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Conditional Value at Risk Applications to the Global Mining Industry

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It is generally accepted that asset returns are not normally distributed, especially during volatile economic circumstances such as those seen during the global financial crisis. Yet portfolio optimisation is often based on lower order moments of mean and standard deviation, which do not take into account the tail of a distribution. The mining industry can be extremely volatile during times of economic downturn. We compare extreme risk in mining share portfolios from each of the world's seven leading mining areas using Conditional Value at Risk (CVaR) which measures those risks beyond traditional Value at Risk (VaR) metrics. We also show how CVaR, as opposed to traditional standard deviation measures, can be used to optimise mining portfolios and minimise extreme risk. We compare CVaR across two different periods and find that relative risk ranking between countries changes as volatility changes. We find significant differences between countries using CVaR as compared to standard deviation risk rankings, as well as differences in portfolios optimised using CVaR compared to portfolios using traditional variance methodology. This indicates that investors will not adequately minimise risk using traditional approaches.

JEL Codes: G0, G11, G15, L72

1. Introduction

Conditional Value at Risk (CVaR) is a metric which measures extreme tail risk – that risk which lies beyond traditional standard deviation and Value at Risk (VaR) measures.
Conditional value at risk has been used to measure problems such as extreme hedge fund risk (Amenc & Martellini, 2002; Berkelaar, Kobor, & Kouwenberg, 2009; Hentati, Kaffel, & Prigent, 2010; Liang & Park, 2007; Menoncin, 2009), relative industry risk (Allen & Powell, 2011; Allen, Powell, & Singh, 2011), bank risk (Allen & Powell, 2012), insurance (Bisgnani, Masala, & Micocci, 2009), optimising mixed asset portfolios (Alexander & Baptista, 2003, 2004; Proeiss & Schweizer, 2009), stock portfolio optimisation (Acerbi & Tasche, 2002; Birbil, Frenk, Kaynar, & Noyan, 2009; Krokhmal, Palmquist, & Uryasev, 2002; Uryasev & Rockafellar, 2000) and credit risk portfolio optimisation (Andersson, Mausser, Rosen, & Uryasev, 2000; Jobst & Zenios, 2001). As CVaR is a measure of extreme risk, it is especially relevant in times of economic stress and high volatility, such as during the Global Financial Crisis (GFC).

The mining industry can be highly volatile in times of extreme economic downturn. Most metals & mineral commodities and share markets showed strong growth and relatively low volatility in the period from 2002 to 2006, leading up to the Global Financial Crisis

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(GFC). These commodities and share markets then entered a period of extreme volatility with very high growth during most of 2007, followed by sharp declines with prices falling by half between July 2008 and January 2009(World Bank, 2011b). Thereafter a very sharp upward trend was resumed for the remainder of 2009, with many of these commodities regaining (and in many cases, surpassing) their pre-GFC prices. To distinguish between these two periods of distinctly different volatility, we will hereafter refer to the 2000-2006 period as the low volatility (LV) period, and to 2007-2009 as the high volatility (HV) period. Mining companies have been shown to have deteriorated further than most other industries during the Global Financial Crisis (GFC) in regards to both market and credit risk (Allen et al., 2011; Powell & Allen, 2009). Given this scenario, it is important for investors to understand extreme risk in this sector in share portfolio allocation. CVaR studies are nowhere near as numerous as studies on VaR. Whilst the previous paragraph shows that CVaR has been applied to various optimisation problems such as hedge funds, insurance, shares and mixed asset portfolios, there are very few studies which compare CVaR over periods which include both pre-GFC and the GFC, and no prior study of which we are aware which applies CVaR to the global mining industry. Thus our spotlight on CVaR in the mining industry, encompassing both pre-GFC and GFC periods, is unique and original, providing new information to investors on tail risk and optimal portfolio allocation in this industry.

