OPTIMIZING THE INDUSTRY MIX OF INDONESIAN PORTFOLIOS

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Abstraksi

Portofolio pada umumnya dioptimalkan dengan menggunakan standar deviasi return. Studi ini mengeksplorasi berbagai metode alternatif untuk mengoptimalkan bauran industri dalam portofolio di Indonesia. Penulis menggunakan dua alat ukur untuk membantu investor menghindari volatilitas ekstrim yang tidak dapat ditangkap oleh standar deviasi. Dua alat ukur tersebut adalah Value at Risk (VaR) dan Conditional Value at Risk (CVaR). VaR mengukur risiko pada batasan yang lebih tinggi daripada standar deviasi, biasanya pada tingkat kepercayaan 95% atau 99%. CVaR berhubungan dengan tingkat risiko yang paling ekstrim, yaitu risiko yang tidak ditangkap oleh VaR. Penulis menggunakan metode parametrik (untuk distribusi normal) dan non-parametrik untuk VaR dan CVaR. Untuk menjelaskan berbagai keadaan ekonomi, digunakanlah data pra-krisis ekonomi global, pada saat krisis ekonomi global dan pasca krisis ekonomi global. Dengan menggunakan pengoptimal risiko ekstrim ini, diharapkan dapat membantu investor untuk menghindari saham-saham yang berisiko tinggi. Volatilitas ekstrim juga merupakan indikator potensi masalah dalam sebuah industri, dan studi ini diharapkan dapat memberikan informasi yang penting mengenai kinerja dan risiko berbagai sektor pasar di Indonesia bagi para kreditor, regulator dan pemerintah.

Kata Kunci: *portofolio, bauran industri, value at risk, conditional value at risk.*

1. INTRODUCTION AND LITERATURE SURVEY

Using a dataset from 2004 – 2011, which spanned pre GFC (Global Financial Crisis), GFC and post GFC periods, Allen, Boffey Kramadibrata, Powell and Singh (2012) showed that parametric methods apear to work equally as well as non-parametric methods when measuring VaR and CVaR across these periods in Indonesian Sectors. This is contradictory to most studies in other markets, which generally report that parametric methods do not work well in times of high volatility as they assume a normal distribution which does not capture the high volatility shown in stock returns in periods of high risk such as the GFC. The authors attribute these somewhat unusual findings to the relatively strong and stable performance of Indonesia during the GFC (arising from factors such as Indonesian Banks having strong regulation and not being involved to any great extent in high risk products such as sub-prime mortgages), and the relatively strong and speedy recovery afterwards. This meant that Indonesian portfolios experienced a more normal distribution of returns over these volatile times than was globally experienced. The interesting question therefore arises as to whether parametric and nonparametric methods work equally as well when extended to the sectoral optimization of Indonesian portfolios.

Against this background, this study uses both parametric and nonparametric VaR and CVaR methods to optimise the industry mix of Indonesian stock portfolios over the 2004-2011 period. Thus four optimising methods (parametric VaR, nonparametric VaR, parametric CVaR, and nonparametric CVaR) are used. Parametric methods, which assume a normal distribution, have been used to optimise industry portfolios in Australia (Allen and Powell, 2011) but nowhere, as far as we are aware, have both parametric and nonparametric VaR and CVaR methods been aplied to sector optimisation, and none of these four methods have been aplied to Indonesian sector optimisation, making this study a first.

The research question addressed in this study is to determine whether there are any significant differences between the optimal portfolio mix when using each of our four optimisation metrics. Significant differences between VaR and CVaR will indicate high risk in the tails of the portfolio mix, which is not captured by the lower risk VaR measure as compared to CVaR. Significant differences between parametric and nonparametric measures will indicate non-normality of distributions.

There have been a number of studies of the Indonesian stock market that have looked at returns on stock market portfolios, but none of them have used the VaR and CVaR methods. For instance, Eko (2008) has analyzed and assessed the optimum performance of portfolios formed from LQ 45 stocks listed on what was then the Jakarta Stock Exchange (JSX) and is now the Indonesian Stock Exchange (ISX). His research raised the problem of how to design an optimal portfolio simulation, that is, a combination of liquid shares LQ 45 in the period of 2002- 2007 by using a single index model and a constant correlation model. The single index model is a model of portfolio analysis using the ratio of excess return to beta as well as a cut-off point (C*) to calculate the optimal shares in the portfolio. The procedure of the constant correlation model is similar to the single index model. However, unlike the single index model, all securities are ranked by excess return to standard deviation instead of excess return to risk. After securities are ranked using the above ratio, securities with greater excess return to standard deviation and cut off point are included into the optimal portfolio.

A second study was that of Salmah (2012) who discussed the forming of optimum portfolios in the Indonesia Data Exchange in the case of shares of plantation, telecommunication, and communication sectors. The sample companies included PT. Astra Agro Lestari Tbk., PT. Indosat Tbk. and PT. Indofood Sukses Makmur Tbk. All these

shares formed part of the LQ 45 index in the period February 2007 until January 2010. The study concluded that a portfolio formed from the shares of PT. Astra Agro Lestari Tbk. and PT. Indosat Tbk. was optimal.

A study by Sitinjak (2011) considered the impact of macro-economic factor on the return of stock portfolios in Indonesia during both bullish and bearish market conditions. From 1998 to 2008, the 500 IDX was increasing. This study found that the changes in inflation expectations, unexpected inflation, unexpected risk free rate, and the rate of economic growth had a significant effect on portfolio capital returns when market conditions were bullish for all forms of portfolios. In contrast, the economic growth rate did not affect portfolios during bearish market conditions. The reason given was that share price movements in Indonesia were still largely influenced by foreign investors.

