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Credit risk measurement methodologies

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Abstract: The significant problems experienced by banks during the Global Financial Crisis have highlighted the critical importance of measuring and providing for credit risk. This paper will examine four popular methods used in the measurement of credit risk and provide an analysis of the relative shortcomings and advantages of each method. The study includes external ratings approaches, financial statement analysis models, the Merton / KMV structural model, and the transition based models of CreditMetrics and CreditPortfolioView. Each model assesses different criteria, and an understanding of the merits and disadvantages of the various models can assist banks and other credit modellers in choosing between the available credit modelling techniques.

Keywords*: credit models; credit value at risk; probability of default*

1. INTRODUCTION

High bank failures and the significant credit problems faced by banks during the Global Financial Crisis (GFC) are a stark reminder of the importance of accurately measuring and providing for a credit risk. There are a variety of available credit modelling techniques, leaving banks faced with the dilemma of deciding which model to choose. Historically, prominent methods include external ratings services like Moody's, Standard & Poor's (S&P) or Fitch, and financial statement analysis models (which provide a rating based on the analysis of financial statements of individual borrowers, such as the Altman z score and Moody's RiskCalc). Credit risk models which measure default probability (such as Structural Models) or Value at Risk (VaR) attained a great deal more prominence with the advent of Basel II. This article examines four widely used modelling techniques, including external ratings, financial statement analysis models, the Merton / KMV structural model and the Transition models of CreditMetrics and CreditPortfolioView, including an overview of the models and a comparison of their relative strengths and weaknesses. Structural models are based on option pricing methodologies and obtain information from market data. A default event is triggered by the capital structure when the value of the obligor falls below its financial obligation (such as the Merton and KMV models). VaR based models provide a measurement of expected losses over a given time period at a given tolerance level. These include the JP Morgan CreditMetrics model which uses a Transition Matrix, and the CreditPortfolioView model which incorporates macroeconomic factors into a Transition approach.

2. CREDIT MODEL METHODOLOGIES

2.1. External Ratings Services

The most prominent of the ratings services are Standard & Poor's (S&P), Moody's & Fitch. The ratings provide a measure of the relative creditworthiness of the entity, taking into account a wide range of factors such as environmental conditions, competitive position, management quality, and the financial strength of the business. Table 1 provides a calibration between the well known rating agencies. The definitions are based on Standard & Poor's (2011). This calibration is important when loan portfolios comprise entities with contains ratings from different ratings services. Based on S&P definitions ratings are:- AAA: Extremely strong capacity to meet financial commitments- highest rating; AA: Very strong capacity to meet financial commitments; A: Strong capacity to meet financial commitments, but somewhat susceptible to adverse economic conditions and changes in circumstances; BBB: Considered lowest investment grade by market participants; BB: Less vulnerable in the near-term but faces major ongoing uncertainties to adverse business, financial and economic conditions; B: More vulnerable to adverse business, financial and economic conditions but currently has the capacity to meet financial commitments; CCC: Currently vulnerable and dependent on favourable business, financial and economic conditions to meet financial commitments; CC: Currently highly vulnerable; C: Currently highly vulnerable obligations and other defined circumstances; D: Payment default on financial commitments.

Table 1 Mapping Ratings

S & P	AAA	AA+	AA	AA-	A+	A-	BBB+	BBB	BBB-	BB+	BB-	B+	B-	CCC+	CCC-	CC	C	D
Moody's	Aaa	Aa1	Aa2	Aa3	A1	A3	Baa1	Baa2	Baa3	Ba1	Ba3	B1	B3	Caa1	Caa3	Ca	C	
Fitch	AAA	AA+	AA	AA-	A+	A-	BBB+	BBB	BBB-	BB+	BB-	B+	B-	CCC+	CCC-	CC	C	D

Source of Calibrations: Bank for international Settlements (2011)