Using CVaR, we compare share price volatility in the most mining intensive countries for the LV and HV periods to answer four research questions. First, which countries display the highest (lowest) extreme risk? Second, does relative risk between these countries change over the HV period as compared to the LV period? Third, is relative risk different using CVaR as compared to standard deviation? Fourth, we show how to optimise a mining portfolio using CVaR and determine whether this is significantly different to using a traditional Markowitz (1952) standard deviation approach.

We find that maximum returns are obtainable from South America during the LV period and China during the HV period. CVaR is minimised in both periods with high weightings in Australian, Chinese and Russian stocks. We also found that relative risk between countries is significantly different using CVaR as compared to standard deviation, leading to differences in optimal portfolio mix.

The next section of the paper provides a literature survey and background information on the mining industry, CVaR and portfolio optimisation. Section 3 deals with data and methodology. Section 4 covers the findings and discussion, with conclusions and implications provided in Section 5.

2. Background and Literature Review

2.1 The Global Resources Industry

The global mining industry is dominated by Australia, Canada, China, Russia, South Africa, South America (predominantly Chile) and the USA. Australia is one of the world's largest metals and minerals producers, with substantial production of a wide range of commodities such as bauxite, iron ore, gold, lead nickel, silver, zinc and zircon. Canada has substantial production of a range of metals and minerals such as aluminium, diamonds, gold and nickel.

China leads the world in the production of several commodities, producing more than 40% of the world's aluminium, coal, iron & steel, lead and tin, as well as producing a wide range of other commodities. South Africa produces a wide range of metals and minerals, leading the world in chrome and platinum and has one of the world's largest gold reserves. Chile leads the world's copper production. Russia is one of the world's largest producers of diamonds and also produces a significant portion of global crude oil, gold nickel, platinum and silver. The USA is a major producer of a wide range of commodities, including coal, gold and silver. Table 1 summarises the world market share of key resources.

Strong growth in global demand for resources has been fuelled largely by demand from resource hungry China, who has experienced a rapidly expanding economy for three decades, with growth in GDP averaging 9.6% for this period (World Bank, 2011a). China consumes almost all their own resource production and is the world's largest importer of minerals. Their demand includes two thirds of the worlds iron ore production, almost half of the world's coal production, as well as a wide range of other metal and minerals (U.S. Geological Survey, 2011). China's demand for resources is in turn being driven by factors such as world demand for low cost Chinese manufacturing exports (Roberts & Rush, 2010) as well as internal factors such as consumption and investment (He & Zhang, 2010).

Table 1: Global Mining Market Share

	Aluminium	Coal	Chrome	Copper	Diamonds	Gold	Iron & Steel
Australia	4.7%	5.7%	0.4%	5.6%	8.9%	9.3%	0.4%
Canada	7.1%	1.1%	0.0%	3.0%	9.0%	3.6%	0.7%
China	40.6%	51.1%	1.6%	7.1%	0.9%	13.9%	51.2%
Russia	9.3%	2.0%	2.3%	4.6%	28.1%	6.9%	4.7%
South Africa	1.9%	0.3%	38.1%	0.6%	5.0%	7.7%	0.4%
S. America	4.8%	1.6%	3.9%	48.0%	1.0%	19.2%	2.7%
United States	4.2%	15.1%	0.0%	6.9%	0.0%	9.3%	5.0%
Other Countries	27.5%	23.1%	53.7%	24.2%	47.2%	30.2%	34.9%
World Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

	Iron Ore	Lead	Nickel	Platinum	Tin	Silver	Zinc
Australia	17.3%	15.1%	9.0%	0.0%	0.8%	8.2%	12.1%
Canada	1.4%	1.6%	10.0%	3.0%	0.0%	2.8%	5.6%
China	37.0%	42.7%	5.0%	0.0%	44.1%	14.5%	29.2%
Russia	4.1%	2.2%	17.1%	13.1%	0.4%	6.8%	2.0%
South Africa	2.3%	1.2%	2.7%	75.3%	0.0%	0.4%	0.3%
S. America	16.4%	11.3%	23.6%	0.5%	19.2%	36.2%	17.3%
United States	2.0%	9.8%	0.0%	1.9%	0.0%	5.6%	6.0%
Other Countries	19.5%	16.1%	32.6%	6.1%	35.6%	25.6%	27.6%
World Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Sources:(British Geological Survey, 2011; International Energy Agency, 2011; MBendi Information Services, 2011; U.S. Geological Survey, 2011).

