1-1-2012

Thumbs Up to Parametric Measures of Relative VaR and CVaR in Indonesian Sectors

David Allen

Ray Boffey
Edith Cowan University

Akhmad Kramadibrata
Edith Cowan University

Robert Powell
Edith Cowan University

Abhay Singh
Edith Cowan University

THUMBS UP TO PARAMETRIC MEASURES OF RELATIVE VaR AND CVaR IN INDONESIAN SECTORS

David E Allen[*], Raymond R Boffey[*], Akhmad R Kramadibrata[*], Robert J Powell[*] and Abhay Kumar Singh[*]

We examine relative share market risk between Indonesian sectors and how this changes during extreme market fluctuations. Ten sectors comprising the IDX Composite Index are examined over an eight-year period spanning the pre-GFC, GFC and post-GFC. Risk is measured using parametric and nonparametric Value at Risk (VaR) and Conditional Value at Risk (CVaR), which measures risk beyond VaR. In contrast to studies on most global markets, and due to relative stability in the Indonesian market, no significant differences are found in relative portfolio risk between the conditional and non-conditional measures, or between parametric and nonparametric measures. The insights are important to investors in choosing the sectoral mix of their portfolio.

Keywords: *Indonesia Stock Exchange, Value at Risk, Conditional Value at Risk, parametric, nonparametric*

I. INTRODUCTION

Indonesia is a vitally important market in the Asia Pacific region. The country has the world's fourth largest population of 241 million people, is a member of the G20 major economies in the world, has the largest economy in South East Asia, and has an annual average GDP growth rate exceeding 6% over the five years to 2011 (Statistics Indonesia, 2012). The World Federation of Exchanges (2011) rated the performance of the Indonesia Stock Exchange (IDX) as the world's fifth best in 2010 and second best in 2011.

The IDX at March 2012 comprised 442 entities with a market capitalisation of nearly 4000 trillion rupiah (approximately USD 400 billion). The IDX was formed through the merger of the Jakarta and Surabaya Stock Exchanges in 2007, and has a daily average of just over four thousand trades.

Indonesia is an emerging economy, which was a Dutch colony prior to receiving independence in 1945. Initially highly reliant on agricultural activity, as well as the oil and gas sectors, the economy has significantly expanded its other industries over the past few decades, with the IDX now having a good spread across a range of sectors including Agriculture, Energy, Banks and Insurance, Consumer Discretionary,

[*] School of Accounting, Finance and Economics, Edith Cowan University, Joondalup, Western Australia.

Consumer Staples, Industrials, Mining, Materials, Real Estate, and IT and Telecommunications (see Table 1 in our data section).

While the strong performance of the IDX makes it an attractive market for investors, it is of course a fundamental truth that higher returns are usually associated with higher risks, and it is therefore important to investors to understand those risks. This paper examines the relative risk of investing in those industry sectors making up the IDX.

Value at Risk (VaR) is a popular volatility metric for measuring market risk, and we use VaR to measure sectoral risk in this paper. A major criticism of VaR, particularly since the GFC, is that it only measures risk up to a selected threshold, and says nothing of the risk beyond that threshold. We thus also use Conditional Value at Risk (CVaR), which does measure extreme risk (the risk beyond VaR). For robustness, we use both parametric VaR as introduced by RiskMetrics (JP Morgan and Reuters, 1996), as well as non-parametric VaR. CVaR is the average of returns beyond these measures. Parametric methods have the advantage of being quick and easy to use as they require only the mean and standard deviation, but if returns are not normally distributed they can be inaccurate as compared to the historical approach which measures actual returns. Similarity in outcomes between the measures will indicate that parametric measures can be confidently applied in the Indonesian market, whereas large differences will indicate their unsuitability.

There are three research questions addressed by this study. Firstly, we explore which are the least (most) risky Indonesian sectors to invest in. Secondly, we examine whether the relative risk changes between sectors using CVaR as compared to VaR. Thirdly, we determine whether the outcome is consistent using both parametric and nonparametric methods.

As far as we are aware, there is no other study offering a comprehensive examination of sectoral risk in Indonesia, using VaR and CVaR metrics, and this study is the first to do so. This in-depth examination can assist investors in their choices of sector composition as well as provide insight into how different metrics can affect the results of the sectoral analysis, particularly during extreme circumstances, as captured by CVaR.

We find that, in direct contrast to studies in most major markets, and due to the relative stability in Indonesia over the GFC as compared to global markets, there is no significant difference in relative industry risk between our VaR and CVaR measures, or between our parametric and nonparametric measures. Also in contrast to most major markets, the Banking industry was relatively stable over the GFC and the industries showing the highest risk in terms of our metrics are Mining and Agriculture, mainly due to volatility in commodity prices.

We survey the literature in Section II, with methodology provided in Section III, results in Section IV, and conclusion in Section V.

