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ABSTRACT

Credit risk modelling has become increasingly important to Banks since the advent of Basel II which allows Banks with sophisticated modelling techniques to use internal models for the purpose of calculating capital requirements. A high level of credit risk is often the key reason behind banks failing or experiencing severe difficulty. The management of sectoral concentration is a critical component of credit risk management, as over concentration of credit in sectors can be a significant contributor to difficulties experienced by Banks. Conditional Value at Risk (CVaR) is gaining popularity as a measurement of credit risk, with the recognition that high lending losses are often impacted by a small number of extreme events. This study examines sectoral probability of default (PD) in an Australian context based on the structural approach of Merton (1974), and more recently modified and popularised by KMV Corporation (Crosbie & Bohn, 2003). In addition to examining PD, we introduce a CVaR type component into structural modelling which we term conditional probability of default (CPD). We also examine the interaction between sectoral credit and market risk using VaR and CVaR models for market risk, and PD and CPD models for credit risk. Significant rank correlation is found between all of the approaches used, showing that those sectors which are risky from a credit perspective are not significantly different from those which are risky from a market perspective.

Keywords: Value at risk; Conditional value at risk; Credit risk, Conditional probabilities of default; Structural modelling

1 Introduction and context:

The Basel II Accord (Bank for International Settlements, 2004) has placed a huge focus within the Banking Industry on risk modelling. Banks are required to set aside capital, calculated as a percentage of their risk weighted assets. There is a significant cost to Banks in holding capital, as opposed to being able to get a market return on these funds. Under the Basel II Accord, Banks who meet certain credit modelling criteria are able to use internal models to help determine risk weighted capital. This could significantly benefit Banks who are able to demonstrate a reduced capital requirement.

The importance of credit modelling, and the understanding and management of credit risk is highlighted by the statement by the then Deputy Reserve Bank Governor, GJ Thompson (1997): "All of the major periods of stress in Australian Banking have been caused by credit losses". This view is supported by the then Group General Manager, Financial and Risk Management of one of the largest Australian Banks the Commonwealth Bank, Michael Ullmer (1997) who notes that "there is overwhelming evidence for the potency of credit related losses on the banking system". Management of Sectoral Risk is a key component of credit risk management. Jackson (1996) notes sectoral or regional over concentration as one of the key reasons for 22 banks in the UK failing or experiencing severe difficulty. Knowledge of relative industry risk is important to Banks for risk management purposes such as setting sector concentration limits and allocating discretionary lending authorities.

Some of the more popular approaches to credit risk measurement have included KMV Credit Monitor (Crosbie & Bohn, 2003), CreditMetrics (Gupton, Finger, & Bhatia, 1997), CreditPortfolioView (Wilson, 1998), CreditRisk+ (Credit Suisse First Boston International, 1997), and reduced form models (e.g. Jarrow, Lando, & Turnbull, 1997).

This study focuses on the structural approach to credit risk, based on methodology used by Merton and KMV, as discussed in Section 2 of this paper. We also introduce a conditional approach to probability of default (CPD), in a similar manner as CVaR is used as an alternative to VaR. Conditional Value at Risk considers extreme events, based on losses exceeding VaR. CVaR studies have traditionally been used in the insurance industry, but are gaining popularity as a credit risk measure, with the increasing recognition that infrequent large losses are an important feature of credit risk measurement. CVaR has also gained popularity as it does not demonstrate some of the undesirable properties of VaR such as lack of subadditivity, see Artzner et al. (1997) and (1999). CVaR has been used in credit risk studies, for example Bucay & Rosen (1999) and Andersson, Mauser, Rosen & Uryasev (2000). These studies have centred around the Creditmetrics transition matrix approach. The Andersson et al. study focuses on the optimisation of portfolios.

This study obtains relative credit risk rankings for Australian industries, based on PD and CPD. We also explore whether there is a link between market risk and credit risk in these industries, i.e. whether the same industries that are risky from a market perspective are also risky from a credit perspective. Numerous studies have been undertaken using structural methodology on various aspects of credit risk, such as asset correlation (Cespedes, 2002; Kealhofer & Bohn, 1993; Lopez, 2002; Vasicek, 1987; Zeng & Zhang, 2001), predictive value and validation (Bharath & Shumway, 2004; Stein, 2002), the effect of default risk on equity returns (Vassalou & Xing, 2002), and fixed income modelling (D'Vari, Yalamanchili, & Bai, 2003). However, we have not identified any studies using a structural approach to ranking industries in Australia, or in applying a CPD approach to structural modelling.

Section 2 provides background to the structural approach, with detailed methodology provided in Section 3. Results and conclusions are presented in Sections 4 and 5.

