2000	1.0700	-2.33	-1.965	-2.51626	-2.12571
RSM	-0.0190	12.4415	-3.9094	2.5900	1.5800	-2.33	-1.965	-3.70043	-3.12373
RSQ	-0.0408	5.2085	-4.7417	1.0706	1.0143	-2.33	-1.965	-2.40411	-2.03389
RSY	-0.0240	3.9678	-3.8979	1.0540	1.0111	-2.33	-1.965	-2.37986	-2.01081

4.6 Back test

Basle (1996) outlines a framework of back test for banks with internal risk model under a 99% confidence level for a one-day holding period and urges banks to review both presumed and actual trading outcomes through back test. By identifying the trading outcomes exceeding presumed value ("exceptions"), banks would know how accurate the internal model is. Three zones are represented by different colors. Green zone indicates that internal risk model is appropriate. Trading results falling into yellow zone show that there is an improvement for the internal risk model. If results are in red zone which the risk models are not acceptable and imply models and/or assumptions are incorrect. VaR back test results for each contract estimated through historical simulation method, variance-covariance method and GARCH are represented in Table 6, 7 and 8 respectively.

Table 6: Back test result of historical simulation method

99%VaR(%)					95%VaR(%)				
Return	Average VaR	No. of exceptions	No. of observations	failure rate	Return	Average VaR	No. of exceptions	No. of observations	Failure rate
RS	-2.66	3	250	1.20%	RS	-1.44	13	250	5.20%
RFM	-2.86	5	250	2.00%	RFM	-1.29	10	250	4.00%
RFQ	-2.74	3	250	1.20%	RFQ	-1.44	10	250	4.00%
RFY	-3.12	3	250	1.20%	RFY	-1.73	11	250	4.40%
RSM	-2.66	4	250	1.60%	RSM	-1.70	10	250	4.00%
RSQ	-2.46	3	250	1.20%	RSQ	-1.58	9	250	3.60%
RSY	-2.46	1	250	0.40%	RSY	-1.39	15	250	6.00%

Table 7: Back test result of variance-covariance method

99% confidence level					95% confidence level				
Return	Average VaR%	No. of exceptions	No. of observations	Failure rate	Return	Average VaR%	No. of exceptions	No. of observations	Failure rate
RS	-3.17	2	250	0.00800	RS	-2.67	2	250	0.00800
RFM	-3.06	4	250	0.01600	RFM	-2.58	5	250	0.02000
RFQ	-2.56	3	250	0.01200	RFQ	-2.16	4	250	0.01600
RFY	-2.91	1	250	0.00400	RFY	-2.45	2	250	0.00800
RSM	-3.11	2	250	0.00800	RSM	-2.62	2	250	0.00800
RSQ	-2.66	3	250	0.01200	RSQ	-2.24	3	250	0.01200
RSY	-2.38	2	250	0.00800	RSY	-2.01	3	250	0.01200

Table8: Back test result of GARCH method

99% confidence level					95% confidence level				
Return	Average VaR%	No. of exceptions	No. of observations	Failure rate	Return	Average VaR%	No. of exceptions	No. of observations	Failure rate
RS	-2.50	3	250	0.01200	RS	-2.10	3	250	0.01200
RFM	-2.80	4	250	0.01600	RFM	-2.37	4	250	0.01600
RFQ	-2.36	3	250	0.01200	RFQ	-2.00	4	250	0.01600
RFY	-2.52	2	250	0.00800	RFY	-2.13	4	250	0.01600
RSM	-3.70	1	250	0.00400	RSM	-3.12	1	250	0.00400
RSQ	-2.40	2	250	0.00800	RSQ	-2.03	5	250	0.02000
RSY	-2.38	1	250	0.00400	RSY	-2.01	2	250	0.00800

4.7 Comparison of VaR estimation

The 99% confidence level in Table 9 shows that historical simulation method estimates VaR for each contract vary from minimum of -2.46% to maximum of -3.12%. Variance-covariance method has range from –2.38% to -3.17% and GARCH method has a range from -2.38% to -3.7%. On 95% confidence level, the results from historical simulation method with VaR range from -1.29% to -1.73%, and the ones from variance-covariance method range from minimum of -2.01% to maximum of -2.67%. GARCH VaR varies from -2% to -3.12%. GARCH has larger range between minimum and maximum of VaRs under the both scenarios of 99% and 95% confidence level. From this observation, we see GARCH is able to capture the volatility. With 99% confidence level, Table 10 presents the back test result of VaR estimated by variance-covariance method and GARCH method for each contract all fall in green zone, which verifies the accuracy of risk model. Only RFM has higher failure rate in historical simulation method, which falls in yellow zone where risk model might be challenged by the banking authority.