II. BACKGROUND AND LITERATURE SURVEY

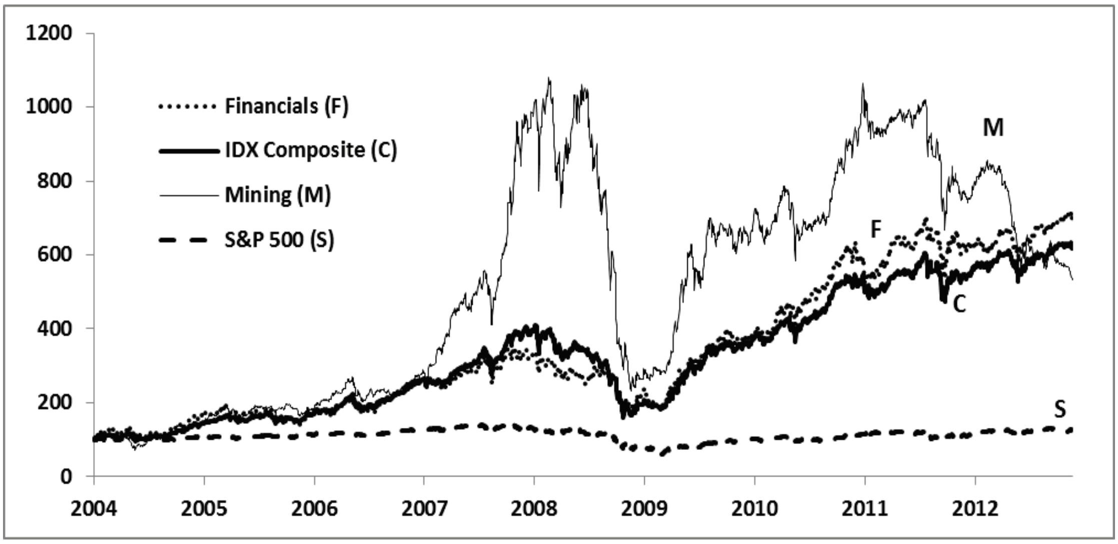
VaR and CVaR are used in this study to measure risk in the Indonesian share market, with CVaR focusing on extreme risk. It is therefore appropriate, as background, to provide an understanding of how the IDX and Indonesian economy has performed relative to global markets, particularly over the GFC which is the extreme risk period of our dataset. This assessment will be undertaken in the following sub-section, which includes a discussion of sectoral impacts on economic trends. Thereafter, we provide a literature survey and discussion on VaR and CVaR metrics.

GFC impacts on the Indonesian share market and economy

In Figure 1, using data from Datastream, we show the IDX composite index compared to a benchmark index, being the S&P 500. As an illustrative example of differences between sectors, we also show two sectors in the graph, including Mining (which we select as an example, as our results will show this to be the highest risk industry in terms of our VaR and CVaR metrics) and Financials (due to this industry being the most affected globally during the GFC, yet our study will show this not to be the case in Indonesia). We see from Figure 1 that over the period shown, the IDX composite has experienced much higher growth than the S&P 500, with much stronger recovery post-GFC. Financials have followed a similar pattern to the IDX composite. Mining, on the other hand, experienced tremendous growth pre-GFC, then very sharp falls, and a lesser recovery.

The literature provides some insight into these patterns. Siregar, Hasanah and Noer (2012) feel that while there were impacts of the GFC, such as a sharp downturn in the share market and a reduction in commodity prices which affected the Agricultural sector, this impact was reduced through prompt policy responses by the government and monetary authorities, resulting in a rapid recovery. The authors believe that the rapid recovery was also due to the fact that the financial instruments responsible for triggering the GFC were not a dominant component of the Indonesian financial markets, and that the slowdown in Indonesia was predominantly due to indirect effects of the crisis and panic by investors.

FIGURE 1: SHARE PRICE TRENDS



With its large, relatively young population, and a policy which has encouraged foreign investment in the Telecommunications sector, Indonesia has experienced strong growth in this sector over the past decade. The Australian Trade Commission (Austrade, 2011) reports Indonesia to be the fastest growing mobile phone market in the Asia Pacific region and one of the most attractive Telecommunication markets for foreign investors.

Basri and Rahardja (2010) examine exports and maintain that while the economy was impacted through a reduction in exports, the impact was relatively limited compared to other countries in the region, including Singapore, Malaysia and Thailand. This was due to Indonesia's relatively small export share to GDP, and appropriate policy responses both from Bank Indonesia and the Indonesian government. These responses included a range of measures such as lowering of interest rates, increasing deposit insurance from Rp 100 million to Rp 2 billion, and a stimulatory package which included tax cuts, duty waivers, subsidies, and increased government expenditure in areas such as infrastructure and rural development.

Baird and Wihardja (2010) report some key aspects of the Indonesian economy just after the height of the GFC as follows: GDP growth being dominated by the trade and communications sector; slow recovery in the manufacturing sector with the growth being quite narrow based (dominated by products such as vehicles and chemicals, with wood, paper and printing, basic metals and steel, and textiles and footwear sub-sectors continuing to contract); growth in exports being spurred by high international demand for commodities, coupled with higher prices; moderate inflationary pressure due to rises in prices from key trading partners; and the banking system being in good health with low percentages for non-performing loans especially for larger banks (with some smaller banks and financial entities having weaker performance). The authors also report that there was a short term negative impact on the markets in 2010 due to the resignation of the Minister of Finance, Sri Mulyani, who had been credited with maintaining Indonesia's sound reputation for economic management during the GFC, and who was moving to the World Bank as Managing Director. However, these events were quickly alleviated through the appointment of a suitable replacement.

More recently, Burke and Resusodarmo (2012) report that, even against a background of problems in Europe, strong domestic demand is continuing to ensure strong output growth in Indonesia, even though there has been a reduction in export growth. There has been strong investment in machinery and equipment, Communications continues its impressive performance, Manufacturing is growing at a slow but steady rate, and the Mining industry is showing strong growth (excluding oil and gas, which is declining in real terms).

In summary, the above picture is one of strong growth in the Indonesian market, which has not been impacted as negatively by the GFC as many other nations. Sectors such as Telecommunications and Finance are reported to have performed particularly well. There has been somewhat slower and more steady growth in Manufacturing, and good growth in the Agriculture and Mining industries, although the latter two have experienced more volatility largely due to fluctuating commodity prices. These trends provide important background information against which to interpret our VaR and CVaR outcomes in Section IV.

Background to risk measurements used in this study

Market risk is measured in this study using VaR and CVaR. VaR, which measures potential losses over a specific time period within a given confidence level, is a well understood and widely used metric for measuring market risk.