2 Structural Model

KMV Credit Monitor (Crosbie & Bohn, 2003) provides an estimated default frequency (EDF) for individual assets, using market information. It is based on a modification of Merton's Asset Value Model (1974).

The Merton / KMV approach as described in Crosbie & Bohn (2003) is based on the option pricing work of Black and Scholes in 1973. In summary, the firm defaults if the debt obligation exceeds the asset value of the firm at a selected time period.

Under the KMV model, probability of default PD is a function of the distance to default DD (number of standard deviations between the value of the firm and the debt).

Using Merton's model, probability of default (PD) can be determined from DD using the normal distribution. KMV 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 EDFs. For example, KMV finds that historical data shows that firms with a DD of 4 have an average default rate of approximately 1% and therefore assign an EDF of 1% to firms with this DD.

Thus the KMV model consists of 3 steps which are estimating the market value and volatility of firms assets, calculating the distance to default, and matching the distance to default to an empirically obtained EDF. Detailed methodology is discussed in Section 3.

3 Methodology

3.1 Summary of our market VaR methodology

Our market VaR methodology is described in our market risk paper (Allen & Powell, 2007). In summary we use the Australian All Ords index and obtain a VaR measurement for each industry based on the universal GICS industry codes. A parametric approach is used for calculating VaR at the 95% level (after considering survivorship bias and adjusting for thin trading) on an undiversified and correlated basis. Market CVaR is calculated as the average of those returns beyond VaR. We used 15 years of data, and calculated VaR using a 7 year rolling window approach (for comparative purposes we also calculated VaR based on 12 month data tranches).

3.2 Credit model methodology

In the Merton approach, equity and the market value of the firm' assets are related as follows

$$\mathrm{E}=\mathrm{VN}(\mathrm{d}_1\ )\text{-}\mathrm{e}^{-rT}FN(d_2) \tag{1}$$

where

E = market value of firms equity
F = face value of firm's debt
r = risk free rate
N = cumulative standard normal distribution function

$$\mathrm{d}_1=\frac{\ln(V/F)+(r+0.5\sigma_v^2)T}{\sigma\nu\sqrt{T}} \tag{2}$$

$$\mathrm{d}_2=d_1-\sigma\sqrt{T}$$

Volatility and equity are related under the Merton model as follows:

$$\sigma_E=\left(\frac{V}{E}\right)N(d_1)\sigma_\nu \tag{3}$$

For our credit model, we use the same equity data and industry codes as used in our VaR calculations. In line with KMV, debt is taken as the value of all current liabilities plus half the book value of all long term debt outstanding. All this information is obtained from Datastream. T is set using common practice of 1 year. The risk free rate is based on a

12 month average Australian Government Bond 1 year rate. We follow the approach outlined by KMV (Crosbie & Bohn, 2003) and Bharath & Shumway (2004).

Initial asset returns are estimated from our historical equity data using the following formula:

$$\sigma_{\nu} = \sigma_E \left(\frac{E}{E+F}\right) \tag{4}$$

Equity returns and their standard deviation are calculated exactly the same as for our market approach, using 7 year rolling windows. These asset returns derived above are applied to equation 3.1 to estimate the market value of assets every day. The daily log return is calculated and new asset values estimated. Following KMV, this process is repeated until asset returns converge, (repeated until difference in adjacent αs is less than 10-3). These figures are used to calculate DD and PD:

$$DD = \frac{\ln(V/F)+(\mu-0.5^2\sigma_v)T}{\sigma_v\sqrt{T}} \tag{5}$$

$$PD = N(-DD) \tag{6}$$

As mentioned in Section 2, KMV has a large worldwide database from which to provide empirically based EDFs. As also noted, EDFs are much larger than the PD's used by Merton (which yield very small values). This is not an issue for our study as we are interested in rankings rather than absolute values. DD, PD and EDF will all yield the same rankings because PD and EDF are all calculated from DD. Although we do not have access to the KMV database, there are studies which provide mapping of EDF values to S&P and / or Moody's rating categories (e.g. Lopez, 2002; The Risk Management Association, 2007) with EDF's ranging from 0.02% for AAA ratings up to 20% for D ratings . Such maps can assist in the calibration of calculated DD's to EDF values, thereby obtaining more meaningful values than the very small values normally provided by PD, without disturbing the ranking.