Suryani (2007) analyzed individual investment in the 15 companies listed on the Jakarta Stock Exchange. The results showed that investing in an individual share did not always give a high profit due to the presence of undiversified risk. Portfolio diversification was seen as a way of reducing this risk.

Utami (2010) assessed the performace of 149 manufacturing companies listed at BEI during 2004-2008 period by using logistic regression. The result shows that the only variable that can predict an overperforming share is Earning Per Share (EPS).

Wardani (2010) studied the optimal portfolio in the company shares listed in the Jakarta Islamic Index by using a single index model. The Single Index Model analyzed a portfolio by calculating the excess return to beta value and cut-off value to get the optimal combination of shares. The results show that in the first period of October to December 2008 and January to March 2009, which is around the time of the Global Financial Crisis, the optimal portfolio was not formed. The value of all shares excess return to beta was smaller than the value of the cut-off return.

Finally, Wiksuana (2009) analyzed the performance of stock portfolios using a momentum investment strategy. The sample consisted of public companies listed on the Jakarta Stock Exchange that were actively traded between the periods of December 2001 until December 2007. A multiphase sampling method was used. The results showed that the momentum investment strategy could not used by the investors and investment managers to form stock portfolios. It could not produce a positive and significant difference in the performance of winner and loser stock portfolios.

2. METHODOLOGY

2.1. Data

We use the same dataset as Allen et al. (2012) which is 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. The data spans pre-GFC, GFC and post-GFC periods. 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 capitalisation. Daily time series data is obtained from Datastream. We classify sectors according to Global Industry Classification Standard (GICS) codes, and the sector categories include Agriculture, Banks and Insurance, Consumer Discretionary, Consumer Staples, Diversified Financials, Energy and Materials, Industrials, IT and Telecommunications, Mining and Real Estate.

2.2. Calculation of 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).

For robustness, we use both methods (parametric and historical) in this article. For the parametric method, to take account of correlations between the individual entities within each sector, we construct a variance-covariance matrix from which the sector standard deviation and VaR is calculated. For historical VaR, there is no need to construct such a matrix, as we calculate VaR from the weighted average of the historical returns for each sector, because the correlations are naturally embedded in these weighted average returns.

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 aplied inconsistently across institutions, as well as lack of tail risk assessment.

Conditional Value at Risk (CVaR) measures extreme returns (the average of those returns 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 aplied to portfolio optimisation problems by several studies (G. J. Alexander and Baptista, 2003; S. Alexander, Coleman, and Li, 2003; Andersson, Mausser, Rosen, and Uryasev, 2000; Birbil, Frenk, Kaynar, and Noyan, 2009; Menoncin, 2009; Rockafellar and Uryasev, 2002; Rockafellar, Uryasev, and Zabarankin, 2006; Uryasev and Rockafellar, 2000),. 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.

We measure VaR at the 95% confidence level. Historical CVaR is the average of returns beyond 95% historical VaR and parametric CVaR is the average of returns beyond 95% parametric CVaR.

2.3. Efficient Frontier using VaR and CVaR

The Markowitz efficient frontier shows the maximum return that can be generated for each risk level, or the minimum risk for each return level. The frontier is based an optimal variance-return or standard deviation-return. Note that both generate the same optimal combinations. In contrast, we use VaR-return and CVaR-return. We first discuss Markowitz, then our aproach. To generate the Markowitz frontier, a variance-covariance matrix is constructed to account for correlation between industry sector returns, from which portfolio return and risk (variance

or standard deviation) is calculated. The portfolio is then optimised to achieve the combination of assets yielding the minimum risk for each selected return level. As the frontier shows the most efficient combinations of risk and return, no combination of risk-return is possible beyond the frontier, and portfolio combinations below the frontier are inefficient. The Markowitz frontier is generated by minimising risk as follows:

$$\min_x \sum_{i=1}^{n} \sum_{k=1}^{n} \sigma_{ik} x_i x_k \qquad (1)$$

Subject to
$$\sum_{i=1}^{n} x_i = 1 \qquad (2)$$
$$\sum_{i=1}^{n} IE[r_i] x_i = r_p \qquad (3)$$
$$0 \le x_i \le v_i \qquad (4)$$

where x_i are portfolio weights, r_i is the rate of return of industry sectors i and k, r_p is the expected return on the portfolio and σ_{ik} is the covariance between returns of industry sectors i and k (and similarly for all other industry sectors). Weighting for any portfolio cannot be negative, and can also be constrained to not exceed a specific weighting v (in order to ensure the portfolio is diversified).

Our optimisation is based on aplications by Uryasev and others (Krokhmal, Palmquist, and Uryasev, 2002; Rockafellar, 2010; Uryasev and Rockafellar, 2000) who use VaR and CVaR to optimise portfolios but not on a sectoral basis. Whilst we use similar optimisation techniques, there are a number of key differences between our work and theirs. First, our study has an Indonesian focus. Second, it considers industry sectors rather than individual companies. Third, it includes the GFC period. Fourth, it includes both historical and parametric methods.

