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David Allen
Edith Cowan University

Akhmad Kramadibrata
Edith Cowan University

Robert Powell
Edith Cowan University

Abhay Singh
Edith Cowan University

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David E. Allen, Akhmad R. Kramadibrata, Robert J. Powell and Abhay K. Singh

Edith Cowan University

Abstract

Using quantile regression, this article examines default risk of emerging and speculative companies in Australia and the United States as compared to established and investment entities. We use two datasets for each of the two countries, one speculative and one established. In the US we compare companies from the S&P 500 to those on the Speculative Grade Liquidity Ratings list (Moody's Investor Services, 2010). For Australia, we compare entities from the S&P/ASX 200 to those on the S&P/ASX Emerging Companies Index (EMCOX). We also divide the datasets into GFC and Pre-GFC periods to examine default risk over different economic circumstances. Quantile Regression splits the data into parts or quantiles, thus allowing default risk to be examined at different risk levels. This is especially useful in measuring extreme risk quantiles, when corporate failures are most likely. We apply Monte Carlo simulation to asset returns to calculate Distance to Default using a Merton structural credit model approach. In both countries, the analysis finds substantially higher default risk for speculative as compared to established companies. The spread between speculative company and established company default risk is found to remain constant in Australia through different economic circumstances, but to increase in the US during the GFC as compared to pre-GFC. These findings are important to lenders in understanding, and providing for, default risk for companies of different grades through varying economic cycles.

Keywords: Quantile Regression, Emerging and speculative companies, extreme risk and return.

JEL Codes: G01, G21, G28

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1. Introduction

The research question investigated by this paper is the extent to which default risk differs for emerging and speculative companies as compared to established companies during different economic cycles. Understanding the default risk of entities can be important to banks in their lending and capital allocation decisions. It can also be important to equity holders, as default risk can lead to risk premia in asset prices as found by Chan, Faff and Koffman (2008) in their investigation into probability of default impacts on asset pricing of Australian microcap stocks. In addressing the cyclical component of the research question, a key issue when measuring default risk is the length of the time series to be used. Periods that are too short do not cover sufficient economic cycles. Default probabilities measured over long periods tend to smooth business cycle impacts, as found for example by Doinne, Gauthier, Hammani, Maurice & Siminato (2010) who investigate default risk in corporate yield spreads and find that probabilities of default estimated from long histories of default data produce default spreads at odds with observed spreads and might underestimate capital required for default in some periods. The importance of the impact of business cycles on credit risk is shown by Reilly, Wright & Gentry (2010), who found credit risk spreads for high yield bonds to be clearly related to the business cycle with significant differences during expansions versus contractions, and that different rating categories showed similar patterns but significantly different mean spreads during economic downturns. In the above mentioned investigation into asset pricing of Australian microcap stocks, Chan, Faff and Koffman (2008) use a period spanning three decades, and find that when they condition on the business cycle, the default risk premium is twice as high during expansions than during contractions.

Most of the literature on the cyclicality of default probabilities and capital requirements (e.g., Catarineu-Rabell, Jackson, & Tsomocos, 2003; Drumond, 2009; Gordy & Howells, 2006; Kashyap & Stein, 2003; Lowe, 2002; Pederzoli & Toricelli, 2005; Rosch & Scheule, 2010) deals with an investigation into the pro-cyclicality of rating approaches and a comparison of the relative benefits of Through the Cycle (TTC) and point in time (PIT) capital adequacy methods. PIT means that banks hold capital based on the current rating of a borrower, causing banks to have to increase capital in bad times and reduce it in good times. TTC means that banks hold one level of capital at all times, based on an assessment of 'average' or 'median' risk over a period of time, smoothing the potential volatility of PD estimates and hence the capital requirements. The European Central Bank (2009) calls the TTC approach into question, stating that the recent financial crisis shows the limits of using TTC ratings and that for banks to maintain credibility, they need to have strong capital during downturns. In summary, the literature uncovers a number of shortfalls with current probability of default and capital adequacy approaches. Neither PIT nor TTC focuses on extreme risk, meaning that banks could be left scrambling for capital, precisely when it is most difficult to obtain.