Parametric methods, which assume a normal distribution, are one of the most popular and easiest methods of measuring VaR. All that is needed is the standard deviation σ of the daily returns of an entity, which is then multiplied by the relevant confidence factor obtained from standard normal tables in order to obtain VaR (for example 1.645σ for 95% VaR, and 2.33σ for 99% VaR). While this is a very useful measure and convenient when returns follow a normal distribution, it may undershoot or overshoot VaR when there is non-normality. This is often the case with stock returns, particularly in times of high volatility such as the GFC, when returns may experience fat tails.

Historical simulation VaR does not make any assumption about the distribution, but sorts returns from best to worst, with VaR being the return at the selected level of confidence (for example, the 95th worst return at a 95% confidence level).

Despite its wide use, VaR has undesirable mathematical properties; such as lack of sub-additivity (Artzner, Delbaen, Eber and Heath, 1999). Perhaps the biggest shortcoming of VaR is that it is focused on risks below a specified threshold and says nothing of the risks beyond VaR. The measurement has been criticised by Standard and Poor's analysts (Samanta, Azarchs and Hill, 2005) due to VaR being applied inconsistently across institutions, as well as lack of tail risk assessment.

Conditional Value at Risk (CVaR) measures extreme returns (those beyond VaR). Pflug (2000) proved that CVaR is a coherent risk measure with a number of desirable properties such as convexity and monotonicity, amongst other desirable characteristics. CVaR has been applied to portfolio optimisation problems by several studies, including Rockafeller and Uryasev (2000, 2002), Andersson *et al.* (2000), Alexander *et al.* (2003), Alexander and Baptista (2003), Birbil, Frenk, Kaynar and Noyan (2009), Menoncin (2009), and Rockafellar *et al.* (2006). CVaR has been explored as a measure of sectoral risk in Europe and Australia by Allen and Powell (2009, 2011) and Allen, Powell and Singh (2011). These authors found CVaR to be a superior metric to VaR in times of economic downturn, as VaR fails to capture the extreme risk that is captured by CVaR.

Whilst there were no particular studies that we located on VaR and CVaR applications to sectors in Asia, some studies were found which have used various other extreme risk measures in Asian markets.

Dimitrakopoulos, Kavussanos and Spyrou (2010) compared a wide range of VaR and EVT models across developed and emerging markets during crisis and post-crisis periods. They found that in the case of the (fatter tailed) emerging market equity portfolios, most VaR models yielded conservative risk forecasts, in contrast to developed market equity portfolios where most models underestimate the realised VaR. VaR estimation during periods of financial turmoil was found to be a difficult task, particularly in the case of emerging markets and especially for the higher loss quantiles. VaR models seem to be affected less by crises periods in the case of developed markets. The performance of the parametric (nonparametric) VaR models improves (deteriorates) during post-crises periods due to the inclusion of extreme events in the estimation sample.

Hsu, Huang and Chiou (2012) found through back-testing, that copula EVT modelling provides better estimates of VaR in Asian markets than conventionally employed empirical distributions. Lee and Su (2012) found the influence of both skewness and fat-tails effects more important than only the effect of fat-tails on VaR estimates in US, Asian and European markets stock markets. Overall the literature reports extreme measures such as EVT and CVaR to be superior to conventional measures in times of high volatility.

III. METHODOLOGY

Data

The study uses Indonesian stocks which comprise the IDX Composite Index. This index contains all the stocks listed on the IDX and is thus representative of the IDX as a whole, containing a range of large and small listed stocks. We use eight years of data to 2011, as this contains a range of economic circumstances with approximately three pre-GFC years (2004-2006), three GFC years (2007-2009), and two post-GFC years (2010-2011). We only use companies which have trading data over the entire period (since 2004), which is 217 companies with total Market Cap of Rp 1,973 trillion (US$205 billion), comprising just over half of all IDX stocks by both number and market cap. Daily time series data is obtained from Datastream. We classify the data according to Global Industry Classification Standard (GICS) codes, with the sectoral breakdown of the data shown in Table 1.

TABLE 1: DATA SUMMARY

Sectors	Number of companies	Market capitalisation (in $000 USD)
Agriculture	10	8,964,031
Banks and Insurance	21	44,474,854
Consumer Discretionary	45	19,178,737
Consumer Staples	27	47,585,953
Diversified Financials	21	6,225,431
Energy and Materials	19	3,611,028
Industrials	35	33,520,022
IT and Telecommunications	7	23,828,877
Mining	10	6,591,861
Real Estate	22	10,671,959
	217	**204,652,753**

Metrics

To calculate VaR, we use the methods outlined in Section II, including the RiskMetrics parametric method as well as the historical simulation method. Following RiskMetrics, daily equity returns are calculated for each of the years in our data sample using the logarithm of daily price relatives. From the standard deviation (σ) of these returns, parametric VaR is calculated at a 95% confidence level, and based on standard tables, $VaR_x = 1.645\sigma_x$. Historical VaR is calculated as the actual 95th percentile worst return. CVaR uses the same methodology as VaR, except we use the average of the returns beyond VaR, that is parametric CVaR is the average of the returns greater than parametric VaR and historical CVaR is the average of the returns greater than historical VaR.

The above calculates VaR and CVaR for individual assets. The portfolio VaR and CVaR (i.e. for each sector) needs to be calculated, factoring in the correlations between the individual assets. For the parametric approach, we follow the RiskMetrics methodology as outlined in Cheung and Powell (2012), which requires the creation of variance and correlation matrices, which are then multiplied together to form a variance-correlation matrix. This in turn is multiplied with the variance matrix to create a variance-covariance matrix, which is then multiplied with the asset weightings (we use market capitalisation) to form a weighted variance-covariance matrix, the sum of which gives the portfolio σ from which VaR can be calculated. Historical portfolio VaR is a relatively simple calculation (as compared to the parametric approach where correlation between the assets is measured and matrix multiplication is used to calculate variance-covariance). The daily total portfolio returns are obtained by calculating the daily weighted average of the returns for each stock, again weighted by market capitalisation. As correlations across assets are naturally embedded in the historical time series, they require no separate estimation. The required confidence level (the 95 percentile worst return in our case) is then applied to the weighted average returns, and this figure is the portfolio VaR.