Let x be a portfolio (sector) within the set of available portfolios X. Let ς be the threshold VaR at level of confidence α and ϕα be average returns beyond the VaR threshold (CVaR). The efficient VaR (CVaR) frontier is obtained by minimising VaR (CVaR):

$$\min_x \varsigma(x), R(x) \ge \rho, x \in X \qquad (5)$$
$$\min_x \varsigma(x), R(x) \ge \rho, x \in X \qquad (6)$$

The selected level of return is ρ, which the reward function $R(x)$ must meet or exceed. We have constrained the minimum portfolio weight for each sector to 0 with no uper bound. Varying ρ traces the efficient frontier. We have constrained ρ to a minimum of 0. This does not necessarily exclude all negative return industry sectors, as an industry sector with a slightly negative return could combine with industry sectors with positive returns to provide an overall portfolio return > 0. At any confidence level α,

$$a \in (0,1) \qquad (7)$$

The relationship between standard deviation, VaR and CVaR for our parametric option is

$$\varsigma(x) = VaR_\alpha(x) = q_\alpha(x) \qquad (8)$$

where q_α is the tail bound of the distribution for VaR, and in a standard normal distribution at 95% confidence level (which is the level we use) = 1.645σ.

$$\phi(x) = CVaR_\alpha(x) = Q_\alpha(x) \qquad (9)$$
$$\sigma_\phi(x) = CVaR_\alpha (x - ex) = Q_{\alpha x}(x - ex) \qquad (10)$$

$\sigma_\phi(x)$ = standard deviation for CVaR, where ex = mean returns. If a normal distribution is used for VaR (as in our case) the optimal percentages of each portfolio will be the same as for the variance aproach used by Markowitz, as VaR is simply a derivation of the variance (1.645σ) thus generating the same efficient frontier. However, CVaR re-shapes the loss distribution, as it is based on actual high losses as oposed to a standard distribution. The

nonparametric method uses a similar aproach except that it is based on the historical simulation VaR and CVaR as outlined in Section 2.2.

Using the mean of daily returns, we calculate the CVaR standard deviation of each industry sector using equation 10 and use these standard deviations to generate a variance-covariance matrix and the CVaR-return efficient frontier. Our optimum VaR portfolio shows the combination of assets that yield the portfolio VaR for each selected level of return. Our optimum CVaR portfolio shows the combination of assets that yield the minimum portfolio CVaR for each selected level of return. The maximum return point is the highest return that can be generated by any industry sector. The minimum return point is the return associated with the lowest possible VaR (or CVaR). We select eight equidistant points between minimum and maximum returns (giving a total of 10 return points) and calculate the minimum portfolio VaR and CVaR associated with each point. These VaR-return and CVaR-return combinations make up the efficient frontier.

3. RESULTS

We commence by looking at the whole period from 2004-2008, and then investigate three different periods within this: Pre-GFC (2004-2007), the height of the GFC (2008) and post GFC (2009-2011). Although the GFC commenced somewhat earlier and ended somewhat later than 2008, it was in 2008 that the major falls in stock prices took place across the globe, so we have isolated this year for examination.

Table 1.
Whole Period Return and Risk: 2004 – 2011

	Annual Returns	Parametric VaR	Parametric CVaR	Historical VaR	Historical CVaR
Agriculture	0.3363	0.0363	0.0596	0.0315	0.0541
Banks & Insurance	0.1954	0.0296	0.0429	0.0263	0.0397
Consumer Discretionary	0.2869	0.0225	0.0380	0.0187	0.0309
Consumer Staples	0.2368	0.0249	0.0395	0.0210	0.0343
Diversified Financials	0.2869	0.0366	0.0557	0.0325	0.0435
Energy & Materials	0.2097	0.0260	0.0429	0.0260	0.0429
Industrials	0.2023	0.0331	0.0548	0.0365	0.0578
IT & Telecom	0.0497	0.0329	0.0464	0.0305	0.0437
Mining	0.2441	0.0455	0.0697	0.0415	0.0663
Real Estate	0.2732	0.0254	0.0372	0.0215	0.0327
All Sectors	0.2375	0.0307	0.0475	0.0283	0.0435

We now use the above information to generate optimal portfolios (as described in Section 2.3) associated with each of the ten levels of return.

Table 2.

Whole Period Optimal Portfolios: 2004 – 2011

Parametric VaR and CVaR Optimal Portfolio

Returns	Parametric VaR	Agriculture	Banks & Insurance	Consumer Discretionary	Consumer Staples	Diversified Financials	Energy & Materials	Industrials	IT & Telecom	Mining	Real Estate
33.63%	3.63%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
32.68%	3.17%	80.82%	0.00%	19.18%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
31.73%	2.77%	61.64%	0.00%	38.36%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
30.79%	2.46%	43.41%	0.00%	53.16%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	3.42%
29.84%	2.22%	27.73%	0.00%	56.19%	0.00%	0.03%	0.00%	0.00%	0.00%	0.00%	16.06%
28.89%	2.09%	14.08%	0.00%	56.93%	2.88%	0.62%	0.00%	0.00%	0.00%	0.00%	25.48%
27.94%	2.01%	6.75%	0.00%	52.24%	14.32%	0.26%	0.00%	0.00%	0.00%	0.00%	26.43%
26.99%	1.96%	1.50%	0.00%	47.63%	20.05%	0.00%	5.39%	0.00%	0.00%	0.00%	25.43%
26.04%	1.94%	0.00%	0.00%	39.56%	23.92%	0.00%	14.15%	0.00%	0.21%	0.00%	22.16%
25.10%	1.94%	0.00%	0.00%	36.43%	23.41%	0.00%	15.39%	0.00%	3.99%	0.00%	20.77%