2.2 CVaR

Value at Risk (VaR) is a widely used metric for the measurement of market risk, measuring potential losses over a specified period at a specified confidence level. A key criticism of VaR is that it says nothing of the risks beyond the threshold measurement (for example, Samanta, Azarchs, & Hill, 2005). In addition, VaR has been found to be a non-coherent measure, having undesirable mathematical characteristics such lack of subadditivity (Artzner, Delbaen, Eber, & Heath, 1997, 1999) .

CVaR, on the other hand, measures risks beyond VaR, and has also been found to be a coherent measure, not having the undesirable characteristics of VaR (Pflug, 2000). If we are measuring VaR at a specified confidence level (β), then CVaR is the average of those risks beyond β, i.e. CVaR is the mean value of the worst (1- β)*100% losses. VaR is normally measured at high confidence intervals such as 95% or 99%. If, for example, we are measuring VaR at a 95% confidence level (β=0.95), CVaR is the average of the 5% worst losses.

2.3 Portfolio Optimisation

The Markowitz (1952) portfolio optimisation approach generates a frontier (as per figure 1) which shows the most efficient combination of risk and return, with risk measured as the standard deviation (*σ)* of portfolio returns. As the frontier shows the maximum possible returns at each level of risk, *σ*-return combinations beyond the frontier are not possible and combinations below the frontier are inefficient. In order to capture extreme risk, our approach uses CVaR-return instead of *σ*-return as an optimisation tool. Use of CVaR as an optimiser in the literature is extremely limited with examples including credit portfolio optimisation (Andersson et al., 2000) and Australian sectoral risk optimisation by the current authors (Allen & Powell, 2011).

3. Methodology

Using Datastream, we obtain ten years of daily price data to calculate CVaR and returns for individual mining companies in each of the key mining areas of Australia, Canada, China, Russia, South Africa, South America and the USA. We use a maximum of 30 mining companies in each area (the 30 largest by market capitalisation). These companies are identified from leading mining indices in each of the areas, including the Datastream and FTSE mining indices for each area as well as the S&P/ASX 300 Resources Index (Australia), S&P/TSX Comp Metals & Mining Index (Canada), FTSE Xinhua 600 Mining Index (China), FTSE/Russia Basic Materials Index (Russia, and the FTSE/JSE Resource Index (South Africa). This provides us with a total of 161 companies comprising the following number of companies in each area: Australia 30, Canada 30, China 30, Russia 7, South Africa 23, South America 11 and US 30. We deem our data sample to be appropriate as it covers both pre-GFC and GFC countries as well as a large number of companies, including all the major mining ones, spanning all the key mining countries.

There are a number of different techniques for measuring VaR and CVaR. We use a 95% historical approach which sorts historical returns from best to worst, with CVaR being the average of the worst 5% of returns. We divide our ten years of data into two periods, as discussed in the introduction, with Low Volatility (LV) being the years between 2000-2006 and High Volatility (HV) the years between 2007-2009. We calculate standard deviation, CVaR and returns for each entity for both periods. We then calculate country returns as the market capitalisation-weighted average returns of the individual companies in each country, and country CVaR being the weighted average of the individual company CVaRs. These are shown in Table 2.