We rank each industry according to risk (parametric VaR, parametric CVaR, historical VaR and historical CVaR). A Spearman Rank Correlation Test is used to determine association between the risk metrics, as shown in Table 2.

IV. RESULTS

The tables below show daily VaR and CVaR during the period 2004-2011. VaR is calculated at a 95% confidence level. Parametric VaR assumes a normal distribution, and is the standard deviation of daily returns multiplied by 1.645 as per normal distribution tables at the 95% level. Historical VaR makes no distribution assumptions and is the actual 95th percentile return. Parametric CVaR is the average of the returns beyond parametric VaR, and historical CVaR is the average of the returns beyond historical VaR. Rankings are from 1 (lowest risk) to 10 (highest risk).

Comparisons are made (in order of appearance below) between parametric VaR and CVaR, historical VaR and CVaR, parametric and historical VaR, and parametric and historical CVaR. A negative difference in ranks shows that the sector has a relatively worse ranking on the latter of the two columns being compared. A Spearman Rank Correlation Test is applied to determine correlation between each pair of metrics. Significance in ranking correlation at the 95% level is denoted by * and at the 99% level by **, with a ‘-‘ indicating no significance.

TABLE 2: VAR AND CVAR RESULTS

Parametric VaR vs Parametric CVaR

Sector	Parametric VaR	Parametric CVaR	Change	Parametric VaR Rank	Parametric CVaR Rank	Diff in ranks	Diff in ranks^2
Agriculture	0.0363	0.0596	-0.0233	8	9	-1	1
Banks & Insurance	0.0296	0.0429	-0.0133	5	5	0	0
Consumer Discretionary	0.0225	0.0380	-0.0155	1	2	-1	1
Consumer Staples	0.0249	0.0395	-0.0146	2	3	-1	1
Diversified Financials	0.0366	0.0557	-0.0191	9	8	1	1
Energy & Materials	0.0260	0.0429	-0.0169	4	4	0	0
Industrials	0.0331	0.0548	-0.0217	7	7	0	0
IT & Telecommunications	0.0329	0.0464	-0.0136	6	6	0	0
Mining	0.0445	0.0697	-0.0252	10	10	0	0
Real Estate	0.0254	0.0372	-0.0118	3	1	2	4
	0.0301	0.0471					8.00
						n	10
						r	0.952
						t	8.749
					critical value 95%		2.565
					critical value 99%		3.499
						significance	**

Historical VaR vs Historical CVaR

Sector	Historical VaR	Historical CVaR	Change	Historical VaR Rank	Historical CVaR Rank	Diff in ranks	Diff in ranks^2
Agriculture	0.0315	0.0541	-0.0226	8	8	0	0
Banks & Insurance	0.0263	0.0397	-0.0134	5	4	1	1
Consumer Discretionary	0.0187	0.0309	-0.0122	1	1	0	0
Consumer Staples	0.0210	0.0343	-0.0133	2	3	-1	1
Diversified Financials	0.0265	0.0435	-0.0170	6	6	0	0
Energy & Materials	0.0260	0.0429	-0.0169	4	5	-1	1
Industrials	0.0365	0.0578	-0.0213	9	9	0	0
IT & Telecommunications	0.0306	0.0437	-0.0131	7	7	0	0
Mining	0.0415	0.0663	-0.0248	10	10	0	0
Real Estate	0.0215	0.0327	-0.0112	3	2	1	1
	0.0266	0.0424					4.00
						n	10
						r	0.976
						t	12.6105
					critical value 95%		2.565
					critical value 99%		3.499
						significance	**

Parametric VaR vs Historical VaR

Sector	Parametric VaR	Historical VaR	Change	Parametric VaR Rank	Historical VaR Rank	Diff in ranks	Diff in ranks^2
Agriculture	0.0363	0.0315	0.0048	8	8	0	0
Banks & Insurance	0.0296	0.0263	0.0033	5	5	0	0
Consumer Discretionary	0.0225	0.0187	0.0038	1	1	0	0
Consumer Staples	0.0249	0.0210	0.0039	2	2	0	0
Diversified Financials	0.0366	0.0265	0.0101	9	6	3	9
Energy & Materials	0.0260	0.0260	0.0000	4	4	0	0
Industrials	0.0331	0.0365	-0.0035	7	9	-2	4
IT & Telecommunications	0.0329	0.0306	0.0022	6	7	-1	1
Mining	0.0445	0.0415	0.0030	10	10	0	0
Real Estate	0.0254	0.0215	0.0039	3	3	0	0
	0.0301	0.0266					14.00
						n	10
						r	0.915
						t	6.4212
						critical value 95%	2.565
						critical value 99%	3.499
						significance	**

[Table 2 continued]

Parametric CVaR vs Historical CVaR							
Sector	Parametric CVaR	Historical CVaR	Change	Parametric CVaR Rank	Historic CVaR Rank	Diff in ranks	Diff in ranks^2
Agriculture	0.0596	0.0541	0.0055	9	8	1	1
Banks & Insurance	0.0429	0.0397	0.0032	5	4	1	1
Consumer Discretionary	0.0380	0.0309	0.0071	2	1	1	1
Consumer Staples	0.0395	0.0343	0.0051	3	3	0	0
Diversified Financials	0.0557	0.0435	0.0122	8	6	2	4
Energy & Materials	0.0429	0.0429	0.0000	4	5	-1	1
Industrials	0.0548	0.0578	-0.0031	7	9	-2	4
IT & Telecommunications	0.0464	0.0437	0.0027	6	7	-1	1
Mining	0.0697	0.0663	0.0034	10	10	0	0
Real Estate	0.0372	0.0327	0.0045	1	2	-1	1
	0.0471	0.0424					14.00
						n	10
						r	0.915
						t	6.4212
						critical value 95%	2.565
						critical value 99%	3.499
						significance	**

The table shows Mining to be the highest risk sector over the period studied by all the four measures; parametric VaR, parametric CVaR, historical VaR and historical CVaR. Diversified Financials, Industrials and Agriculture are also reasonably high on all measures. Consumer Discretionary, Consumer Staples, and Real Estate are low risk on all measures. Banks and Insurance are right in the middle. IT and Telecommunications has slightly higher relative risk.