| Returns	Parametric CVaR	Agriculture	Banks & Insurance	Consumer Discretionary	Consumer Staples	Diversified Financials	Energy & Materials	Industrials	IT & Telecom	Mining	Real Estate
33.63%	5.96%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
32.51%	5.09%	77.35%	0.00%	22.65%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
31.39%	4.38%	55.42%	0.00%	40.00%	0.00%	1.96%	0.00%	0.00%	0.00%	0.00%	2.62%
30.27%	3.81%	37.12%	0.00%	41.81%	0.00%	2.70%	0.00%	0.00%	0.00%	0.00%	18.36%
29.15%	3.41%	18.83%	0.00%	43.62%	0.00%	3.45%	0.00%	0.00%	0.00%	0.00%	34.10%
28.03%	3.22%	7.66%	0.00%	40.29%	10.05%	3.15%	0.00%	0.00%	0.00%	0.00%	38.86%
26.91%	3.11%	0.04%	0.00%	35.18%	21.46%	2.39%	2.26%	0.00%	0.00%	0.00%	38.67%
25.79%	3.08%	0.00%	0.00%	29.53%	23.36%	1.10%	7.65%	0.00%	2.74%	0.00%	35.62%
24.67%	3.06%	0.00%	0.00%	26.76%	22.68%	0.54%	8.70%	0.00%	7.36%	0.00%	33.96%
23.55%	3.05%	0.00%	0.00%	23.96%	22.02%	0.00%	9.80%	0.00%	11.96%	0.00%	32.25%

Historical VaR and CVaR Optimal Portfolio

Returns	Historical VaR	Agriculture	Banks & Insurance	Consumer Discretionary	Consumer Staples	Diversified Financials	Energy & Materials	Industrials	IT & Telecom	Mining	Real Estate
33.63%	3.15%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
32.86%	2.82%	84.40%	0.00%	15.60%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
32.09%	2.51%	68.81%	0.00%	31.19%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
31.32%	2.24%	53.21%	0.00%	46.79%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
30.55%	2.03%	38.69%	0.00%	57.43%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	3.88%
29.77%	1.87%	26.00%	0.00%	59.62%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	14.38%
29.00%	1.77%	13.44%	0.00%	61.68%	0.18%	0.00%	0.00%	0.00%	0.00%	0.00%	24.70%
28.23%	1.70%	7.62%	0.00%	57.36%	9.66%	0.00%	0.00%	0.00%	0.00%	0.00%	25.36%
27.46%	1.66%	1.80%	0.00%	53.04%	19.13%	0.00%	0.00%	0.00%	0.00%	0.00%	26.03%
26.69%	1.65%	0.00%	0.00%	45.58%	27.54%	0.00%	1.19%	0.00%	0.78%	0.00%	24.91%

Returns	Historical CVaR	Agriculture	Banks & Insurance	Consumer Discretionary	Consumer Staples	Diversified Financials	Energy & Materials	Industrials	IT & Telecom	Mining	Real Estate
33.63%	5.41%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
32.74%	4.74%	81.96%	0.00%	18.04%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
31.85%	4.13%	63.92%	0.00%	33.82%	0.00%	2.26%	0.00%	0.00%	0.00%	0.00%	0.00%
30.96%	3.61%	45.88%	0.00%	47.22%	0.00%	6.90%	0.00%	0.00%	0.00%	0.00%	0.00%
30.06%	3.20%	30.78%	0.00%	50.51%	0.00%	8.09%	0.00%	0.00%	0.00%	0.00%	10.62%
29.17%	2.90%	16.40%	0.00%	51.34%	0.00%	8.46%	0.00%	0.00%	0.00%	0.00%	23.81%
28.28%	2.74%	5.19%	0.00%	49.89%	4.47%	8.33%	0.00%	0.00%	0.00%	0.00%	32.12%
27.39%	2.66%	0.00%	0.00%	43.45%	17.07%	7.01%	0.00%	0.00%	0.00%	0.00%	32.47%
26.50%	2.64%	0.00%	0.00%	37.65%	22.75%	5.60%	0.00%	0.00%	2.62%	0.00%	31.37%
25.60%	2.63%	0.00%	0.00%	35.41%	22.58%	5.06%	0.00%	0.00%	6.47%	0.00%	30.48%

We see from Table 2 that an investor wising to maximize returns would invest all their funds in Agriculture. An investor wishing to minimize VaR, both parametric and historical, though with slightly different weightings, would have a more diversified portfolio, including large weightings towards Consumer Discretionary, Consumer Staples and Real Estate. Agriculture's prominence reduces as more conservative returns are sought, due to high volatility. Banks and Insurance, Diversified Financials, Industrials and Mining do not feature as attractive investments from an optimal risk-return perspective. When using CVaR, both parametric and historical, we note that Real Estate becomes much more prominent at the bottom of the tables, due to its relatively lower tail risk.

Figure 1 shows how the frontier shifts to the right when using CVaR. There are some differences evident in the historical and parametric frontiers although we have yet to undertake tests of significance on these.
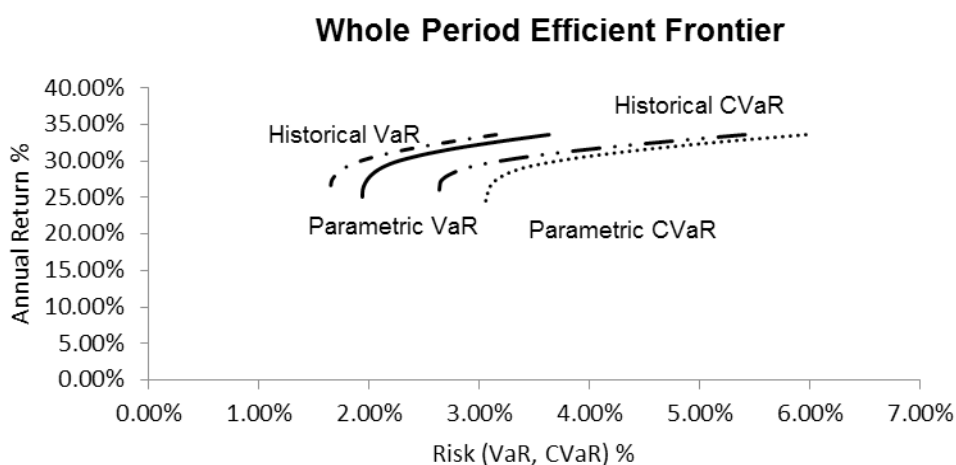
Figure 1.
Whole Period Efficient Frontier: 2004-2011

We now split the analysis into different economic periods, commencing with the pre-GFC period.

