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Extreme Equities Risk in Emerging Markets: Evidence from Australia

D.E. Allen*, A.R. Kramadibrata*, R.J. Powell* and A.K. Singh*

The huge volatility experienced by equities markets during the Global Financial Crisis (GFC) underlined the importance of understanding market risk in extreme economic conditions. Whilst the Australian economy is widely considered to have fared better than many of its global counterparts during the GFC, there was nonetheless extreme volatility experienced in Australian financial markets. To understand the extent to which emerging Australian entities were impacted by these extreme events as compared to established entities, this paper compares entities comprising the Emerging Markets Index (EMCOX) to established entities comprising the S&P/ASX 200 Index using four risk metrics. The first two are Value at Risk (VaR) and Distance to Default (DD) which are traditional measures of market and credit risk. The other two focus on extreme risk in the tail of the distribution and include Conditional Value at Risk (CVaR) and Conditional Distance to Default (CDD), the latter metric being unique to the authors and which applies CVaR techniques to default measurement. We apply these measures both prior to and during the GFC, including an analysis of high, medium and low risk quantiles and find that Emerging Market shares show higher risk for all metrics used, the spread between the emerging and established portfolios narrows during the GFC period and that the default risk spread between the two portfolios is greatest in the tail of the distribution. This information can be important to both investors and lenders in determining share or loan portfolio mix in extreme economic circumstances.

JEL Codes: G01, G11

1. Introduction

Emerging markets have long been considered to offer better risk-adjusted returns than established markets. In an analysis of eleven emerging markets, Arora, Jain and Das (2009) found that investors can earn superior returns in these markets and that the benefits of investing in emerging markets are not lost in periods of falling stock markets. Given these potential benefits, it is important to investors to understand the risks involved in investing in emerging entities and this study is motivated by providing Australian investors with such an understanding. Australia is an important world market with the Australian stock exchange being the world's sixth largest financial market. The question investigated by this article is the extent to which the risk profile of Australian emerging market entities differs to that of established entities over different economic circumstances. In particular, a core aspect of the motivation of this article is to provide an understanding of the extreme risk experienced in the tail of the distribution of emerging entity returns, as it is in these extreme circumstances when investors or lenders to these entities are exposed to the highest potential losses. The Global Financial Crisis (GFC) has underlined the importance of measuring and understanding risk in extreme circumstances and there is growing appreciation that returns are not normally distributed, with a need to focus on extreme events, or Black Swans as these types of outlying events are referred to by Taleb (2007).

*School of Accounting, Finance and Economics, Faculty of Business & Law, Edith Cowan University, Western Australia. *Email:* a.kramadibrata@ecu.edu.au

Estrada (2008, 2009) showed that outliers can have a massive impact on the returns of portfolios and demonstrated that, in 16 emerging markets based on 110,000 daily returns, avoiding just the 0.15% worst trading days resulted in portfolios 337.1% more valuable than a passive investment.

Our analysis spans both credit risk (potential losses by lenders) and market risk (potential losses by investors). To ensure a thorough investigation of the topic, we use four risk metrics including Value at Risk (VaR), Conditional Value at Risk (CVaR), Distance to Default (DD) and Conditional Distance to Default (CDD).

VaR measures potential losses over a specified time period at a selected threshold (level of confidence) and is a widely used and well understood metric for measuring market risk. A major shortfall of VaR is that it excludes risk beyond the threshold measure. We thus also use CVaR, which was traditionally used by the insurance industry to measure extreme losses (those beyond VaR) and which is gaining popularity as a measure of extreme share market risk.

The Merton (1974) DD model, as modified by KMV (Crosbie & Bohn 2003), hereafter referred to as the Merton / KMV model (described in Section 3), is widely used by banks to measure credit risk based on a combination of fluctuations in market asset values and the debt to equity structure of the balance sheet. We use this model as a measure of credit risk. Again, this model does not capture extreme credit risk in the tail of the distribution which is when banks are most likely to fail. To address this issue, the authors have devised a CDD which applies CVaR techniques to the Merton / KMV model and we use this model to measure extreme risk in this study.