The discussion in the literature survey mentioned the Agriculture and Mining industries to be relatively more volatile than other sectors due to fluctuations in commodity prices, which accounts for the higher risk shown by our metrics. The literature survey showed Telecommunications to be a strongly growing sector, and our metrics show this to have been coupled with slightly high volatility relative to other sectors. The 'medium' risk shown by banks is directly in contrast to what happened in major markets such as the USA and Europe, where this industry experienced substantial difficulty over the GFC. This is also supported by our literature survey which showed Indonesian banks to be not as badly affected as most other nations during the GFC, due to little involvement in sub-prime mortgages, and due to appropriate policy responses to the crisis by the government and the central bank. The graph in Figure 1 shows Financials (which includes Banks and Insurance and Diversified Financials) to have followed a very similar pattern to the IDX composite over the studied period, with only a slightly bigger drop in prices over the GFC, followed by a slightly stronger recovery. This is consistent with the relatively average risk shown by our VaR and CVaR figures. The higher volatility experienced by Diversified Financials is consistent with the literature survey finding that major Indonesian Banks experienced lower risk than smaller financial entities over the GFC.

The low risk of Consumer Staples is to be expected, with consumers generally continuing to purchase essential goods throughout different economic cycles. Consumer Discretionary can be very volatile in risky times, due to customers delaying essential purchases, however, given that Indonesia did not experience the same level of downturn as many countries during the GFC and had very rapid recovery thereafter, there was no need for consumers to make major changes to buying patterns.

What is extremely interesting is the significant correlation between all the metrics. Firstly, there is significant correlation (at the 99% level) between VaR and CVaR. This means that the industries, in general, do not have particularly fat (or thin) tails. Indeed, Real Estate is the only industry which shows more than one ranking shift (between parametric VaR and parametric CVaR), meaning that it has a slightly narrower tail relative to the other industries. Secondly, there is high correlation (99% significance) between parametric and historical measures, meaning that the industries, in general, follow a fairly normal distribution. There are some small exceptions, with the parametric measures slightly undershooting VaR and CVaR for Industrials and overshooting the measures for Diversified Financials.

FIGURE 2: CHANGES IN VAR AND CVAR RANKINGS

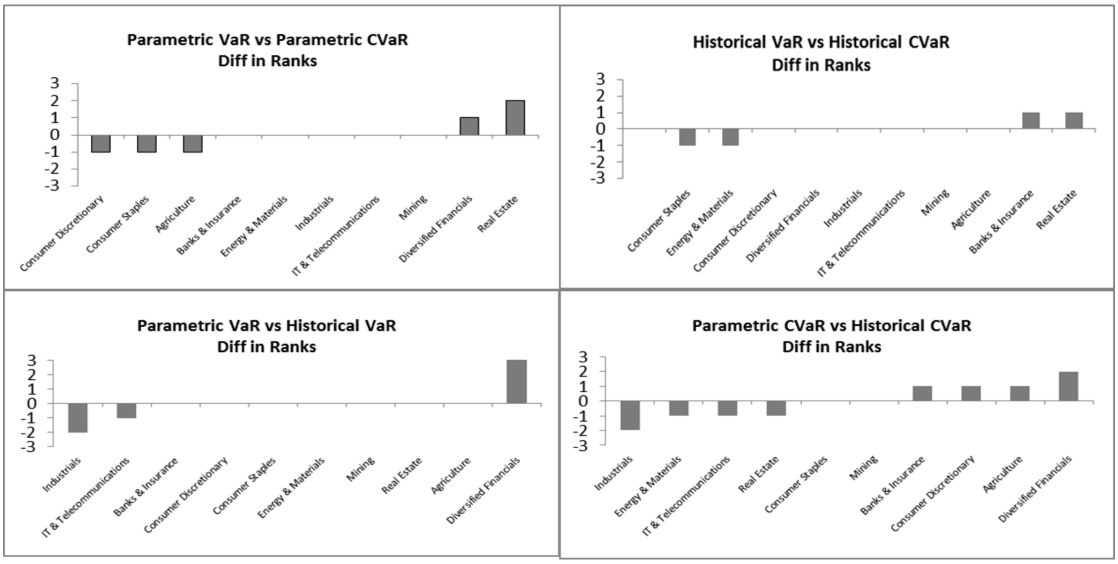


Figure 2 provides a graphical representation of the ranking differences between the various measures. The upper graphs show the differences in VaR and CVaR rankings. In general, the graphs are very flat with most sectors being in the middle “zero difference” zone and only small differences in the left “fatter tailed” zone and right “thinner tailed” zone of each graph. It is interesting to note that, although there are some differences between VaR and CVaR, they are not as prevalent as those shown in the European study by Allen, *et al.* (2011), where no significance at all was found between VaR and CVaR rankings. The reason for this is that Europe experienced a far more severe GFC than Indonesia, leading to high CVaRs for some industries as compared to VaRs, the banking industry most notably. The bottom two graphs show that there is not a great deal of difference between historical and parametric VaR and CVaR, meaning that the parametric measures provide a reasonable estimate of market risk in Indonesia. This is not the case with most other studies reported in our literature survey. For example, Hsu, Huang and Chiou (2012) reported extreme measures such as EVT to be more accurate at measuring risk across a range of Asian markets than normally distributed measures. Again, this comes down to Indonesia having experienced a less severe GFC than most.