Table 3.
Pre GFC Return and Risk: 2004 -2007

	Annual Returns	Parametric VaR	Parametric CVaR	Historical VaR	Historical CVaR
Agriculture	0.5975	0.0278	0.0430	0.0241	0.0375
Banks & Insurance	0.2595	0.0260	0.0375	0.0265	0.0356
Consumer Discretionary	0.2713	0.0207	0.0315	0.0196	0.0323
Consumer Staples	0.1481	0.0223	0.0376	0.0210	0.0355
Diversified Financials	0.2856	0.0321	0.0515	0.0316	0.0467
Energy & Materials	0.3578	0.0277	0.0474	0.0274	0.0406
Industrials	0.2518	0.0321	0.0579	0.0353	0.0604
IT & Telecom	0.2154	0.0320	0.0440	0.0336	0.0443
Mining	0.5853	0.0395	0.0634	0.0376	0.0622
Real Estate	0.3824	0.0246	0.0424	0.0241	0.0338
All Sectors	0.3215	0.0285	0.0456	0.0281	0.0429

Expectedly, returns are higher and risk is lower as measured by all for metrics.

Table 4.

Pre-GFC Optimal Portfolios: 2004 – 2007

Parametric VaR and CVaR Optimal Portfolio

Returns	Parametric VaR	Agriculture	Banks & Insurance	Consumer Discretionary	Consumer Staples	Diversified Financials	Energy & Materials	Industrials	IT & Telecom	Mining	Real Estate
59.75%	2.78%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
56.21%	2.46%	68.10%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	16.39%	15.51%
52.68%	2.29%	57.65%	0.00%	4.42%	0.00%	0.00%	2.16%	0.00%	0.00%	12.73%	23.04%
49.15%	2.15%	49.58%	0.00%	14.08%	0.00%	0.00%	3.72%	0.00%	0.00%	9.35%	23.26%
45.61%	2.03%	41.51%	0.00%	23.75%	0.00%	0.00%	5.28%	0.00%	0.00%	5.97%	23.48%
42.08%	1.94%	33.68%	0.00%	32.84%	0.59%	0.00%	6.65%	0.00%	0.00%	2.68%	23.56%
38.54%	1.86%	28.44%	0.00%	35.48%	7.45%	0.00%	6.10%	0.31%	0.00%	0.33%	21.90%
35.01%	1.81%	21.72%	0.00%	37.53%	14.51%	0.00%	4.91%	1.61%	0.00%	0.00%	19.71%
31.48%	1.78%	14.77%	0.00%	39.55%	21.68%	0.00%	3.63%	2.88%	0.00%	0.00%	17.49%
27.94%	1.77%	7.83%	0.00%	41.54%	28.87%	0.00%	2.34%	4.17%	0.00%	0.00%	15.26%

Returns	Parametric CVaR	Agriculture	Banks & Insurance	Consumer Discretionary	Consumer Staples	Diversified Financials	Energy & Materials	Industrials	IT & Telecom	Mining	Real Estate
59.75%	4.30%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
56.26%	3.87%	70.95%	0.00%	1.59%	0.00%	0.00%	0.00%	0.00%	0.00%	14.49%	12.97%
52.78%	3.62%	62.90%	0.00%	11.89%	0.00%	0.00%	0.00%	0.00%	0.00%	11.50%	13.70%
49.30%	3.40%	54.86%	0.00%	22.20%	0.00%	0.00%	0.00%	0.00%	0.00%	8.51%	14.44%
45.82%	3.21%	46.76%	0.00%	32.18%	0.00%	0.00%	0.62%	0.00%	0.00%	5.47%	14.97%
42.33%	3.06%	38.99%	2.27%	40.17%	0.00%	0.00%	1.41%	0.00%	0.00%	2.39%	14.77%
38.85%	2.95%	32.23%	6.48%	44.03%	2.58%	0.00%	1.10%	0.00%	0.00%	0.00%	13.57%
35.37%	2.87%	24.94%	7.85%	45.69%	8.56%	0.00%	0.00%	0.00%	1.14%	0.00%	11.82%
31.89%	2.82%	17.39%	8.53%	47.09%	14.13%	0.00%	0.00%	0.00%	3.01%	0.00%	9.85%
28.40%	2.80%	9.85%	9.34%	48.34%	19.69%	0.00%	0.00%	0.00%	4.93%	0.00%	7.86%