Our research question has three sub-questions: Firstly, to what extent does risk, as measured by our metrics, differ between the emerging and established portfolios using the traditional VaR and DD metrics? Secondly, how does that relationship change using extreme CVAR and CDD metrics? Thirdly, does the risk spread between the emerging and established portfolios change during the GFC as compared to pre-GFC?

There are very few studies on emerging entity risk in Australia and, as shown in the following section, these focus on aspects such as default premia in microcaps, sector and country factors and the mining industry. The only Australian speculative study, located in the following section, which looks at extreme risk is an unpublished working paper by the same authors, which uses quantile regression as opposed to the metrics used in this study. Thus, this article is original and unique.

The next section of the paper provides a literature survey and background information on the topic, including information on the indices used, what has been done before in Australia in regards to emerging markets and background to the metrics. Section 3 deals with data and methodology which includes explanation of the VaR, CVaR, DD and CDD metrics. Formulation of hypotheses is also undertaken in Section 3. Section 4 covers the results and analysis with conclusions and implications provided in Section 5.

2. Background and Literature Review

The S&P Emerging Companies Index incorporates entities outside the S&P/ASX top 300 companies which are considered as smaller and less liquid than the higher value companies. The S&P/ASX 200, on the other hand, is considered as the benchmark index. Emerging or speculative entities are generally considered by investors as having potentially higher returns but higher losses during extreme circumstances.

Established indices like the S&P/ASX 200 are much more researched than emerging or small cap indices. The following are some examples of Australian research on smaller or emerging companies. Chan, Faff and Koffman (2008) find that default risk can lead to risk premia in Australian microcap asset prices. O'Shea, Worthington, Griffiths, & Gerace (2008) examine the effects of disclosure on volatility in speculative industries with focus on the mining industry. Ferris (2001) examines the future of the venture capital market in Australia. Dolan & Yu (2002), in a study including Australia among other countries, show that for small cap stocks country level factors persist in generally having the strongest impact on stock returns but that sector level factors are also becoming a stronger driver of stock returns. Hyde & Beggs (2009) show the value spread to be positively related to the value premium in the Australian market, especially for small cap portfolios. Allen, Kramadibrata, Powell, & Singh (2011, 2011a) use quantile regression to examine default risk for speculative companies, finding much higher default risk for speculative than established companies and that the spread between these two categories is more volatile for US companies than Australian ones.

Value at Risk (VaR), a widely used metric for the measurement of market risk, has attracted criticism as it says nothing of the risks beyond the threshold measurement (for example, Allen & Powell, 2011; Samanta, Azarchs, & Hill, 2005; Triana, 2009). In addition, VaR has been found to be a non-coherent measure having undesirable mathematical characteristics such the lack of sub-additivity (Artzner, Delbaen, Eber, & Heath, 1997, 1999) and has also been criticised on the basis of inconsistent results produced by different VaR methods (Beder,1995).

CVaR is a metric which does measure tail risk, i.e., those risks beyond VaR. It has been found to be coherent without 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 ($1-\beta$)*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. Examples of the use of CVaR include credit portfolio optimisation (Andersson, Mausser, Rosen, & Uryasev, 2000), sectoral share portfolio analysis in Australia (Allen & Powell, 2011), currency hedging decisions (Topaloglou, Vladimirou, & Zenios, 2002) and portfolio investment decisions (Alexander & Baptista, 2004).

The Merton / KMV model, as described in Section 3, measures DD based on a combination of fluctuating assets and balance sheet structure of companies. Its traditional application is to measure corporate default risk and the literature has wide coverage of its use, including applications such as calculating credit spreads (Dubey, 2010), determining capital thresholds (Chan-Lau & Sy, 2006) , comparison of the performance of option-based and accounting-based models (Gharghori, Chan, & Faff, 2007) and calculating default risk in equity returns (Vassalou & Xing, 2004).