To allow comparison between a traditional Markowitz variance-return approach and our CVaR-return approach, we calculate efficient frontiers based on both methods. To construct the σ-return frontier, we construct a variance-covariance matrix to account for correlation between our country returns, from which portfolio return and portfolio σ is calculated. The portfolio is then optimised to achieve the combination of assets yielding the minimum risk for each selected return level:

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

Subject to

$$\sum_{i=1}^{n} x_i = 1 \tag{2}$$

$$\sum_{i=1}^{n} \mathrm{IE}[r_i] x_i = r_p \tag{3}$$

$$0 \leq x_i \leq v_i \tag{4}$$

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 $\sigma_{ik}$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).

For our CVaR-return frontier, we apply the same approach as above, except we use the standard deviation of the worst 5% of returns instead of the standard deviation of all returns. Our optimum σ-return (or CVaR-return) portfolio shows the combination of assets that yield the minimum portfolio σ (or CVaR) for each selected level of return. Our maximum return point is the highest return that can be generated by any country portfolio. The minimum return point is the return associated with the lowest possible σ (or CVaR). We select eight equidistant points between minimum and maximum returns (giving a total of 10 return points) and calculate the minimum portfolio σ or CVaR associated with each point. These σ-return and CVaR-return combinations make up the efficient frontier, which we generate for the LV and HV periods.

4. Results and Analysis

Table 2 shows the standard deviation and CVaR risk measures and the returns for each country's mining portfolio. Rankings are shown in Table 4.

Table 2: Standard Deviation, Annual Returns and CVaR

HV period	Standard Deviation	Annual Returns	Historical CvaR	LV period	Standard Deviation	Annual Returns	Historical CvaR
Australia	0.0199	0.1546	0.0528	Australia	0.0180	0.1802	0.0333
Canada	0.0283	0.1445	0.0811	Canada	0.0213	0.2025	0.0433
China	0.0282	0.2913	0.0682	China	0.0194	-0.0276	0.0377
Russia	0.0314	0.0405	0.0554	Russia	0.0227	0.2195	0.0333
South Africa	0.0236	-0.0091	0.0640	South Africa	0.0209	0.1691	0.0491
South America	0.0245	0.1280	0.0603	South America	0.0202	0.2594	0.0364
United States	0.0262	0.0784	0.0652	United States	0.0191	0.1272	0.0433

Standard deviation and CVaR are daily average figures for the period. CVaR is the average of the worst 5% of returns as per the methodology section. The HV category is the 3 years from 2007-2009, while the LV is the 7 years from2000to2006.

Both periods generally show positive returns, but different volatilities, especially using CVaR. Whilst the LV period was generally a period of sustained growth, the HV period was one of high growth, high decline, then high growth again. To better understand the HV period, a more comprehensive breakdown of returns during this time is shown in table 3. Most countries experienced strong growth in 2007, particularly China. The exception was South Africa with a small negative return. In 2009, Australia, Canada, South America and the US all gained more than they lost in 2008 in an impressive turnaround. Although China and Russia had exceptionally strong negative returns in 2008, they both showed an overall increase during HV due to the strong growth in 2007 and 2009.

Table 3: Global Annual Returns – Mining Industry: HV

	2007	2008	2009	Average
Australia	0.2999	-0.2770	0.4410	0.1546
Canada	0.3507	-0.2602	0.3429	0.1445
China	0.8880	-0.6285	0.6143	0.2913
Russia	0.2139	-0.8140	0.7216	0.0405
South Africa	-0.0124	-0.4464	0.4316	-0.0091
South America	0.3553	-0.4877	0.5163	0.1280
United States	0.2040	-0.2648	0.2961	0.0784

The table above shows the annual returns for our sample of mining entities in each of the major mining countries during the HV period, with the final column being the average annual return for the 3 years.