2.2. Financial Statement Analysis Models

These models provide a rating based on the analysis of various financial statement items and ratios of individual borrowers. Examples include the z score and Moody's RiskCalc. Edward Altman (1968, 2000) developed the z score which uses five ratios in the prediction of bankruptcy. The ratios and their weightings are 0.012 (working capital / total assets), 0.014(retained earnings / total assets), 0.033(earnings before interest and taxes / total assets), 0.006(market value equity / book value of total liabilities), and 0.999(sales / total assets ratio). Moody's KMV Company (2003) RiskCalc model provides an Estimated Default Frequency (EDF) for private firms. In Australia, the research database is calibrated using 93,701 financial statements and 2,519 defaults from 26,636 Australian companies. EDF is calculated from 11 financial measures, including size (assets), liquidity (current ratio; cash /assets), profitability (retained earnings / assets; EBITDA / interest expense; NI-extraordinary items / sales; previous year NI / sales), activity: (inventory / sales), and gearing (tangible net worth / tangible assets). Variants of these financial models have been introduced by researchers, including among others, Beaver (1966), Ohlson (1980) who uses 8 ratios, and Zmijewski (1984) who uses three ratios.

2.3. Structural Model

The model measures changes to default probabilities based on the distance to default (DD) of a firm which is a combination of asset values, debt, and the standard deviation of asset value fluctuations, from which Probabilities of Default (PD) can be calculated per equation 7. The point of default is considered to be where debt exceeds assets, and the greater the volatility of the assets, the closer the entity moves to default. Equity and the market value of the firm' assets are related as follows:

$$E = VN(d_1) - e^{-rT} FN(d_2) \tag{1}$$

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

$$d_1 = \frac{\ln(V/F) + (r + 0.5\sigma_v^2)T}{\sigma v \sqrt{T}} \tag{2}$$

$$d_2 = d_1 - \sigma_v \sqrt{T} \tag{3}$$

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

$$\sigma_E = \left(\frac{V}{E}\right) N(d_1)\sigma_V \tag{4}$$

KMV takes debt as the value of all current liabilities plus half the book value of all long term debt outstanding. T is commonly set at1 year. Per the approach outlined by KMV (Crosbie & Bohn, 2003) and Bharath & Shumway (2008), initial asset returns are estimated from historical equity data using the following formula:

$$\sigma_V = \sigma_E \left(\frac{E}{E+F}\right) \tag{5}$$

Daily log equity returns and their standard deviations are calculated for each asset for the historical period. These asset returns derived above are applied to equation 1 to estimate the market value of assets every day. The daily log asset return is calculated and new asset values estimated. Following KMV, this process is repeated until asset returns converge. These figures are used to calculate DD and PD:

$$DD = \frac{\ln(V/F) + (\mu - 0.5_v^2)T}{\sigma_V \sqrt{T}} \tag{6}$$

$$PD = N(-DD) \tag{7}$$

Correlation can be calculated through producing a time series of returns 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, Yalamanchili, & Bai, 2003; Kealhofer & Bohn, 1993).

2.4. CreditMetrics (Transition)

CreditMetrics (Gupton, Finger, & Bhatia, 1997) incorporates a transition matrix showing the probability (ρ) of a borrower moving from one credit grade to another, based on historical data. For a BBB rated asset:

BBB	ρ_{AAA}	ρ_{AA}	ρ_{A}	ρ_{BBB}	ρ_{BB}	ρ_{B}	$\rho_{CCC/C}$	ρ_{D}

To capture all probability states, the sum of probabilities in each row must equal 1. Transition probability tables are provided by raters such as Moody's and Standard & Poor's. The CreditMetrics model obtains forward zero curves for each category (based on risk free rates) expected to exist in a year's time. Using the zero curves, the model calculates the loan market value (V), including the coupon, at the one year risk horizon. Probabilities in the table are multiplied by V to obtain a weighted probability. Based on the revised table, VaR is obtained by calculating the probability weighted portfolio variance and standard deviation (σ), then calculating VaR using a normal distribution (for example 1.645σ for a 95% confidence level).