Fluctuating assets are measured by the DD model using the standard deviation of asset returns. As with VaR, this approach does not capture extreme risk. Thus, we have developed a CDD model which, similar to CVaR's application to extreme market risk, measures extreme credit risk using the asset value fluctuations beyond a selected threshold (in our case we use the extreme 5% of asset value fluctuations). The model is described in further detail in the following section. As the model is unique to the authors, it has had very limited literature coverage thus far, predominantly quantile regression applications of the model (for example, Allen, Boffey, & Powell, 2011; Allen, Kramadibrata, Powell, & Singh, 2011, 2011a).

3. Methodology

3.1 Data

We obtain 10 years of daily share price data from Datastream. This time-frame is considered appropriate as it covers both the pre-GFC and GFC periods. We split the data into two periods, being pre-GFC (2000-2007) and GFC (2007-2009). These data are used to calculate VaR and CVaR and are also a component of the DD and CDD calculations explained in this section. The balance sheet data (debt and equity) required for the DD and CDD calculations are also obtained from Datastream. Both the S&P/ASX 200 (“Established” portfolio) and the EMCOX (“Emerging” portfolio) have 200 companies. We exclude any companies which do not have at least 12 months of data in both the pre-GFC and GFC periods.

3.2 Methodology

There are 3 main methods of measuring VaR. Parametric VaR is based on a normal distribution assumption. Historical VaR sorts the returns from largest to smallest with VaR being the return corresponding to the selected level of confidence, for example, the 95th worst return for a 95% confidence level. Monte Carlo VaR generates thousands of simulations from which VaR is then calculated using the selected confidence level. CVaR is the average of returns beyond the selected VaR threshold (if VaR is being calculated at the 95% confidence level, then CVaR is the average of the worst 5% returns). Parametric methods are not suitable in our instance as our study is focussed on extreme risk which does not usually follow a normal distribution. We select historical VaR for our study as it does not have the computational complexities associated with Monte Carlo and also it makes no assumption about the distribution of returns which makes it suitable for capturing extreme risk. VaR is normally calculated at the 95% or 99% level of confidence. We use 95% VaR with CVaR being based on the average of the remaining 5%. We chose the 95% level as 99% would leave too few observations for meaningful CVaR analysis. We calculate VaR and CVaR for each individual entity with portfolio level figures being the market capitalisation weighted average of the individual entity figures.

The Merton (1974) DD model is based on the option pricing work of Black & Scholes (1973). The model assumes that the firm has one single debt issue (F) and one single equity issue (E). F consists of a bond that matures at time (T). The initial asset value (V) of the firm is;

$$V_0 = E_0 + F_0 \tag{1}$$

At T, the firm pays off the bond and the remaining equity is paid to the shareholders. The firm defaults if F > V at T. In this case the bondholders take ownership of the firm and the shareholders get nothing (due to limited liability of shareholders the amount will not be negative). Thus, the value of a firms stock at debt maturity:

$$E_T = max(V_T - F, 0) \quad (2)$$

This is the same as the payoff of a call option on the firm's value with strike price F. If, at T, assets exceed loans, the owners will exercise the option to repay the loans and keep the residual as profit. If loans exceed assets, then the option will expire unexercised and the owners (who have limited liability) default. The call option is in the money where V_T - F > 0, and out of the money where V_T - F < 0. Merton uses the assumption that asset values are log normally distributed, calculating DD as

$$DD = \frac{ln(V/F) + (\mu - 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}} \quad (3)$$

where μ is an estimate of the annual return (drift) of the firm's assets which we measure as the mean of the change in lnV of the period being modelled as per Vassalou & Xing (2004) and σ_V is the standard deviation of asset value returns. On this basis DD is measured as the number of asset value standard deviations the firm is from defaulting. Probability of Default (PD) is calculated by Merton using a cumulative normal standard normal distribution function (N):

$$PD = N(-DD) \quad (4)$$

KMV (Crosbie & Bohn, 2003) find that the normal distribution approach followed by Merton results in PD values much smaller than defaults observed in practice. KMV has a large world-wide database from which to provide empirically based Estimated Default Frequencies (EDF) which they align to DD values instead of using the normal distribution approach. For our study this PD difference between Merton and KMV does not matter as we restrict our analysis to the DD rather than PD level.