The Quantile Regression approach addresses this issue. Rather than using an 'average, or 'median' or 'point in time' approach, it divides data over time into sections or quantiles. Thus long time series of data can be used without smoothing the data and allowing the researcher to isolate, measure and examine particular segments of the data. Most importantly, it allows measurement of the extreme risk segments, which is when businesses are most likely to fail. The Merton (1974) model as modified by Moody's KMV (Crosbie & Bohn, 2003), hereafter referred to as the Merton / KMV model, measures distance to default (DD) and probability of default (PD) over selected time periods using a combination of balance sheet components (debt and equity) and fluctuating market asset values, and we use this methodology in our study. However, instead of using the standard Merton / KMV methodology, we use a modified approach which incorporates Quantile Regression and Monte Carlo Simulation, Quantile Regression allows us to compare the established and emerging entities over different risk quantiles. However, dividing the dataset into parts reduces the number of observations examined in each segment, and Monte Carlo simulation is particularly useful in cases of lesser observations, as it enriches the dataset by expanding the observations used. This combination of Monte Carlo simulation and quantile regression is unique to the authors and has been used in other settings such as Asian bank risk and comparison of Australian default risk to the USA (Allen, Kramadibrata, Powell, & Singh, 2010, 2011a, 2011b), but its use in the comparison of emerging and speculative companies to established companies is a first.

Our methodology is expanded on in Section 2, followed by results in Section 3, and conclusions in Section 4.

2. Methodology

Our 'established' data for the US is obtained from the S&P 500 and for Australia from the S&P/ASX 200. 'Speculative' data is obtained for the US from the Moody's Speculative Grade Liquidity Ratings list (Moody's Investor Services, 2010) and for Australia from the S&P/ASX Emerging Companies Index (EMCOX). We split all data into GFC (2007-2009) and Pre-GFC (2000-2006). The rationale for a 7 year period is that this aligns with Basel Advanced credit model requirements. Daily prices, together with balance sheet data required for the Merton model, are obtained from Datastream. Entities with insufficient data to undertake the modelling are excluded (for example those which do not have sufficient Worldscope balance sheet data on Datastream or at least 12 months equity data in both the GFC and Pre-GFC periods), resulting in 'established' datasets of 208 US and 118 Australian entities, and 'speculative' datasets of 170 US and 116 Australian entities.

We use the data to calculate Distance to Default (DD), per the Merton / KMV structural model for each entity. Detailed information on the model is beyond the scope the of this paper and can be obtained from Bharath & Shumway (2008) and Moody's KMV (Crosbie & Bohn, 2003). Suffice it to say that default is the point where liabilities exceed assets, which will be impacted by the volatility of those assets as follows:

$$DD = \frac{\ln(V/F) + (\mu - 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}} \tag{1}$$

Where: V = market value of firm's assets; F= face value of firm's debt (in line with KMV, this is defined as current liabilities plus one half of long term debt); μ = an estimate of the annual return (drift) of the firm's assets (we measure μ as the mean of the change in lnV of the period being modelled as per Vassalou & Xing (2004)), σ_V is the standard deviation of the firm's asset values and T is the time period which we set to 1 year in accordance with usual practice.

As discussed in Section 1, we use Quantile Regression to divide our daily asset returns into segments or quantiles. Quantile regression per Koenker & Basset (1978) and Koenker and Hallock (2001) minimises the sum of symmetrically weighted absolute residuals, yielding the median where, for the 50% quantile, 50 percent of observations fall either side. Similarly, other quantile functions are yielded by minimising the sum of asymmetrically weighted residuals, where the weights are functions of the quantile in question per equation 2. This makes quantile regression robust to the presence of outliers.

$$\min_{\varepsilon \in R} \sum p_r (y_1 - \varepsilon) \tag{2}$$

where $p_r(.)$ is the absolute value function, providing the r^{th} sample quantile with its solution.

When calculating asset returns, rather than using actual returns, which provide us with only a limited number of extreme returns with which to model the quantiles, we use Monte Carlo simulation to generate 20,000 simulated asset returns (based on the standard deviation and mean of historical asset returns) for every company in our dataset thereby increasing the richness of the data.

3. Results

The DD, Beta (β) and asset value fluctuations (σ_V) for various quantiles are shown in Figure 1 for Australia and Figure 2 for the US. The figures show substantial differences in DD between EMCOX and S&P/ASX 200 as well as Speculative and S&P 500. We make three key observations from the Australian results in Figure 1. Firstly, in every quantile, EMCOX has a much lower DD than the associated quantile for the S&P/ASX200. This is to be expected, given the speculative nature of the former data set. Secondly, the difference between the two datasets remains fairly constant throughout the quantiles with the S&P/ASX 200 DD being between 1.7 to 1.9x higher than each corresponding EMCOX quantile. This shows the relative relationship between the two datasets does not change to any great degree over differing economic circumstances. Thirdly, there is a substantial reduction in DD in the more risky quantiles, with the 95% GFC quantile for both Australian datasets having a DD 3x lower than the 10 year 50% quantile.