Table 4: Rankings

HV period	Standard Deviation	Annual Returns	Historical CvaR
Australia	7	2	7
Canada	2	3	1
China	3	1	2
Russia	1	6	6
South Africa	6	7	4
South America	5	4	5
United States	4	5	3

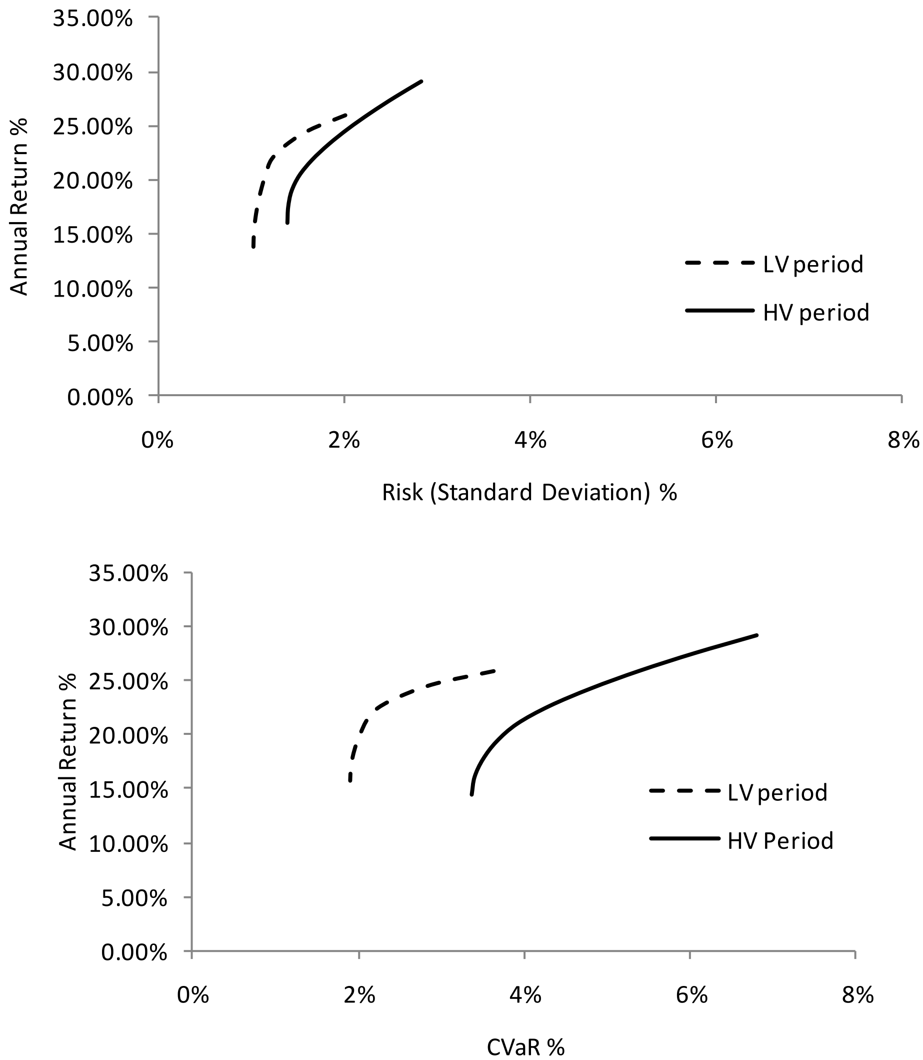
LV period	Standard Deviation	Annual Returns	Historical CvaR
Australia	7	4	6
Canada	2	3	2
China	5	7	4
Russia	1	2	7
South Africa	3	5	1
South America	4	1	5
United States	6	6	3

The rankings are based on the figures in table 2 with 1 being the highest risk (or return) and 7 being the lowest. For example Russia has the highest risk based on standard deviation, whereas Australia has the lowest risk.

There are some key differences between LV and HV rankings. China's annual returns are ranked 7th during the LV period and 1st during the HV period. South America's returns show the reverse, going from 1st to 4th. There are also substantial differences between standard deviation and CVaR rankings for both the LV and HV periods. This is especially the case with Russia who was ranked highest risk on standard deviation in both periods but had a very low CVaR risk ranking. A Spearman rank correlation test shows no significant correlation at either the 99% or 95% level between standard deviation and CVaR rankings, meaning that a standard deviation risk measure fails to identify extreme risk. We also found no significant correlation between risk rankings in the HV period as compared to the LV period, meaning relative risk between the countries changes with changing economic circumstances.