We commence by estimating the initial vale of the firm using equation 1. We then estimate asset volatilities following an intensive estimation, iteration and convergence procedure as outlined by studies such as Bharath & Shumway (2009) and Vassalou & Xing (2009). We apply these asset volatilities to equation 3 to estimate DD. Note that in KMV, debt is taken as the value of all short-term liabilities (one year and under) plus half the book value of all long-term debt outstanding and we follow this approach. We also follow the usual practice of setting T as 1 year.

3.3 Hypotheses

The three research sub-questions outlined in the introduction sought to ascertain, firstly, to what extent risk differs between the emerging and established portfolios using traditional VaR and DD metrics, secondly, whether that relationship changes using extreme CVAR and CDD metrics, and thirdly, whether the risk spread between the emerging and established portfolios changes during the GFC as compared to pre-GFC. In relation to these questions we have the following three hypotheses (expressed in the alternate format):

H_1: Risk, as measured by VaR and DD, is significantly higher for the Emerging portfolio than for the Established portfolio.

H_2: Extreme risk, as measured by CVaR and CDD, is significantly higher for the Emerging portfolio than the for the Established portfolio.

H_3: The risk spread between the Emerging portfolio and the Established portfolio remains constant over the GFC as compared to the pre-GFC period.

4. Results and Analysis

Table 1: Pre-GFC and GFC Results

	VaR	CVaR	DD	CDD	Equity Stdev	Mean Equity Return	Asset Stdev	Mean Asset Return
Pre-GFC								
EMCOX	0.0515	0.0855	5.6972	1.4562	0.0402	0.0002	0.0395	0.0071
S&P/ASX 200	0.0233	0.0378	10.4872	3.4312	0.0175	0.0005	0.0109	0.0003
GFC								
EMCOX	0.0717	0.1050	3.4547	0.9300	0.0514	-0.0018	0.0459	-0.0025
S&P/ASX 200	0.0403	0.0573	5.4783	1.7390	0.0272	0.0001	0.0155	0.0000

All VaR, CVaR, standard deviation and return figures shown in the table are daily average figures for the specified period, with all risk measures calculated as described in Section 3.

Across the board, the figures show higher risk for EMCOX than for S&P/ASX 200, for VAR and DD. F Tests, which test for significance in volatility differences, were undertaken on VaR and DD to test for volatility differences between the established and emerging portfolios. For both VaR and DD, in both of the periods (pre-GFC and GFC) the volatility differences were significant at the 99% level. Thus, we accept our alternate hypothesis (H_1) of risk being significantly higher for the emerging portfolio as measured by VaR and DD. It is also of note that, despite the higher risk for EMCOX, returns are lower than S&P/ASX 200 in both periods, thus, investors are not being rewarded for the additional risk taken. In regards to our extreme risk measures of VCVaR and CDD, the spread between the portfolios is similar for VaR and CVaR (and is also significant at the 99% level). Thus, we accept our alternate hypothesis (H_2) of risk being significantly higher for the emerging portfolio as measured by CVaR and CDD. Here we note that the higher DD risk for EMCOX is even more marked in the tail, for example, the pre-GFC differential in DD between the two portfolios is 1.8x, whereas CDD is 2.4x. A point in favour of EMCOX, is that the gap between the two portfolios narrows during the GFC with the spread in VaR between the portfolios narrowing from 2.2x to 1.8x, CVaR from 2.3x to 1.8x, DD from 1.8x to 1.6x and CDD from 2.3x to 1.9x. These differences in volatility spreads are significant at the 99% level, thus, we can reject our alternative hypothesis that the risk spread between the emerging portfolio and the established portfolio remains constant over the GFC as compared to the pre-GFC period. This last point is due to heavy falls in values of many investment grade companies over the GFC such as banks which fell some 59% with the emerging companies already being priced as higher risk and not falling to the same extent.