3.3 Structural correlation

Correlation can be calculated through calculating a time series analysis for each firm and then calculating a correlation between each pair of assets. KMV have instead adopted a factor modelling approach to their correlation calculation. KMV produce country and industry returns from their database of publicly traded firms, and their correlation model uses these indices to create a composite factor index for each firm depending on the industry and country (D'Vari et al., 2003; Kealhofer & Bohn, 1993). We do not have access to the KMV database or factors, and hence use the former approach to derive a diversified standard deviation. The undiversified standard deviation that was used in the calculation of the undiversified DD and PD is substituted with the diversified asset standard deviation when calculating the diversified DD and PD.

3.4 CPD Calculation

For the purposes of this study we define CPD as being PD on the condition that standard deviation of asset returns exceeds standard deviation at the 95% confidence level, i.e. the worst 5% of asset returns. We calculate CPD using nonparametric and parametric methods. CPD values can also be calibrated to EDF values as described in Section 3.2.

3.4.1 Nonparametric CPD

We calculate the standard deviation of the worst 5% of daily asset returns for each rolling 7 year period to obtain a conditional standard deviation (CStdev). We then substitute CStdev into the formula used to calculate DD, to obtain a Conditional DD (CDD). CPD is calculated by substituting DD with CDD into the CPD formula.

$$CDD = \frac{\ln(V/F) + (\mu - 0.5\sigma_v^2)T}{CStdev_v\sqrt{T}} \tag{7}$$

and

$$CPD = N(-CDD) \tag{8}$$

3.4.2 Parametric CPD

CStdev is calculated as being the tail 5% of a normal distribution using the formula

$$CStdev_\alpha = \frac{\exp(-\frac{q_\alpha^2}{2})}{\alpha\sqrt{2\pi}}\sigma \tag{9}$$

Where q_α is the tail 100_α percentile of a standard normal distribution (e.g. 1.645 as obtained from standard distribution tables for 95% confidence).

4 Results

Technology (Hardware and Software) ranks high on the risk front for both models. Some noticeable differences are Banks and Insurance which rank as higher risk on the credit scale than the market scale due to balance sheet structure (lower equity percentage).

Using a Pearson Rank Correlation Test (95% confidence level) we find no significant difference in rankings between VaR and PD, VaR and CVaR, PD and CPD, or CVaR and CPD. When substituting diversified VaR / PD for undiversified VaR / PD in the above tests, we obtained the same outcomes (no significant difference in rankings).

Both the Credit model and the Market model show significant association in rankings over time using the 7 year rolling window approach, but not when using 1 year data tranches.

5 Conclusions

There is significant similarity between industry risk rankings obtained using Market VaR methodology and Credit PD methodology. This shows that the same industries that are risky from a market perspective are also risky from a credit perspective. This relationship is further supported by the ranking correlation evidenced between CVaR and CPD and the consistency over time between the market and credit models. Our new CPD model produces results consistent with all the modelling techniques used in this study and is deemed a viable alternative for calculating industry risk ranking. The fact that all these modelling techniques (VaR, CVaR, PD, CPD, undiversified/diversified, parametic/nonparametic) all yield a significantly similar result, highlights the robustness and consistency of these methods in measuring relative industry risk, a critical component of credit and market risk measurement and management.

Because 1 year data tranches yield different results to 7 year rolling windows, it is deemed important to use both long and short time frames in measuring market or credit risk in order to capture varying cycles as well as focus on current trends.

Table 1 Structural Model – Results Summary

The table provides industry ranking, with 1 being the highest risk and 25 the lowest risk. The market model calculates Value at Risk at the 95% confidence level, and CVaR is the average losses beyond VaR. The Credit model PD is based on the Merton-KMV Structural approach, with CPD based on the worst 5% of asset returns.

	Market Model		Credit Model	
	Annual Undiversified 95% VaR	Nonparametric CVaR	Undiversified PD	Nonparametric CPD
Automobiles & Components	7	7	5	3
Banks	25	25	9	15
Capital Goods	15	15	11	9
Chemicals	18	17	13	12
Commercial Services & Supplies	8	8	8	8
Construction Materials	17	19	22	23
Consumer Durables & Apparel	10	10	15	13
Diversified Financials	19	18	24	22
Energy	5	6	19	19
Food & Staples Retailing	23	24	21	21
Food Beverage & Tobacco	20	21	18	17
Healthcare Equipment & Services	11	11	14	10
Hotels Restaurants & Leisure	12	9	16	16
Insurance	9	5	1	1
Media	16	16	20	20
Metals & Mining	6	12	12	18
Paper & Forest Products	4	4	4	5
Pharmaceuticals & Biotechnology	3	3	7	6
Real Estate	21	20	23	24
Retailing	13	13	6	7
Software & Services	2	2	3	4
Technology Hardware & Equipment	1	1	2	2
Telecommunication Services	24	23	17	14
Transportation	14	14	10	11
Utilities	22	22	25	25

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