To calculate joint probabilities, Creditmetrics (Gupton et al., 1997) requires that the mean values and standard deviations are calculated for each issue. Each 2 asset sub portfolio needs to be identified and the following equation (using a 3 asset example) applied

$$\sigma_p^2 = \sigma^2(V_1+V_2)+\sigma^2(V_1+V_3)+\sigma^2(V_2+V_3)-\sigma^2(V_1)-\sigma^2(V_2)-\sigma^2(V_3) \tag{8}$$

Creditmetrics (Gupton et al., 1997, p.p.85-89), also provide a Monte Carlo option as alternative method of calculating VaR. The model maintains that there is a series of asset values that determine a company's rating. If a company's asset value falls or increases to a certain level, at the end of that period, its new asset value will determine the new rating at that point in time. These bands of asset values are referred to by Creditmetrics as asset thresholds. The percent changes in assets (or 'asset returns') are assumed to be normally distributed and, using the probabilities from the transition matrix table, probabilities (*Pr*) of asset thresholds Z_{Def}, Z_{CCC} and so on, can be calculated as follows:

$$Pr_{(Default)} = \Phi(Z_{Def}/\sigma)$$

$$Pr_{(CCC)} = \Phi(Z_{CCC}/\sigma) - \Phi(Z_{Def}/\sigma)$$

and so on, where Φ denotes the cumulative normal distribution, and

$$Z_{Def} = \Phi^{-1}\sigma \tag{9}$$

CreditMetrics apply the asset thresholds to Monte Carlo modelling using three steps. Firstly, asset return thresholds, as discussed above, need to be generated for each rating category. Second, scenarios of asset returns need to be generated using a normal distribution. The third step is to map the asset returns in step 2 with the credit scenarios in Step 1. A return falling between ratings corresponds to the rating above it. Thousands of scenarios are normally generated from which a portfolio distribution and VaR are calculated.

2.5. CreditPortfolioView

This section provides a summary of the model as presented by various sources, including Wilson (1998), Saunders & Allen (2002), Pesaran, Schuermann, Treutler & Weiner (2003), and Crouhy, Galai & Mark (2000). CreditPortfolioView (CPV) uses a transition matrix approach, but is based on the premise that there is not equal transition probability among borrowers of the same grade, as is assumed by CreditMetrics. CreditPortfolioView creates migration adjustment ratios by linking macroeconomic factors to migration probability, such as GDP growth, unemployment rates and interest rates. CPV provides standard values that can be chosen should the user not want to calculate all of the individual shifts. The migration adjustment ratios (denoted by *i*) with CreditMetrics to calculate an adjusted VAR figure:

BBB	ρ_{AAAi}	ρ_{AAi}	ρ_{Ai}	ρ_{BBBi}	ρ_{BBi}	ρ_{Bi}	$\rho_{CCC/Ci}$	ρ_{Di}

3. CRITIQUE

A strength of external credit ratings is that they are formulated through a comprehensive analysis of an entities business, financial, and economic environmental risks. A further plus is that the ratings are readily available to banks and researchers, thus requiring no modelling to produce them. However, it should be noted that rating agents such as Standard and Poor's and Moody's stress that ratings are not absolute measures of default, but rather a relative ranking of one entity to another, which do not ratchet up and down with economic conditions. Standard and Poor's (2011) maintain that "Ratings opinions are not intended as guarantees of credit quality or as exact measures of the probability that a particular debt issue will default. Instead, ratings express relative opinions about the creditworthiness of an issuer or credit quality of an individual debt issue, from strongest to weakest, within a universe of credit risk." Although credit ratings are meant to be relative risk ratings and not absolute measures of default, they are nonetheless used by banks for measuring default probabilities and credit VaR, In addition, external credit ratings are used by banks under the standardised Basel approach for allocating capital. If the ratings themselves do not fluctuate with market conditions, then neither does the capital allocated. Allen and Powell (2011) , in an Australian study, found that despite impaired assets of Banks having increased fivefold over the GFC period, the underlying ratings of corporate assets indicated that there had been negligible change to credit risk over this period.