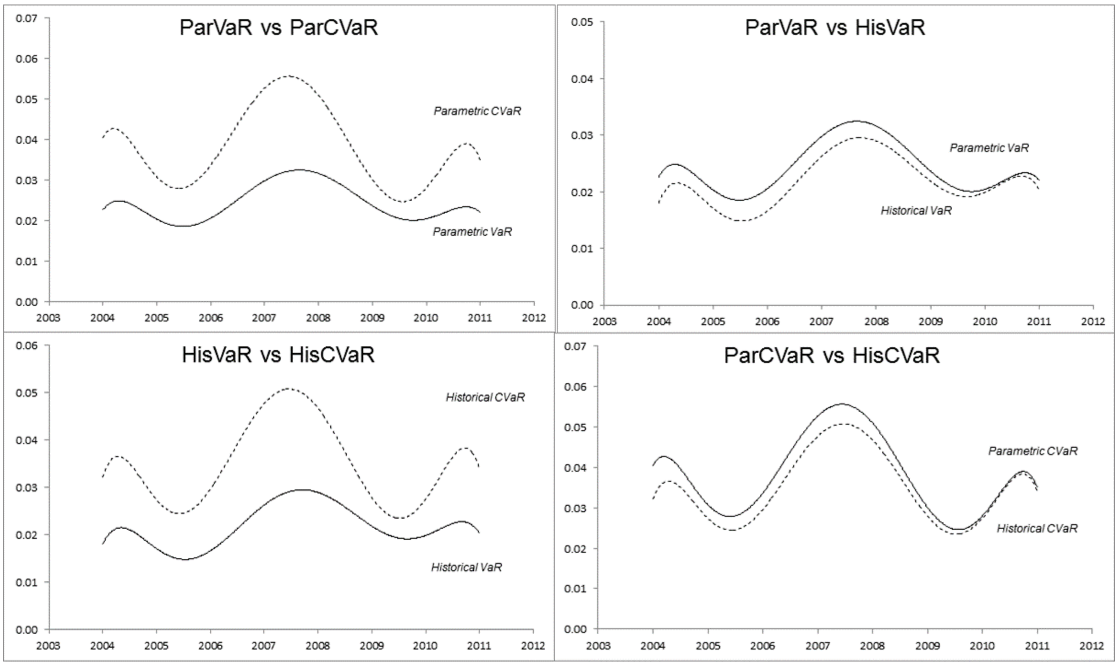
In order to better illustrate our metrics over time, we have shown the annual VaR and CVaR measures for each year in Table 3 and have shown a polynomial trend line for these measures in Figure 3. As an example, we also show the annual figures for Mining and Banking & Insurance (this allows comparison with the trends shown in our example in Figure 1). As mentioned in Section II, the mining industry is selected as an example due to its higher volatility and the financial industry due to it being the most affected globally during the GFC, yet being relatively stable in Indonesia.

TABLE 3: COMPARISON OF TRENDS IN PARAMETRIC VAR, PARAMETRIC CVAR, HISTORICAL VAR AND HISTORICAL CVAR

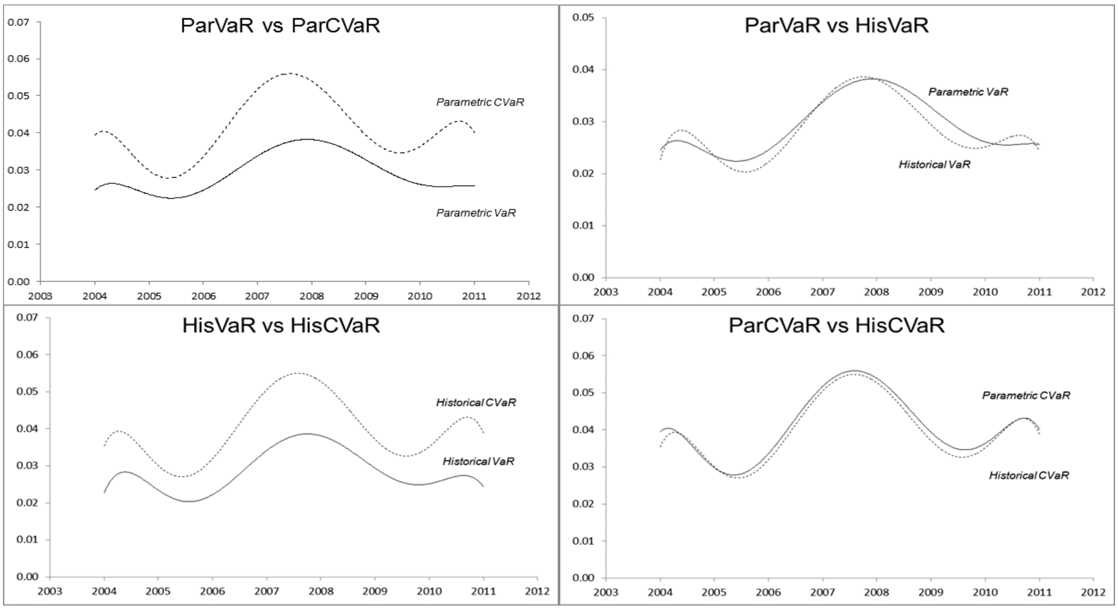
All				
Year	**Parametric VaR**	**Parametric CVaR**	**Historical VaR**	**Historical CVaR**
2004	0.0226	0.0406	0.0182	0.0324
2005	0.0199	0.0301	0.0162	0.0262
2006	0.0218	0.0356	0.0193	0.0331
2007	0.0276	0.0495	0.0218	0.0419
2008	0.0338	0.0541	0.0334	0.0525
2009	0.0223	0.0282	0.0192	0.0244
2010	0.0208	0.0287	0.0208	0.0287
2011	0.0219	0.0350	0.0203	0.0339
Banks and Insurance				
Year	**Parametric VaR**	**Parametric CVaR**	**Historical VaR**	**Historical CVaR**
2004	0.0246	0.0397	0.0229	0.0357
2005	0.0226	0.0282	0.0222	0.0282
2006	0.0269	0.0386	0.0260	0.0375
2007	0.0298	0.0435	0.0277	0.0411
2008	0.0422	0.0622	0.0445	0.0622
2009	0.0303	0.0344	0.0256	0.0315
2010	0.0269	0.0380	0.0264	0.0371
2011	0.0255	0.0399	0.0242	0.0386
Mining				
Year	**Parametric VaR**	**Parametric CVaR**	**Historical VaR**	**Historical CVaR**
2004	0.0409	0.0654	0.0350	0.0577
2005	0.0277	0.0499	0.0263	0.0482
2006	0.0398	0.0634	0.0441	0.0697
2007	0.0494	0.0750	0.0479	0.0733
2008	0.0788	0.1122	0.0771	0.1088
2009	0.0524	0.0775	0.0548	0.0786
2010	0.0371	0.0601	0.0353	0.0580
2011	0.0349	0.0577	0.0259	0.0478