For the US datasets, whilst there are some similarities to the findings to the Australian datasets, there are also some differences. Firstly, as with Australia, Speculative shows lower DDs than the S&P 500. However secondly, unlike the Australian datasets, the relationship between the two US databases changes from the pre-GFC to the GFC period. At the pre-GFC 50% quantile, DD is 1.2x higher than the speculative set, which increases to 1.8x higher at the GFC 50% quantile. Thirdly, as with the Australian datasets but to an even greater extent, the DD's narrow substantially in the more risky quantiles, with Speculative having a GFC 95% quantile DD 4x lower (S&P 500 3x) than the 50% 10 year quantile.

Figure 1. Australian Quantile Results – EMCOX and S&P/ASX 200

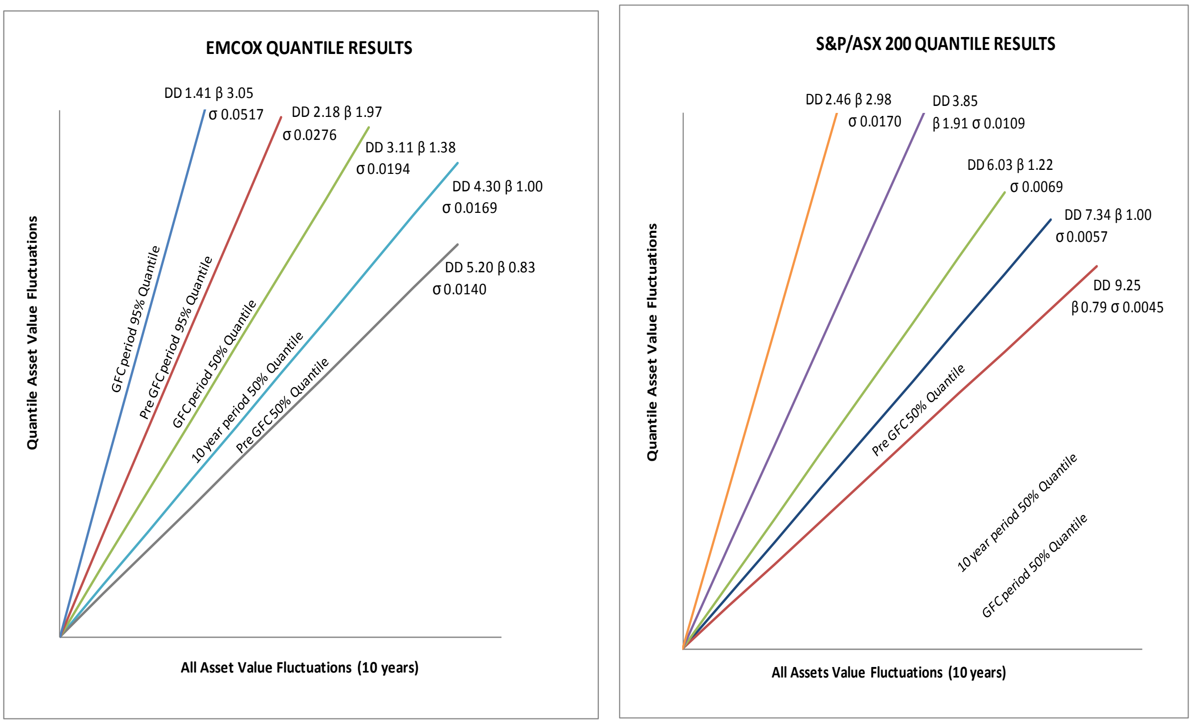
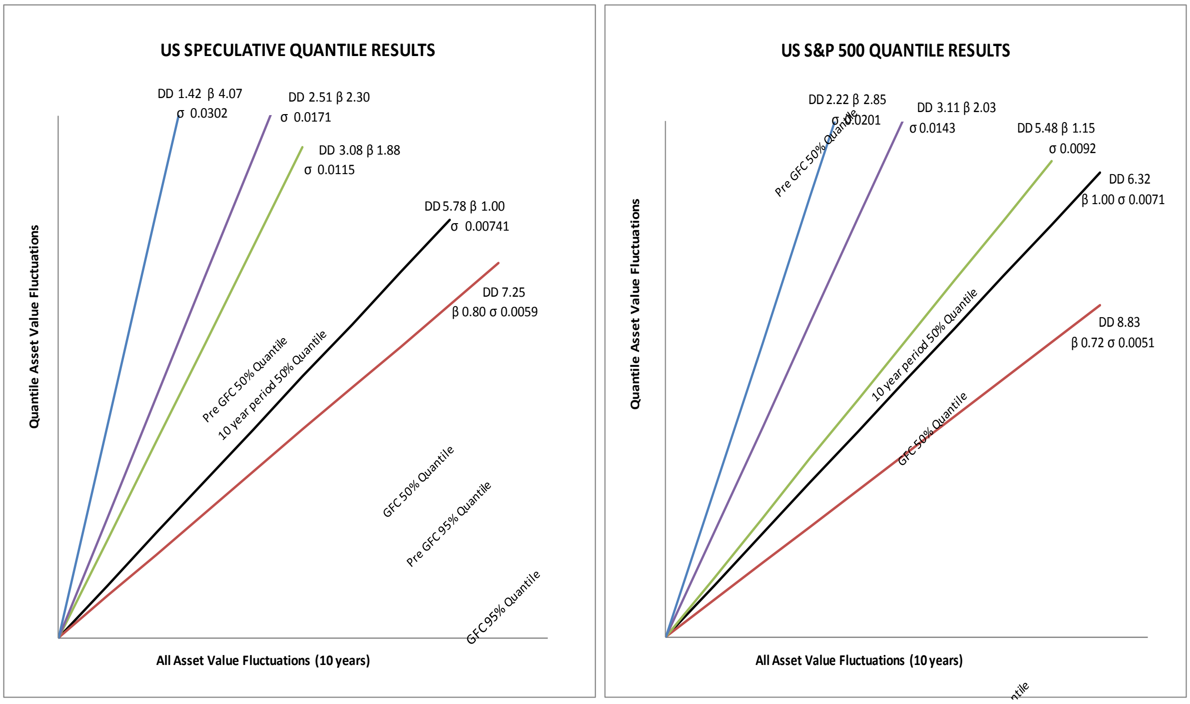