Table 9: Comparison VaR in three methods

99% confidence level				**95% confidence level**			
Return	HS	VC	GARCH	Return	HS	VC	GARCH
RS	-2.66	-3.17	-2.50	RS	-1.44	-2.67	-2.10
RFM	-2.86	-3.06	-2.80	RFM	-1.29	-2.58	-2.37
RFQ	-2.74	-2.56	-2.36	RFQ	-1.44	-2.16	-2.00
RFY	-3.12	-2.91	-2.52	RFY	-1.73	-2.45	-2.13
RSM	-2.66	-3.11	-3.70	RSM	-1.70	-2.62	-3.12
RSQ	-2.46	-2.66	-2.40	RSQ	-1.58	-2.24	-2.03
RSY	-2.46	-2.38	-2.38	RSY	-1.39	-2.01	-2.01

Table 10: Comparison of back test result at 99% confidence level

Return	HS			VC			GARCH		
	No. of exceptions	Zone	Failure rate	No. of exceptions	Zone	Failure rate	No. of exceptions	Zone	Failure rate
RS	3	Green	1.20%	2	Green	0.80%	3	Green	1.20%
RFM	5	Yellow	2.00%	4	Green	1.60%	4	Green	1.60%
RFQ	3	Green	1.20%	3	Green	1.20%	3	Green	1.20%
RFY	3	Green	1.20%	1	Green	0.40%	2	Green	0.80%
RSM	4	Green	1.60%	2	Green	0.80%	1	Green	0.40%
RSQ	3	Green	1.20%	3	Green	1.20%	2	Green	0.80%
RSY	1	Green	0.40%	2	Green	0.80%	1	Green	0.40%

For 95% confidence level, six of seven contracts of VaR estimated by historical simulation method reach red zone, which indicates risk models are not acceptable, details as per Table 18. Variance-covariance method and GARCH method have similar performance for VaR estimation, where only one contract falls in yellow zone and others fall in green zone. As far as the total numbers of exceptions is concerned, Table 12 demonstrates that GARCH is superior to historical simulation method and variance-covariance on 99% confidence level, but variance-covariance performs better than historical simulation method with GARCH under 95% confidence level. The table also illustrates GARCH is superior to variance-covariance to estimate VaR at higher confidence level.

Table 11: Comparison of back test result at 95% confidence level

Return	HS			VC			GARCH		
	No. of exceptions	Zone	Failure rate	No. of exceptions	Zone	Failure rate	No. of exceptions	Zone	Failure rate
RS	13	Red	5.20%	2	Green	0.80%	3	Green	1.20%
RFM	10	Red	4.00%	5	Yellow	2.00%	4	Green	1.60%
RFQ	10	Red	4.00%	4	Green	1.60%	4	Green	1.60%
RFY	11	Red	4.40%	2	Green	0.80%	4	Green	1.60%
RSM	10	Red	4.00%	2	Green	0.80%	1	Green	0.40%
RSQ	9	Yellow	3.60%	3	Green	1.20%	5	Yellow	2.00%
RSY	15	Red	6.00%	3	Green	1.20%	2	Green	0.80%

Table12: Total numbers of exceptions through back test

99%VaR(%)				95%VaR(%)		
	HS	VC	GARCH	HS	VC	GARCH
Sum of no. of exceptions	22	17	16	78	21	23

4.8 Volatilities of cross contracts

Following GARCH (1,1) to represent volatility of each individual return, this section further uses diagonal VECH, CCC and diagonal BEKK of MGARCH to investigate the cross volatility of various contracts in six combinations which consist of RS/RFM, RS/RFQ, RS/RFY, RS/RSM, RS/RSQ, RS/RSY.