Xiong and Idzorek (2011) argue that if assets follow a normal distribution, then the gap between the standard deviation (σ) and CVaR, will be equal. Assume VaR is measured at the 95% level, then VaR = -1.65σ, using standard normal distribution tables and CVaR = -2.06σ, which is the approximate average of the worst 5% of returns. However, because returns are not generally normally distributed, especially during the volatility of a crisis, the first two moments do not explain CVaR, which is impacted by the higher third and fourth moments of skewness and kurtosis. Following this logic, if returns were normally distributed, then there would be no difference between our σ and CVaR rankings. This is clearly not the case with our mining portfolio, where we found no significant correlation between σ and CVaR rankings, meaning the portfolios are not normally distributed, and are characterized by non-standard skewness and kurtosis, which is why the first two moments fail to account for extreme mining portfolio risk. We find, for example, Russia to be characterized by high kurtosis and low tail risk, with CVaR being -1.76σ (global portfolio average 2.48σ) in the HV period and -1.47σ (global portfolio average 1.96σ) in the LV period, both much lower than the -2.06σ associated with a normal distribution. South Africa, on the other hand shows the opposite. The LV CVaR of 1.96σ for the aggregated global portfolio is lower than that associated with a normal distribution, whereas, the HV CVaR of 2.48σ for the global portfolio is higher than that of a normal distribution. These all illustrate the non-normality of returns and how these change with economic circumstances. The non-normality of returns found here is consistent with that found by other studies (including for example Agarwal & Naik, 2004; Bradley & Taqqu, 2003; Uryasev & Rockafellar, 2000) particularly in the context of times of higher volatility such as during a financial crisis (such as found by Allen & Powell, 2011; Harvey, Liechty, Liechty, & Muller, 2010; Xiong & Idzorek, 2011).Figure 1 shows the LV and HV efficient frontier based on CVaR and standard deviation.

Figure1: Efficient Frontier



The upper graph is based on standard deviation, with the lower graph based on CVaR. The frontier moves to the right during the HV period, showing the increase in risk. The CVaR graph is substantially more to the right, demonstrating the extreme risk which is not captured in the standard deviation approach. Optimal portfolios are shown in Tables 5 and 6, firstly using standard deviation, then CVaR, to minimise risk.

Table 5: Optimal Portfolio using Standard Deviation

LV period

Returns	StDev	Weightings						
		Aus	Can	Chi	Rus	Saf	Sam	US
25.94%	2.02%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%
24.60%	1.64%	0.00%	9.62%	0.00%	19.97%	0.00%	70.41%	0.00%
23.25%	1.38%	12.19%	16.03%	0.00%	20.31%	0.00%	51.47%	0.00%
21.91%	1.22%	25.95%	20.92%	0.00%	19.71%	0.00%	33.42%	0.00%
20.57%	1.16%	29.51%	21.70%	3.07%	18.50%	2.03%	25.18%	0.00%
19.22%	1.11%	28.52%	20.54%	7.95%	17.32%	3.01%	22.30%	0.36%
17.88%	1.08%	27.59%	18.07%	11.96%	16.12%	3.85%	19.18%	3.24%
16.53%	1.05%	26.66%	15.59%	15.96%	14.92%	4.69%	16.06%	6.13%
15.19%	1.03%	25.72%	13.11%	19.96%	13.72%	5.53%	12.94%	9.02%
13.85%	1.03%	24.78%	10.68%	23.98%	12.53%	6.36%	9.81%	11.86%