FIGURE 3: GRAPHICAL COMPARISON OF TRENDS IN PARAMETRIC VAR, PARAMETRIC CVAR, HISTORICAL VAR AND HISTORICAL CVAR

All Sectors

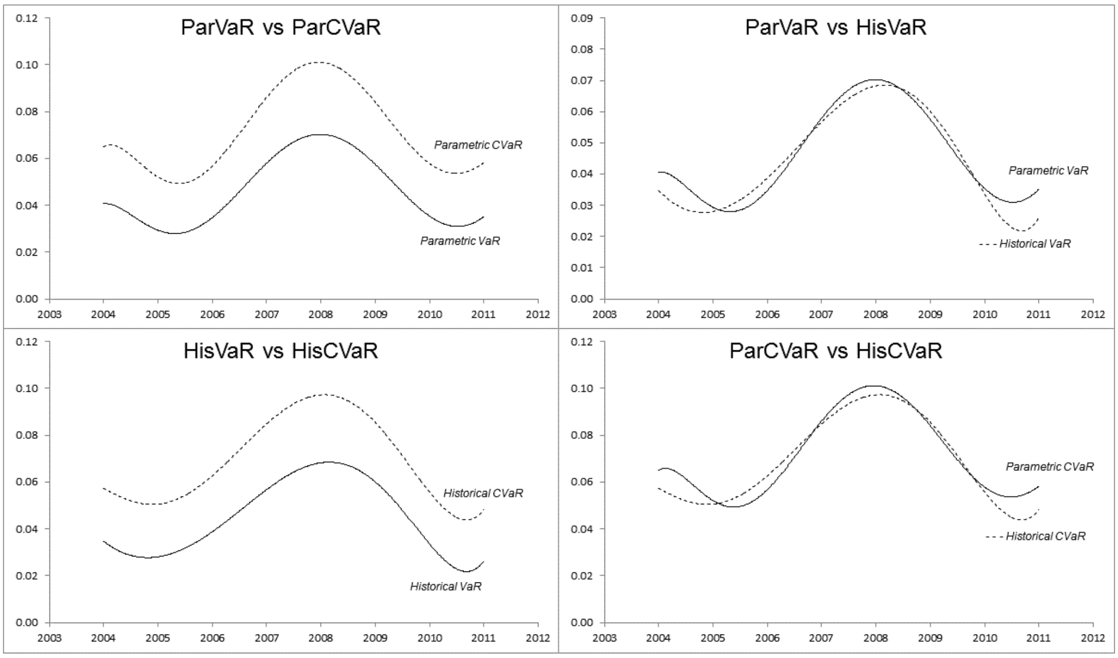


Banks and Insurance



[Figure 3 continued]

Mining



The trends in the All sectors tables and graphs show how VaR and CVaR are very low during the pre-GFC boom economic times, and then increase sharply in 2008 and 2009, reducing again thereafter. We also see how the gap between VaR and CVaR increases during the GFC. The Banks and Insurance sector shows a very similar trend to the All sectors trend, right through the pre-GFC, GFC and post-GFC periods, confirming its relative stability. The Mining sector, while following a similar trend, shows consistently higher volatility on all metrics throughout the studied period, also consistent with the graph in Figure 1 showing the volatility in share prices.

V. CONCLUSION

We will firstly conclude specifically in respect of our research questions. The first research question related to the relative risk between industries. Our metrics found Mining, Agriculture, and Diversified Financials to be at the higher risk end, and Consumer Discretionary, Consumer Staples and Real Estate to be at the lower end. We were able to find support in the literature for these results such as volatility in commodity prices, and a stable Banks & Insurance and Consumer Discretionary industry relative to other markets. The second research question related to differences between VaR and CVaR, and the third to differences between parametric and nonparametric (historical) measures. We found no significant differences in relation to either question.