4.9 MGARCH

We applied three methods of MGARCH including diagonal VECH, CCC and diagonal BEKK to compare cross returns volatility between spots, futures and swaps contracts with monthly, quarterly and yearly maturity respectively. We start with finding adequate GARCH (1, 1) for each individual variable and adjust mean equation by cross correlation between variables until no residual autocorrelations of covariance and white noise conditions are satisfied. This section examines volatilities correlation between pair contracts. Table13 indicates that CCC model explains cross volatility better than diagonal VECH and most diagonal BEKK based on minimizing AIC, besides RS/RFM. Diagonal BEKK explain better cross volatilities of RS/RFM than diagonal VECH and CCC. In diagonal VECH, RS/RFQ has high correlation of volatility with AIC value of 6.35573 and RS/RSM has the least reliability of AIC, 7.33824. In CCC estimate, RS/RFQ represent relatively higher cross volatilities of AIC 6.32905 and the least one is RS/RFY of AIC 6.74915. RS/RFQ has higher cross volatilities in diagonal BEKK model, too. On the other side, RS/RSM has the highest AIC of 7.135824. From the empirical results of MGARCH, diagonal VECH, CCC and diagonal BEKK demonstrate that volatility of RS/RFQ is higher than other combinations. The residual of RS/RFQ satisfies white noise, and autocorrelation is within 2 standard errors bounds. On further examination, three MGARCH models with all combinations have no high volatility as conditional correlation, varied from minimum of 0.099211 to maximum of 0.51086. This finding can be utilized to choose risk instrument and develop hedging strategy for future study.

Table 13: Summary of empirical results of MGARCH

	Diagonal VECH			CCC			Diagonal BEKK		
Combination	Log-likelihood	AIC	Conditional Correlation	Log-likelihood	AIC	Conditional Correlation	Log-likelihood	AIC	Conditional Correlation
RS/RFM	-2324.117	6.54679	0.42078	-2324.97	6.54361	0.38766	-2323.737	6.540186	0.49149
RS/RFQ	-2317.153	6.35573	0.47315	-2309.241	6.32905	0.42451	-2317.041	6.350044	0.40949
RS/RFY	-2465.833	6.77672	0.51086	-2457.687	6.74915	0.33488	-2480.455	6.81102	0.33623
RS/RSM	-2666.802	7.33824	0.15092	-2381.608	6.55676	0.35645	-2594.415	7.135824	0.20649
RS/RSQ	-2415.58	6.53775	0.16731	-2405.195	6.50455	0.38635	-2420.543	6.545692	0.10454
RS/RSY	-2400.671	6.49777	0.16379	-2389.348	6.46206	0.31777	-2406.315	6.507546	0.09921

5 Conclusions

Markets now are facing more challenges for price forecasting. This study targets on VaR calculation by means of historical simulation method, variance-covariance and GARCH method. The empirical results demonstrate that both variance-covariance method and GARCH model pass Basle's back test at 99% confidence level which outperform historical simulation method. Meanwhile, variance-covariance and GARCH model also have good performance at 95% confidence level, as most contracts pass back test, except that RFM falls into yellow zone in variance-covariance method and RSQ falls into yellow zone in GARCH method. Historical simulation method is the poorest of the three methods to calculate VaR of coal return series. The empirical result of MGARCH shows that volatility of RS/RFQ is higher than other combinations in diagonal VECH, CCC and diagonal BEKK model. However, the degree of closeness of the three MGARCH models in explaining all combinations shows no high cross volatilities. This finding displays that the VaR of various contracts can help to choose risk management instrument and develop hedging strategy for future study. The managerial implication is that most Asian owners of coal-fired power plants heavily depend on their procurement experience and historical trace to manage their market risk.

Quantifying coal price volatility risk can help owners of coal-fired power plants to decide the right time and quantity of coal procurement, mitigate impact when markets go beyond normal conditions, and enhance their cash flows management. VaR is definitely an adequate model to apply in the coal market as it is widely used and extended to various industries. Future study is suggested to consider returns' distribution into VaR calculation to remove the concern of underestimating risk. In addition, a longer observation period, structure change and extreme value theory can be incorporated for future study. Further applying MGARCH to search adequate risk management instruments, optimal hedging ratio and hedge strategy could be a challenging task for a coal-fired power plant.

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