HV period

Returns	StDev	Weightings						
		Aus	Can	Chi	Rus	Saf	Sam	US
29.13%	2.82%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%
27.66%	2.54%	10.75%	0.00%	89.25%	0.00%	0.00%	0.00%	0.00%
26.19%	2.28%	19.12%	2.21%	78.67%	0.00%	0.00%	0.00%	0.00%
24.72%	2.04%	25.43%	6.34%	68.23%	0.00%	0.00%	0.00%	0.00%
23.25%	1.83%	30.07%	8.97%	58.21%	0.00%	0.00%	2.74%	0.00%
21.78%	1.65%	33.48%	10.50%	48.51%	0.00%	0.00%	7.51%	0.00%
20.32%	1.51%	36.88%	12.03%	38.81%	0.00%	0.00%	12.28%	0.00%
18.85%	1.43%	40.28%	13.56%	29.10%	0.00%	0.00%	17.06%	0.00%
17.38%	1.39%	40.48%	11.48%	23.83%	3.60%	0.00%	15.28%	5.33%
15.91%	1.39%	39.13%	8.89%	20.73%	5.52%	3.44%	12.01%	10.28%

The optimal portfolio weightings are calculated as per the methodology section, whereby the portfolio is optimised to achieve the combination of assets yielding the minimum risk (as measured by the standard deviation) for each selected return level. For example, an investor seeking to maximise return at 25.94% in the LV period, would invest all their funds in South America, whereas an investor seeking to minimise risk, would achieve a return of 13.85% by allocating 24.78% of their investment to Australia, 10.68% to Canada and so on. The risk – return relationship from the above is then used to plot the Markowitz's efficient frontier in Figure 1.

Table 6: Optimal Portfolio using CVaR

LV period

Returns	CVaR	Weightings						
		Aus	Can	Chi	Rus	Saf	Sam	US
25.94%	3.64%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%
24.80%	2.95%	0.00%	0.53%	0.00%	27.97%	0.00%	71.50%	0.00%
23.65%	2.53%	5.94%	9.24%	0.00%	32.47%	0.00%	52.35%	0.00%
22.51%	2.24%	17.96%	13.16%	0.00%	31.74%	0.00%	37.14%	0.00%
21.36%	2.10%	27.04%	16.05%	1.04%	30.85%	0.00%	25.03%	0.00%
20.21%	2.03%	26.74%	15.68%	5.38%	29.44%	0.00%	22.75%	0.00%
19.07%	1.97%	26.46%	15.31%	9.72%	28.04%	0.00%	20.47%	0.00%
17.92%	1.93%	26.17%	14.95%	14.05%	26.64%	0.00%	18.19%	0.00%
16.78%	1.90%	25.92%	13.86%	17.96%	25.27%	0.00%	15.78%	1.21%
15.63%	1.89%	25.71%	12.33%	21.54%	23.97%	0.00%	13.17%	3.28%

HV Period

Returns	CVaR	Weightings						
		Aus	Can	Chi	Rus	Saf	Sam	US
29.13%	6.82%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%
27.50%	6.08%	11.89%	0.00%	88.11%	0.00%	0.00%	0.00%	0.00%
25.88%	5.41%	20.35%	3.18%	76.46%	0.00%	0.00%	0.00%	0.00%
24.26%	4.82%	25.87%	5.69%	65.36%	0.00%	0.00%	3.08%	0.00%
22.63%	4.32%	29.60%	6.87%	54.69%	0.00%	0.00%	8.85%	0.00%
21.01%	3.93%	33.32%	8.05%	44.01%	0.00%	0.00%	14.61%	0.00%
19.38%	3.68%	34.73%	8.84%	35.52%	3.28%	0.00%	17.63%	0.00%
17.76%	3.52%	33.29%	7.71%	30.42%	9.99%	0.00%	15.60%	2.98%
16.13%	3.42%	32.07%	5.42%	25.72%	15.89%	0.00%	12.44%	8.46%
14.51%	3.38%	30.85%	3.14%	21.02%	21.80%	0.00%	9.27%	13.92%

This table uses the same methodology as table 5, except CVaR (as opposed to standard deviation) is used as the risk measure.