Historical VaR and CVaR Optimal Portfolio

Returns	Historical VaR	Agriculture	Banks & Insurance	Consumer Discretionary	Consumer Staples	Diversified Financials	Energy & Materials	Industrials	IT & Telecom	Mining	Real Estate
59.75%	2.41%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
56.43%	2.19%	73.83%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	11.41%	14.76%
53.12%	2.07%	65.68%	0.00%	9.15%	0.00%	0.00%	0.00%	0.00%	0.00%	8.73%	16.44%
49.81%	1.96%	57.65%	0.00%	18.26%	0.00%	0.00%	0.85%	0.00%	0.00%	6.00%	17.23%
46.49%	1.87%	49.59%	0.00%	27.08%	0.00%	0.00%	2.29%	0.00%	0.00%	3.23%	17.81%
43.18%	1.80%	42.93%	0.00%	32.54%	3.37%	0.00%	2.76%	0.00%	0.00%	0.90%	17.49%
39.87%	1.74%	36.69%	0.00%	35.00%	9.90%	0.00%	2.19%	0.00%	0.00%	0.00%	16.21%
36.56%	1.70%	29.77%	0.00%	37.35%	16.66%	0.00%	1.38%	0.00%	0.00%	0.00%	14.85%
33.24%	1.67%	22.84%	0.00%	39.67%	23.42%	0.00%	0.57%	0.00%	0.00%	0.00%	13.49%
29.93%	1.66%	15.89%	0.00%	41.81%	30.23%	0.00%	0.00%	0.00%	0.00%	0.00%	12.08%

Returns	Historical CVaR	Agriculture	Banks & Insurance	Consumer Discretionary	Consumer Staples	Diversified Financials	Energy & Materials	Industrials	IT & Telecom	Mining	Real Estate
59.75%	3.75%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
56.73%	3.43%	77.90%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	8.58%	13.52%
53.72%	3.22%	66.18%	0.00%	0.00%	0.00%	0.00%	0.49%	0.00%	0.00%	6.23%	27.11%
50.71%	3.06%	58.09%	0.00%	6.65%	0.00%	0.00%	2.72%	0.00%	0.00%	3.87%	28.66%
47.70%	2.92%	50.46%	0.00%	14.43%	0.00%	0.00%	4.22%	0.00%	0.00%	1.56%	29.33%
44.69%	2.81%	42.15%	0.00%	22.29%	0.00%	0.00%	5.59%	0.00%	0.00%	0.00%	29.98%
41.68%	2.74%	34.38%	3.08%	26.06%	2.36%	0.00%	5.21%	0.00%	0.00%	0.00%	28.90%
38.67%	2.68%	28.02%	4.80%	28.01%	7.65%	0.00%	4.22%	0.00%	0.00%	0.00%	27.31%
35.66%	2.65%	21.64%	6.55%	29.91%	12.93%	0.00%	3.21%	0.00%	0.00%	0.00%	25.75%
32.65%	2.64%	15.19%	8.60%	31.01%	17.86%	0.00%	2.38%	0.00%	0.68%	0.00%	24.27%

Agriculture shows high prominence in this period across all metrics even when minimizing VaR and CVaR at the bottom of the table. Consumer Discretionary, Consumer Staples and Real Estate continue to be preferred selections in the diversified portfolio. The preferred industries are fairly consistent across the parametric and nonparametric metrics, although Agriculture and Real Estate feature more prominently when minimizing risk using the historical method, showing that parametric measures for these industries apear to be slightly overestimating the tail risk.
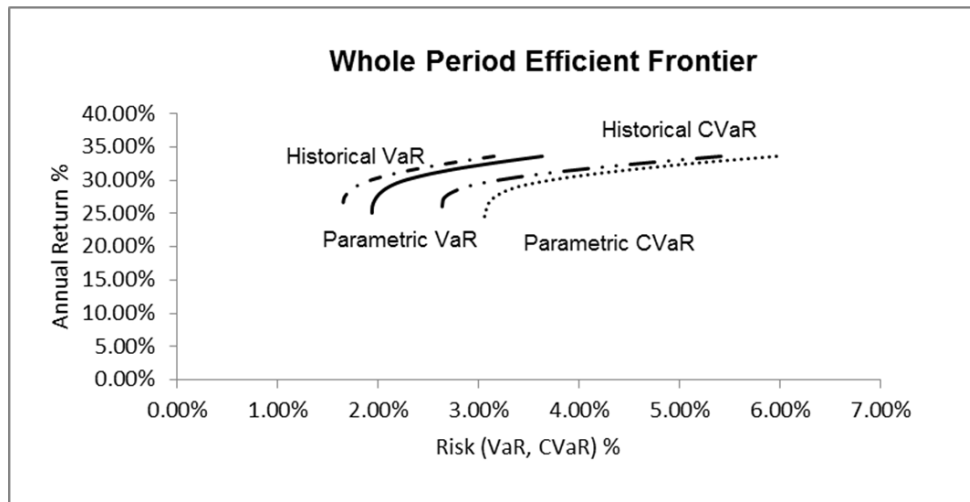
Figure 2.
Pre-GFC Efficient Frontier: 2004-2007

The efficient frontier is more elongated, given the higher returns achievable in this period. Parametric measures show slightly higher risk than historical measures, indicating that the distribution has thin tails.

Table 5.
GFC Return and Risk: 2008

	Annual Returns	Parametric VaR	Parametric CVaR	Historical VaR	Historical CVaR
Agriculture	-0.7386	0.0708	0.1083	0.0711	0.1083
Banks & Insurance	-0.3194	0.0422	0.0622	0.0455	0.0622
Consumer Discretionary	-0.3823	0.0283	0.0456	0.0249	0.0422
Consumer Staples	-0.1200	0.0370	0.0590	0.0286	0.0512
Diversified Financials	-0.5274	0.0394	0.0737	0.0345	0.0656
Energy & Materials	-0.4370	0.0378	0.0587	0.0353	0.0528
Industrials	-0.5311	0.0481	0.0899	0.0626	0.0921
IT & Telecom	-0.3896	0.0466	0.0737	0.0345	0.0656
Mining	-0.8126	0.0788	0.1122	0.0771	0.1088
Real Estate	-0.3764	0.0249	0.0382	0.0198	0.0335
All Sectors	-0.3863	0.0454	0.0722	0.0434	0.0682