Table 2 shows VaR, CVaR, DD and CDD for each of the 10 years in the study with these trends depicted in Figure 1.

Table 2: Annual Risk Results

EMCOX

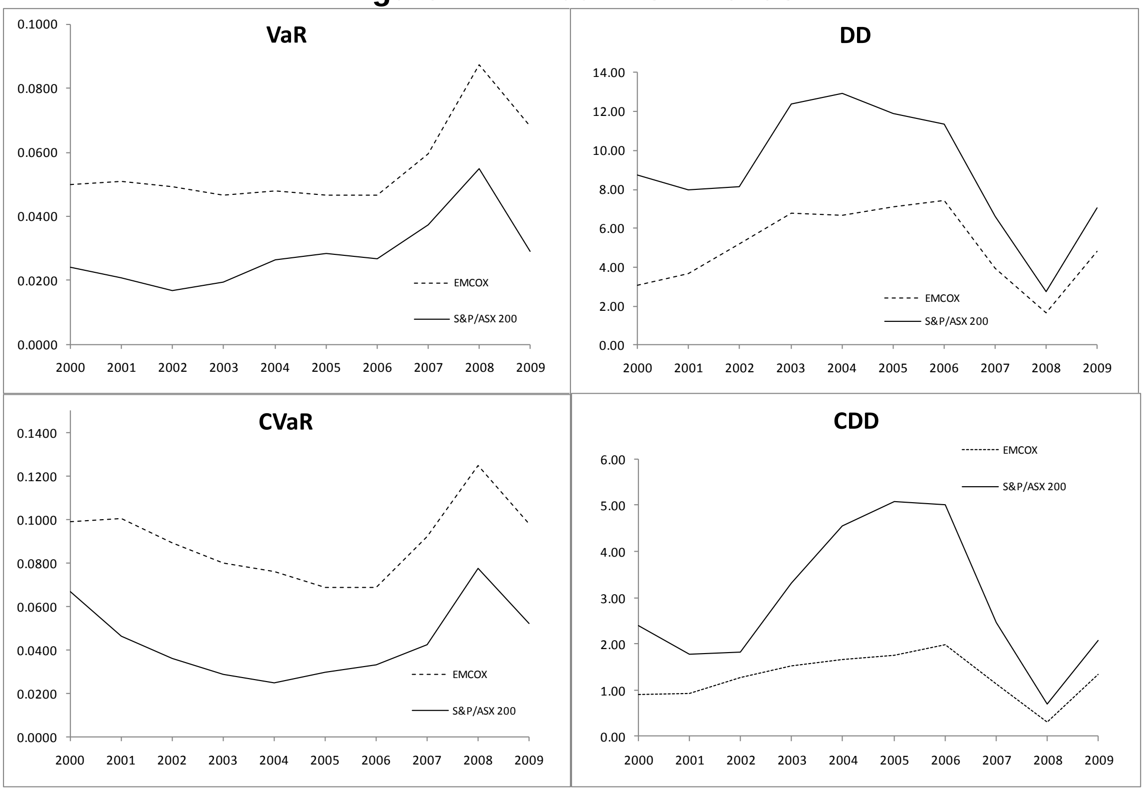
	VaR	CVaR	DD	CDD
2000	0.0500	0.0989	3.06	0.91
2001	0.0510	0.1004	3.64	0.93
2002	0.0494	0.0893	5.22	1.28
2003	0.0466	0.0797	6.80	1.53
2004	0.0480	0.0759	6.68	1.67
2005	0.0465	0.0686	7.08	1.75
2006	0.0465	0.0685	7.40	1.99
2007	0.0596	0.0920	3.93	1.14
2008	0.0874	0.1250	1.65	0.32
2009	0.0681	0.0981	4.78	1.33