Accounting models have some strong points. They are generally easy to use. In most cases, all that has to be done is to plug the financial figures into the model, which will calculate the ratios for the user. It is relatively straightforward to replicate the models on a spreadsheet, as they comprise a few basic ratios. The models have also been shown to be fairly accurate when applied to industries and economic conditions that were used to develop the model. For example, Ohlson (1980) identified about 88 percent of 105 bankrupt firms accurately one year before bankruptcy. Altman (1968) showed bankrupt accuracy rates of up to 95% using a sample of 91 manufacturing firms over the same period as his model was developed. The accounting models have also attracted criticism. They were generally designed using specific industries, for example the z-score was developed using manufacturing firms. Several authors (Grice & Dugan, 2001; He & Kamath, 2006; Platt & Platt, 1990) have questioned the applicability of the ratios to industries other than those for which the models were developed and have found accuracy lower when applied to other industries. Platt and Platt (1990) recommended that industry-relative ratios should be used in model development. Grice & Dugan (2001) also found low accuracy when the models were applied to time periods or stress situations different to those used to develop the model. Gutzeit & Yozzo (2011) found that during times of recession, the model accurately determined which firms failed but classified many survived firms as potential bankrupts, and the model was shown to have low accuracy when prediction period was more than two years out. Zavgren (1985) was concerned about the time lag in receiving the financial information. Several other researchers have expressed concern about the static nature of accounting information in assessing credit risk (see for example Katz, Lilien, & Nelson, 1985; Queen & Roll, 1987) and proposed the incorporation of market based variables into credit modelling. Vassalou and Xing (2004) criticised accounting models as being backward looking as opposed to the Merton model which uses market prices reflecting investor expectations of future performance. Vassalou and Xing also make the point that accounting models imply that firms with similar financial ratios will have similar default probabilities, whereas firms with similar debt and equity levels might have very different default probabilities if the volatility of their assets differ.

Structural models, on the other hand do incorporate market data as a key component, making the models responsive to changing conditions. This is a major advantage over most models as it allows banks to identify potential problems at an early stage. A downside is that commercial structural models can be prohibitively expensive to purchase, and their complexity makes them very time consuming to replicate. Criticism of structural models has predominantly focussed on the information contained in the model being insufficient to generate meaningful default probabilities or spreads, and that the model therefore suffers from incomplete causality. Huang and Huang (2003) find that structural models generate extremely low spreads for investment grade bonds. Eom, Helwege, & Huang (2004), find the Merton model provides spreads that are too low, but also examine four other variations of structural models finding them all to have difficulty in accurately predicting credit spreads, providing spreads on the high side. KMV (Crosbie & Bohn, 2003) find the probabilities of default generated by the Merton model are too small to be of practical use. Allen and Powell (Allen & Powell, 2011) found that the structural model understated credit risk in the pre-GFC period, but overstated it during the highly volatile GFC times. KMV calculates DD based on the Merton approach, but instead of using a normal distribution to calculate PD, KMV use their own worldwide database, which contains information on thousands of corporate defaults, to determine PD associated with each default level. Accuracy can be improved by calibrating the DD values to a more accurate source such as the KMV EDF values. Du and Suo (2007), find that distance to default on its own is an insufficient determinant of credit quality and that results can be significantly improved by adding additional variables. Sy (2007, 2008) maintains that distance to default is not a sufficient determinant of default as many firms continue to trade while technically insolvent due to liabilities exceeding assets, and the author proposes a revised causal framework for estimating default which incorporates serviceability. The structural model has also been criticised because it assumes exact information about the point of default (which the model takes as the point where asset values fall below liability values), which some deem as unrealistic, preferring instead a reduced form approach (see Jarrow, Lando, & Turnbull, 1997) which views default as an unexpected event (a jump to default).