Figure 2. US Quantile Results – Speculative Stocks and S&P 500



The difference between asset value fluctuations at the 95% quantile compared to the 50% quantile is significant for all our datasets at the 99 percent confidence level using F tests for changes in volatility. The discrepancy between our credit risk measurements at various quantiles, for both speculative and established portfolios, has significant implications for banks. Where credit risk is calculated on ‘average’ measurements (such as TTC, 50% quantile, or OLS), provisions and capital will not be adequate during periods of extreme downturn (such as in the 95% quantile). Prior work by the authors (e.g., Allen et al., 2010) has shown that a shift in DD requires an equivalent shift in capital to counter it. This is because, as σ_A is the denominator of the DD equation (equation 1), as σ_A increases (reduces) from one level to another (i.e. from σ_1 *to* σ_2), DD reduces (increases) by the same proportion. Thus the numerator of the equation (a measure of capital – the distance between as assets and liabilities) needs to increase to restore DD to the same level, i.e. capital will need to increase by the same proportion as the change in DD (approximately 3x for EMCOX, S&P ASX 200 and S&P 500, and 4x for speculative US). Thus, using average type measurements can cause a shortfall in capital just when banks need it most. This is consistent with the findings of Doinne, Gauthier, Hammani, Maurice & Siminato (2010) mentioned in Section 1, who observe that default probabilities measured over long periods tend to smooth business cycle impacts, and can understate capital required in some periods. With the three to fourfold increases in market asset value fluctuations seen in our results, capital would be insufficient for the investment and speculative shares portfolio if based on an ‘average’ measurement.

4. Conclusions

This paper demonstrated how Monte Carlo simulation and Quantile Regression can be applied to credit risk models in investigating the difference between investment grade shares and speculative grade shares during extreme downturns in the Australian and US markets. Default risk is found to be much higher for speculative shares for all quantiles in both countries. In Australia, the extent of the DD difference between the speculative and established datasets is found to hold constant between the quantiles, whereas the difference between the two US datasets becomes larger during the riskier quantiles, showing that US speculative shares are more susceptible to changing economic circumstances than established shares.

In all cases, speculative or established, if shifting risk profiles are not accounted for in credit risk modelling, then default probabilities and the associated capital requirement could, at times, be significantly understated.

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