We note that returns are negative across all sectors. In particular, Agriculture and Mining show huge falls, as well as extremely high volatility across all metrics. Consumer staples fares the best from a return perspective and real estate has the lowest volatility across the board. As our frontier is bounded by zero, we do not undertake an optimization, although it is clear from the table that investors wishing to minimize losses would avoid Agriculture and mining and weight their selections towards Consumer Staples and Banks and Insurance. Real estate and Consumer Discretionary would feature strongly for investors wishing to minimize volatility. The relatively strong performance of Consumer Discretionary and Banks is counter to what hapened globally. In particular Banks suffered the largest falls in large markets such as the US and the UK. This is consistent with our literature survey which mentions the relatively strong performance of Indonesian Banks, due to strong regulation and not being involved to any great extent in high risk products such as sub-prime mortgages.

Table 6.
Post-GFC Return and Risk: 2009–2011

	Annual Returns	Parametric VaR	Parametric CVaR	Historical VaR	Historical CVaR
Agriculture	0.3464	0.0315	0.0466	0.0285	0.0430
Banks & Insurance	0.2816	0.0276	0.0374	0.0254	0.0357
Consumer Discretionary	0.5307	0.0208	0.0349	0.0175	0.0283
Consumer Staples	0.4739	0.0231	0.0327	0.0201	0.0292
Diversified Financials	0.5600	0.0332	0.0482	0.0338	0.0513
Energy & Materials	0.2279	0.0238	0.0380	0.0227	0.0377
Industrials	0.3808	0.0294	0.0464	0.0354	0.0488
IT & Telecom	-0.0248	0.0275	0.0378	0.0276	0.0376
Mining	0.1414	0.0421	0.0651	0.0387	0.0615
Real Estate	0.3441	0.0244	0.0375	0.0249	0.0341
All Sectors	0.3335	0.0283	0.0425	0.0275	0.0407

Extremely strong recovery is noted in the Diversified Financials, Consumer Discretionary and Consumer Staples Sectors, although not so with Mining, and IT and Telecom. Returns and volatility for All Sectors has returned very close to the pre-GFC period, showing that the market has had a very short GFC with a rapid recovery.

As per Table 7, an investor would maximize returns in this period by investing all their funds in Diversified Financials. Consumer Discretionary and Consumer Staples continue to feature strongly in the optimal mix, both when maximizing returns and when minimizing risk. Contrary to the pre-GFC period, Agriculture does not feature strongly in any of the mixes. There are strong similarities between parametric and historical metrics for the industries that feature in the selection (from both a maximizing return and minimizing risk perspective), as well as between VaR and CVaR metrics.

Table 7.

Post GFC Optimal Portfolios: 2009 – 2011

Parametric VaR and CVaR Optimal Portfolio

Returns	Parametric VaR	Agriculture	Banks & Insurance	Consumer Discretionary	Consumer Staples	Diversified Financials	Energy & Materials	Industrials	IT & Telecom	Mining	Real Estate
56.00%	3.32%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%
53.75%	2.06%	0.00%	0.00%	76.63%	0.00%	23.37%	0.00%	0.00%	0.00%	0.00%	0.00%
51.50%	1.90%	0.00%	0.00%	59.27%	29.26%	10.36%	0.00%	0.00%	0.00%	0.00%	1.11%
49.25%	1.86%	0.00%	0.00%	51.70%	28.93%	8.02%	2.48%	0.00%	0.00%	0.00%	8.86%
47.01%	1.83%	0.00%	0.00%	47.98%	27.56%	7.22%	5.54%	0.00%	2.30%	0.00%	9.40%
44.76%	1.81%	0.00%	0.00%	44.74%	26.06%	6.57%	7.68%	0.00%	5.17%	0.00%	9.78%
42.51%	1.79%	0.00%	0.00%	41.51%	24.55%	5.92%	9.83%	0.00%	8.04%	0.00%	10.15%
40.26%	1.78%	0.00%	0.00%	38.28%	23.04%	5.27%	11.97%	0.00%	10.92%	0.00%	10.53%
38.01%	1.77%	0.00%	0.00%	35.04%	21.53%	4.61%	14.12%	0.00%	13.78%	0.00%	10.92%
35.76%	1.77%	0.00%	0.00%	31.81%	20.03%	3.96%	16.18%	0.00%	16.68%	0.00%	11.35%

Returns	Parametric CVaR	Agriculture	Banks & Insurance	Consumer Discretionary	Consumer Staples	Diversified Financials	Energy & Materials	Industrials	IT & Telecom	Mining	Real Estate
56.00%	4.82%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%
53.35%	3.21%	0.00%	0.00%	59.25%	10.62%	30.13%	0.00%	0.00%	0.00%	0.00%	0.00%
50.69%	2.91%	0.00%	0.00%	38.74%	44.52%	15.18%	0.00%	0.00%	0.00%	0.00%	1.56%
48.04%	2.84%	0.00%	0.00%	32.11%	43.54%	12.40%	0.00%	0.00%	1.87%	0.00%	10.09%
45.39%	2.79%	0.00%	0.00%	29.15%	41.37%	11.53%	1.65%	0.00%	5.77%	0.00%	10.52%
42.74%	2.74%	0.00%	0.00%	26.15%	39.15%	10.65%	3.70%	0.00%	9.51%	0.00%	10.84%
40.08%	2.69%	0.12%	0.00%	20.39%	34.88%	9.41%	7.55%	0.18%	16.12%	0.00%	11.36%
37.43%	2.68%	0.00%	1.06%	19.94%	34.53%	8.90%	7.64%	0.00%	16.67%	0.00%	11.25%
34.78%	2.67%	0.27%	0.00%	14.72%	30.66%	8.33%	11.28%	0.42%	22.49%	0.00%	11.85%
32.12%	2.66%	0.00%	2.45%	13.67%	29.85%	7.16%	11.50%	0.00%	23.77%	0.00%	11.59%