Highest returns are obtained by investing in South America in the LV period and China in the HV period. South Africa does not feature as an attractive investment in either period on either an σ-return or CVaR-return basis. Minimising risk using standard deviation sees Australia and China featuring strongly in both periods. Using CVaR sees Russia come strongly into play, with optimal portfolio share increasing four-fold from 5.5% on a standard deviation basis to 21.8% during the LV period, and with China and the US also showing small increases. These three countries take optimal share away from Australia and Canada in the main, who lose a quarter and two thirds of their optimal share respectively, and also some from South Africa and South America. Thus, whilst the shifts across the board may not be that startling, individual country weightings can change quite substantially due to the standard deviation approach not catering adequately for extreme risk.

To summarise our above results we refer back to our four research questions in our introduction. The first question was which countries display the highest (lowest) extreme risk? To answer this we provided risk rankings in Table 4, which showed Russia followed by Australia to have the lowest CVaR in the LV period, with Australia followed by Russia having the lowest CVaR in the HV period. South Africa followed by Canada had the highest CVaR in the LV period, whereas Canada followed by China had the highest CVaR in the LV period. The second question was does relative risk between these countries change over the HV period as compared to the LV period? We found this to be the case with no significant correlation in country rankings between the two periods. The third question asked if relative risk is different using CVaR as compared to standard deviation? We confirmed this to be true, with no significant correlation between the two measures when measuring country rankings, with the standard deviation measure failing to account for extreme tail risk. The fourth question related to showing how to optimise a mining portfolio using CVaR and determining whether this is significantly different to using a traditional Markowitz (1952) standard deviation approach. We showed how individual country holdings can change quite substantially in the portfolio mix when using CVaR as compared to standard deviation.

The shifts in the frontier and the remix of assets in the optimal portfolio is consistent with CVaR findings both in earlier pre-GFC papers, as well as later studies. Earlier papers which optimised portfolios using CVaR and found it to be more efficient than VaR or standard deviation include Andersson et al., (2000), Uryasev and Rockafellar (2000), Jobst and Zenios (2001), and Krokhmal et. al(2002). Recent papers which include the GFC support CVaR as being appropriate in times of high volatility. Xiong and Idzorek (2011) maintain that whilst it is well known that asset returns are not normally distributed, especially in times of high volatility, the implications for portfolio choice are not well known. They found that an asset universe with mixed tails (varying kurtosis and skewness) leads to different optimal mixes when using CVaR as the optimiser as compared to the standard deviation. Using a mixed asset portfolio Hentati et.al. (2010 also found that optimal allocation between assets changes when using a range of different optimisers in dynamic circumstances, and that CVaR tends to perform better than other optimisers for high volatility. Allen and Powell (2011), examining relative portfolio risk between industries over both pre-GFC and GFC periods, showed how industry risk rankings and optimal portfolio mix differ using VaR as compared to CVaR, with CVaR being a more effectively the tail risk measure. All of these other studies are consistent with this paper in finding changes to optimal mix using CVaR as an optimiser as compared to more traditional optimisers, with CVaR being a measure which can assist investors in identifying and minimising extreme risk, especially in periods of high volatility. Although results are consistent with prior research on CVaR and portfolio optimisation, the prior studies were across different periods and industries. Ours is the first study of its type in the mining industry, particularly in its application across the pre-GFC and GFC periods, thus providing new information on portfolio choices.

5. Conclusions and Implications

The study shows that optimal resource portfolio composition changes over different economic circumstances as measured by our HV period as compared to the LV period. The optimal portfolio is also found to be somewhat different when using CVaR as an optimiser as compared to the standard deviation. The latter is because CVaR measures extreme risk which is not captured by using traditional volatility measures such as standard deviation or VaR. This means that resources investors need to re-evaluate portfolio mix as economic circumstances change and investors wishing to minimise extreme risk could consider CVaR as an optimisation tool.

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