S&P/ASX 200

	VaR	CVaR	DD	CDD
2000	0.0241	0.0668	8.75	2.40
2001	0.0209	0.0463	7.96	1.78
2002	0.0170	0.0360	8.13	1.83
2003	0.0195	0.0285	12.38	3.32
2004	0.0263	0.0249	12.95	4.54
2005	0.0284	0.0294	11.88	5.09
2006	0.0269	0.0329	11.36	5.02
2007	0.0373	0.0422	6.63	2.46
2008	0.0547	0.0776	2.74	0.69
2009	0.0289	0.0520	7.06	2.07

All VaR and CVaR figures shown in the table are daily average figures for each year, with all risk measures calculated as described in Section 3.

Figure 1: Annual Risk Trends



The trends in Table 2 and Figure 1 confirm the higher risk across both periods for all metrics (H_1 and H_2) and show how risk decreases during the mid-2000's, then increases dramatically during the GFC, improving somewhat in 2009. The graphs illustrate how the risk spread between the portfolios for all metrics, particularly DD and CDD, narrows during the GFC supporting our findings that spreads do not stay the same over these two periods (H_3).

Table 3: Quantile Analysis

	DD 2006		CDD 2006		DD 2008		CDD 2008	
	EMCOX	ASX	EMCOX	ASX	EMCOX	ASX	EMCOX	ASX
Worst Third	2.38	5.06	0.44	1.31	0.04	0.23	0.01	0.05
Mid Third	4.86	7.96	1.05	2.19	1.58	2.06	0.24	0.42
Best Third	9.88	12.26	2.36	3.45	3.34	4.25	0.67	1.03

All DD and CDD figures shown in the table are daily average figures for the specified period, with risk measures calculated as described in Section 3. There are the same number of entities (one third) in each quantile.

Whilst, so far, we have seen that on a portfolio basis ASX is less risky than EMCOX, this does not necessary apply to all individual entities in the respective portfolios. The above table compares the two portfolios at 2006 (immediately before the GFC) with 2008 (height of the GFC) by dividing the datasets into 3 quantiles: worst, mid and best third, with the same number of entities, one third, in each quantile. We note that in 2006 (for DD and CDD), only the best third for EMCOX is less risky than the worst third for ASX. In 2008, both the mid and best third EMCOX quantiles are less risky than the worst third for ASX. This confirms the point (H_3) that the risk differential between the portfolios is lessened in more volatile times.

5. Conclusion

The study has provided a comprehensive analysis of market and credit risk associated with emerging as compared to established entities in Australia. This analysis covered both traditional measures in the form of VaR and DD as well as the extreme measures of CVaR and CDD. The analysis supports our hypotheses that emerging companies have a much higher risk, as measured by our metrics, than established ones. This is broadly consistent with prior research in relation to differences in risk between emerging and established markets, globally as well as in Australia. We also find that returns are not compensating for this. The default risk spread between the portfolios is found to be even higher in the tail. It was of interest to find, in contrast to our hypothesis of constant risk spreads over time, that the risk profile of the established companies increased relatively more than the emerging ones during the GFC causing the risk spread between the two portfolios to narrow due to established companies no longer being perceived as low risk. No other studies of which we are aware examine risk spreads between emerging and established portfolios pre- and post-GFC (H_3) and certainly not using the extreme metrics of CVaR and CDD used in this article and the narrowing of these spreads in the volatile circumstances of the GFC provides new important information. The study contributes to the understanding and measurement of extreme risk in emerging and established markets which can assist investors in the portfolio mix choices and banks with their credit portfolio mix and risk management policies for these markets.

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