These findings make Indonesia a somewhat unusual market in many respects. Firstly, the market is distinguished by much higher growth in share prices and a much quicker recovery than other markets. Secondly, the Banking industry did not involve itself to any great extent in high-risk products such as sub-prime mortgages, and this sector performed very well in relation to global markets over the GFC. Thirdly, overwhelmingly, the literature finds that in times of high volatility, extreme risk measures such as CVaR, and nonparametric measures are much more appropriate than non-extreme or parametric measures. Yet our study shows this not to be the case in Indonesia, where VaR and parametric measures were found to have no significant difference to CVaR and nonparametric measures in ranking industry risk. Again, this comes down to the relatively strong and stable performance of Indonesia during the GFC period and shows that in more stable markets, extreme and nonparametric measures are not necessarily going to be a better measure.

ACKNOWLEDGEMENTS

We thank the Australian Research Council for funding support.

REFERENCES

Alexander, G.J., and Baptista, A.M. (2003). *CVaR as a Measure of Risk: Implications for Portfolio Selection*: Working Paper, School of Management, University of Minnesota.

Alexander, S., Coleman, T.F., and Li, Y. (2003). Derivative Portfolio Hedging Based on CVaR. In G. Szego (Ed.), *New Risk Measures in Investment and Regulation* (pp. 339-363). Hoboken: Wiley.

Allen, D.E., and Powell, R.J. (2009). Transitional Credit Modelling and its Relationship to Market Value at Risk: An Australian Sectoral Perspective. *Accounting and Finance, 49*(3), 425-444.

Allen, D.E., and Powell, R.J. (2011). Measuring and Optimising Extreme Sectoral Risk in Australia. *Asia Pacific Journal of Economics and Business, 15*(1), 1-14.

Allen, D.E., Powell, R.J., and Singh, A.K. (2011). Beyond Reasonable Doubt: Multiple Tail Risk Measures Applied to European Industries. *Applied Economics Letters, 19*(7), 671-676.

Andersson, F., Mausser, H., Rosen, D., and Uryasev, S. (2000). Credit Risk Optimization with Conditional Value-at Risk Criterion. *Mathematical Programming, 89*(2), 273-291.

Artzner, P., Delbaen, F., Eber, J., and Heath, D. (1999). Coherent Measures of Risk. *Mathematical Finance, 9*, 203-228.

Austrade. (2011). ICT To Indonesia. Retrieved 12 December 2012 from http://www.austrade.gov.au/ICT-to-Indonesia/default.aspx.

Baird, M., and Wihardja, M.M. (2010). Survey of Recent Developments. *Bulletin of Indonesian Economic Studies, 46*(2), 143-170.

Basri, M.C., and Rahardja, S. (2010). The Indonesian Economy Amidst the Global Crisis: Good Policy and Good Luck. *ASEAN Economic Bulletin. (Apr. 2010), 27*(1), 77.

Birbil, S., Frenk, H., Kaynar, B., and Noyan, N. (2009). Risk Measures and Their Applications in Asset Management. In G. Gregoriou (Ed.), *The VaR Implementation Handbook* (pp. 331-338). New York: McGraw-Hill.

Burke, P.J., and Resosudarmo, B.P. (2012). Survey of Recent Developments. *Bulletin of Indonesian Economic Studies, 48*(3), 299-324.

Cheung, Y.H., and Powell, R.P. (2012). Anybody Can Do Value at Risk: A Teaching Study Using Parametric Computation and Monte Carlo Simulation. *In Press, Australasian Accounting, Business and Finance Journal, 6*(5).

Dimitrakopoulos, D.N., Kavussanos, M.G., and Spyrou, S.I. (2010). Value at Risk Models for Volatile Emerging Markets Equity Portfolios. *The Quarterly Review of Economics and Finance, 50*, 515-526.

Hsu, C., Huang, C., and Chiou, W.P. (2012). Effectiveness of Copula-Extreme Value Theory in Estimating Value-at-Risk: Empirical Evidence from Asian Emerging Markets. *Review of Quantitative Finance & Accounting, 39*(4), 447-468.

JP Morgan and Reuters. (1996). RiskMetrics Technical Document). Retrieved 13 December 2012 from http://www.msci.com.

Lee, C., and Su, J. (2012). Alternative Statistical Distributions for Estimating Value-at-Risk: Theory and Evidence. *Review of Quantitative Finance and Accounting, 39* (3), 309-331.

Menoncin, F. (2009). Using CVaR to Optimize and Hedge Portfolios. In G.N. Gregoriou (Ed.), *The VaR Modeling Handbook* (pp. 71-96). New York: McGraw Hill.

Pflug, G. (2000). Some Remarks on Value-at-Risk and Conditional-Value-at-Risk. In S. Uryasev (Ed.), *Probabilistic Constrained Optimisation: Methodology and Applications*. Dordrecht, Boston: Kluwer Academic Publishers.

Rockafellar, R.T. and Uryasev, S. (2000). Optimisation of Conditional Value-at-Risk. *Journal of Risk, 2*(3), 21-41.

Rockafellar, R.T., and Uryasev, S. (2002). Conditional Value-at-Risk for General Loss Distributions. *Journal of Banking and Finance, 26*(7), 1443-1471.

Rockafellar, R.T., Uryasev, S., and Zabarankin, M. (2006). Master Funds in Portfolio Analysis with General Deviation Measures. *Journal of Banking and Finance, 30*(2), 743-776.

Samanta, P., Azarchs, T., and Hill, N. (2005). Chasing Their Tails: Banks Look Beyond Value-At-Risk. *RatingsDirect, July*. Retrieved 12 February 2012 from http://www.standardandpoors.com.

Siregar, H., Hasanah, H., and Noer, A.A. (2012). Impact of the Global financial Crisis on the Indonesian Economy: Further Analysis using Export and investment Channels. *European Journal of Social Sciences, 30*(3), 438-450.

Statistics Indonesia. (2012). Retrieved 4 December 2012, from http://www.bps.go.id/eng/index.php.

World Federation of Exchanges. (2011). WFE Market Highlights. Retrieved 11 December 2012, from http://world-exchanges.org/statistics.