Historical VaR and CVaR Optimal Portfolio

Returns	Historical VaR	Agriculture	Banks & Insurance	Consumer Discretionary	Consumer Staples	Diversified Financials	Energy & Materials	Industrials	IT & Telecom	Mining	Real Estate
56.00%	3.38%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%
54.47%	2.18%	0.00%	0.00%	52.13%	0.00%	47.87%	0.00%	0.00%	0.00%	0.00%	0.00%
52.94%	1.71%	0.00%	0.00%	84.44%	6.76%	8.80%	0.00%	0.00%	0.00%	0.00%	0.00%
51.41%	1.63%	0.00%	0.00%	67.36%	30.35%	2.29%	0.00%	0.00%	0.00%	0.00%	0.00%
49.88%	1.62%	0.00%	0.00%	63.18%	31.01%	1.36%	3.97%	0.00%	0.47%	0.00%	0.00%
48.35%	1.61%	0.00%	0.00%	60.76%	30.13%	1.06%	5.68%	0.00%	2.37%	0.00%	0.00%
46.82%	1.60%	0.00%	0.00%	58.32%	29.17%	0.71%	7.27%	0.00%	4.24%	0.00%	0.29%
45.29%	1.59%	0.00%	0.00%	55.88%	28.19%	0.37%	8.88%	0.00%	6.10%	0.00%	0.59%
43.76%	1.59%	0.00%	0.00%	53.51%	27.20%	0.00%	10.50%	0.00%	7.97%	0.00%	0.82%
42.23%	1.59%	0.00%	0.00%	50.79%	26.15%	0.00%	12.15%	0.00%	9.85%	0.00%	1.06%

Returns	Historical CVaR	Agriculture	Banks & Insurance	Consumer Discretionary	Consumer Staples	Diversified Financials	Energy & Materials	Industrials	IT & Telecom	Mining	Real Estate
56.00%	5.13%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%
54.11%	3.10%	0.00%	0.00%	64.27%	0.00%	35.73%	0.00%	0.00%	0.00%	0.00%	0.00%
52.23%	2.63%	0.00%	0.00%	70.89%	19.66%	9.46%	0.00%	0.00%	0.00%	0.00%	0.00%
50.34%	2.51%	0.00%	0.00%	54.12%	39.69%	3.16%	0.00%	0.00%	0.00%	0.00%	3.03%
48.46%	2.48%	0.00%	0.00%	48.77%	39.19%	1.90%	0.00%	0.00%	1.50%	0.00%	8.64%
46.57%	2.45%	0.00%	0.00%	46.27%	37.85%	1.51%	0.00%	0.00%	4.64%	0.00%	9.73%
44.68%	2.43%	0.00%	0.00%	43.76%	36.52%	1.12%	0.00%	0.00%	7.79%	0.00%	10.82%
42.80%	2.42%	0.00%	0.00%	41.27%	35.12%	0.73%	0.00%	0.00%	10.91%	0.00%	11.97%
40.91%	2.41%	0.00%	0.00%	38.66%	33.77%	0.34%	0.88%	0.00%	13.73%	0.00%	12.63%
39.03%	2.41%	0.00%	0.00%	35.94%	32.40%	0.00%	2.39%	0.00%	16.31%	0.00%	12.96%
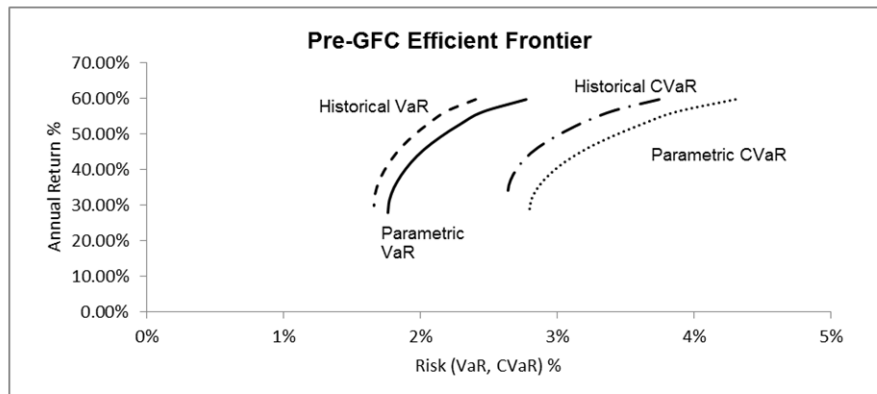
Figure 3.
Post-GFC Efficient Frontier 2009 – 2011

Again we see that the parametric measures tend to have a higher VaR and CVAR than the historical measures, showing that this period is also characterized by short tails.

4. CONCLUSIONS

The analysis shows that while there are some similarities in the selections between the periods (such as Consumer Discretionary and Consumer Staples featuring strongly), there are also some differences (Agriculture featuring strongly in the pre-GFC period, but not post GFC, and Diversified Financials doing the oposite). We also note that there are strong similarities in industry selections between parametric and historical metrics, indicating a normal distribution of returns, and between VaR and CVaR returns, showing low tail risk. The aparent normality of Indonesian return data is a theme that was identified in the paper by Allen, Boffey Kramadibrata, Powell and Singh (2012).

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