CreditMetrics is based on external ratings and therefore has many of the same advantages and disadvantages as external ratings as noted in the first paragraph of this section. However, the model does have advantages over the straight rating approach in that it links the transition to market spreads, and to default probabilities provided by external raters. Therefore, whilst the underlying rating may not have changed, modellers can update the VaR measurement by incorporating updated default probabilities into the model. However, these default probabilities are usually only provided annually by raters, meaning the transition model is nowhere near as responsive to market conditions as the structural model which can incorporate continuously changing market conditions. The CreditMetrics model uses a VaR approach which measures risk below a threshold. VaR has had many criticisms, most notably because it says nothing of the extreme risks beyond VaR (Allen & Powell, 2009; Samanta, Azarchs, & Hill, 2005). It is precisely in times of extreme risk that firms are most likely to fail, such as happened during the Global Financial Crisis, and the criticisms of VaR escalated since the onset of this crisis (see for example Allen & Powell, 2011; Lechner & Ovaert, 2010).

As CreditPortfolioView is also based on a transition matrix, it has similar strengths and weaknesses to the CreditMetrics model. The exception is that it does recognise that different industries transition differently, and has the advantage of incorporating of industry adjustment factors, which are obtained through multiple regression of macroeconomic factors to obtain an industry index. However, the model requires extensive analysis of the current state of the economy to determine conditional transition probability, using factors such as GDP growth, unemployment rates and interest rates. These traditional approaches to measurement of industry risk are not popular in Australia as noted by APRA (1999) in their statement "Currently none of the Australian banks favours a credit risk modelling approach conditioned on the state of the economy. Apart from the additional modelling complexity involved, the banks express concern that errors in forecasting economic turning points could lead, in particular, to a shortfall in desired capital coverage just as the economy turns sharply downwards". Simpler approaches to incorporate market conditions into credit models have been proposed through the use of share market prices (Allen & Powell, 2009; Jarrow, 2001).

The strengths and weaknesses are summarised in Table 1, where H shows that the criteria in column 1 is met to a high degree, M is moderate and L is low.

Table 2 Summary of Strengths and Weaknesses of each model

	External Ratings	Accounting	Structural	CreditMetrics	CreditPortfolioView
Detailed Customer Specific Financial Analysis	**H** Detailed analysis of financials	**H** Detailed analysis of financials	**L** Only debt and asset values	**H** Based on external ratings which includes detailed financial analysis	**H** Based on external ratings which includes detailed financial analysis
Industry differentiation	**M** Industry factors incorporated at time of rating	**L** Most accounting models do not differentiate between industries	**H** Based on market fluctuations which will vary with industry risk	**M** Based on ratings which incorporate industry factors at time of rating	**H** Have a specific Industry transition adjustment
Fluctuates with market (no time delays)	**L** No fluctuations with market	**L** No fluctuations with market	**H** Highly responsive to market fluctuations	**L** No fluctuations with market	**M** Can update industry adjustment factors from time to time
Easy to model	**H** Ratings readily available to researchers	**M** Relatively easy to duplicate models on a spreadsheet	**L** Complex techniques	**L** Complex techniques	**L** Complex techniques
Accuracy	High at time of rating Lower as time passes	High at time of rating Lower as time passes	Medium – Does fluctuate with market but can over- or understate depending on market volatility. Calibration can improve accuracy	High at time of rating Lower as time passes	High at time of rating Lower as time passes

4. CONCLUSIONS

The analysis shows that there is no one best model, with each model having its strengths and weaknesses. External ratings based models (including transition models) and accounting models provide a comprehensive analysis of the individual customer's financial strength, but are static and don't fluctuate with the market. The structural model provides the opposite. Banks should (and larger ones generally do) make use of more than one approach. The external ratings and accounting based models allow banks to measure and provide for individual customer circumstances, whereas the market based structural model allows banks to continuously monitor fluctuating default risk, thus detecting potential problems at an early stage.

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