Tail Risk for Australian Emerging Market Entities

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ABSTRACT

Whilst the Australian economy is widely considered to have fared better than many of its global counterparts during the Global Financial Crisis, there was nonetheless extreme volatility experienced in Australian financial markets. To understand the extent to which emerging Australia 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 focuses 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, 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.

Keywords: Conditional value at risk; Conditional distance to default; Australian emerging markets

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1. Introduction

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, we are concerned with the extreme risk experienced in the tail of the distribution as it is in these extreme circumstances when investors or lenders to these entities are exposed to the highest potential losses. 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? Third, does the risk spread between the emerging and established portfolios change during the GFC as compared to Pre-GFC?

The next section of the paper provides a literature survey and background information on the topic, 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

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 lack of subadditivity (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- 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. 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

We obtain 10 years of daily share price data from Datastream which we split into two periods, being Pre-GFC (2000-2007) and GFC (2007-2009). This data is used to calculate VaR and CVaR, and is 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, is also obtained from Datastream. Both the S&P/ASX 200 and the EMCOX 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.

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 is 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:

$$E_T = max(V_T – F, 0) \tag{2}$$

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 the money where V_T - F < 0. Merton uses the assumption that asset values are log normally distributed, calculating DD as

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

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):

$$PD = N(-DD) \tag{4}$$

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 worldwide 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 usual practice of setting T as 1 year.

4. Findings and Discussion

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.

There are four key points of note regarding the results. First, across the board, the figures show higher risk for EMCOX than for S&P/ASX 200, with higher VAR and CVaR for EMCOX and lower DD and CDD. Second, 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. Third, whilst the spread between the portfolios is similar for VaR and CVaR, 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. Fourth (and this time a point in favour of EMCOX), 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. The latter 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

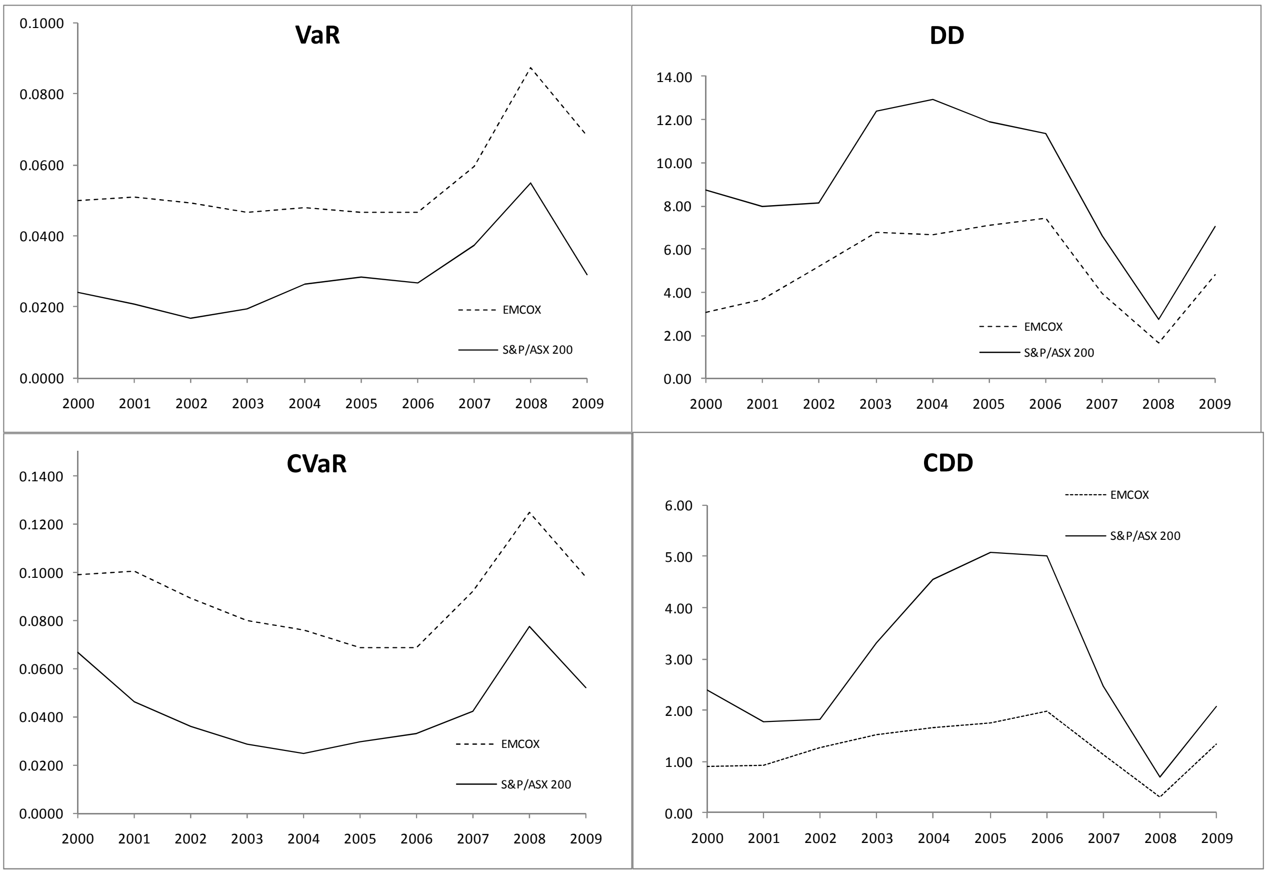
	VaR	CVaR	DD	CDD
2000	0.0500	0.0989	3.06	0.91
2001	0.0510	0.1004	3.64	0.93
2002	0.0494	0.0893	5.22	1.28
2003	0.0466	0.0797	6.80	1.53
2004	0.0480	0.0759	6.68	1.67
2005	0.0465	0.0686	7.08	1.75
2006	0.0465	0.0685	7.40	1.99
2007	0.0596	0.0920	3.93	1.14
2008	0.0874	0.1250	1.65	0.32
2009	0.0681	0.0981	4.78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



These trends show how risk decreases during the mid-2000’s then increases dramatically during the GFC, improving somewhat in 2009. The graphs illustrate how the spread between the portfolios for DD and CDD narrows during the GFC.

5. Conclusions and Implications

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. We find that emerging companies have a much higher risk, as measured by our metrics, than established ones and that returns are not compensating for this. The default risk spread between the portfolios is even higher in the tail. It was of interest to find that 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. 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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