

1-1-2011

Comparing Australian and US Corporate Default Risk Using Quantile Regression

David E. Allen
Edith Cowan University

Akhmad R. Kramadibrata
Edith Cowan University

Robert J. Powell
Edith Cowan University

Abhay K. Singh
Edith Cowan University

Follow this and additional works at: <https://ro.ecu.edu.au/ecuworks2011>



Part of the [Corporate Finance Commons](#)

This is an Author's Accepted Manuscript of: Allen, D. E., Kramadibrata, A.R., Powell, R.J. , & Singh, A.K. (2011). Comparing Australian and US corporate default risk using quantile regression. Paper presented at the 2011 Australasian Meeting of the Econometric Society. Adelaide, Australia. Available [here](#)
The copyright to this article is held by the Econometric Society, <http://www.econometricsociety.org/>. It may be downloaded, printed and reproduced only for personal or classroom use. Absolutely no downloading or copying may be done for, or on behalf of, any for-profit commercial firm or for other commercial purpose without the explicit permission of the Econometric Society.
This Conference Proceeding is posted at Research Online.
<https://ro.ecu.edu.au/ecuworks2011/719>

Comparing Australian and US Corporate Default Risk using Quantile Regression.

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

Edith Cowan University

Abstract

The severe bank stresses of the Global Financial Crisis (GFC) have underlined the importance of understanding and measuring extreme credit risk. The Australian economy is widely considered to have fared much better than the US and most other major world economies. This paper applies quantile regression and Monte Carlo simulation to the Merton structural credit model to investigate the impact of extreme asset value fluctuations on default probabilities of Australian companies in comparison to the USA. Quantile regression allows modelling of the extreme quantiles of a distribution which allows measurement of capital and PDs at the most extreme points of an economic downturn, when companies are most likely to fail. Daily asset value fluctuations of over 600 Australian and US investment and speculative entities are examined over a ten year period spanning pre-GFC and GFC. The events of the GFC also showed how the capital of global banks was eroded as defaults increased. This paper therefore also examines the impact of these fluctuating default probabilities on the capital adequacy of Australian and US banks. The paper finds highly significant variances in default probabilities and capital between quantiles in both Australia and the US, and shows how these variances can assist banks and regulators in calculating capital buffers to sustain banks through volatile times.

Keywords: Probability of Default, Quantile Regression; Australian Banks; United States Banks

JEL Codes: G01, G21, G28

Acknowledgements: We thank the Australian Research Council and Edith Cowan University for funding support.

1. Introduction

From a credit perspective, there is generally considered to be strong evidence to demonstrate the resilience of Australian banks during the extreme conditions of the GFC. The 4 largest Australian banks remained profitable throughout the GFC (for example, showing collective profits of USD \$18 billion in 2008), and all 4 are among only 8 banks in the world to be rated AA, maintaining these ratings throughout the GFC. No Australian banks failed over this period. In contrast, US banks experienced capital shortages, losses (for example, nearly \$50 billion by the 5 major banks in 2008) and rating downgrades. Several banks failed (25 banks in 2008 and 140 in 2009), most notably Lehman Brothers. In 2009, impaired assets of Australian banks were less than 1%, as compared to 8.8% in the US. All this paints a sound credit risk picture in Australia compared to the US. Nonetheless, Table 1 shows that, whilst at lower levels than the US, Australian bank impaired assets increased 5 fivefold during the GFC, not very different from the US. The share markets in Australia plunged around 55%, similar to the US, having a severe impact on the market value of corporate assets.

Table 1. Impaired Assets – Australian and US Banks

	Australia	US
Mar-2000	0.61%	1.85%
Mar-2001	0.59%	2.13%
Mar-2002	0.69%	1.94%
Mar-2003	0.58%	1.64%
Mar-2004	0.41%	1.41%
Mar-2005	0.27%	1.36%
Mar-2006	0.21%	1.46%
Mar-2007	0.19%	2.35%
Mar-2008	0.34%	4.79%
Mar-2009	0.95%	8.80%

Australian figures are calculated from RBA Statistics (2009) for all banks operating in Australia. Non-bank entities (Building Societies and Credit Unions) are not included. Australian Bank impaired assets refer to non-accrual (income may no longer be accrued ahead of its receipt because there is doubt about the ultimate collectability of principal and/or interest) and restructured assets (modified to provide for concessions of interest or principal exposures), both on- and off-balance sheet, plus any assets acquired through the enforcement of security conditions. US figures include commercial banks as classified by the Federal Reserve Bank (FRB), and all figures are obtained from FRB (2009) statistical reports. The US impaired asset figures comprise loans classified as delinquent, which are loans past thirty days or more and still accruing interest as well as those in non-accrual status, measured as a percentage of end-of period loans.

Against this background, the research question addressed by this paper is how do the asset value fluctuations of Australian companies over both pre-GFC and GFC periods compare to those of the US, and what are the implications for capital buffers in both markets? Using quantile regressions, we show how despite having fared better than global peers, based on fluctuating asset values the default probabilities of Australian corporates were severely impacted during the GFC, as was the case in the US.

Many prevailing credit models were designed to measure credit risk on the basis of ‘average’ credit risks over a period, or credit risk at a specific point in time. The problem with these approaches is that they are not designed to measure the most extreme losses, i.e. the tail of the credit loss distribution. It is precisely during these extreme circumstances when firms are most likely to fail. Some examples of well known models in this category include the z score developed by Altman (1968 and revisited Altman, 2000) which uses five balance sheet ratios to predict bankruptcy; Moody’s KMV Company (2003) RiskCalc model, which uses 11 financial measures to provide an Estimated Default Frequency (EDF) for private firms; Ratings agencies which provide credit ratings based on customer creditworthiness, but which are not designed to ratchet up and down with changing market conditions; CreditMetrics (Gupton, Finger, & Bhatia, 1997) which incorporates credit ratings into a transition matrix that measures the probability of transitioning from one rating to another, including the probability of default; and the Basel Accord standardised approach which measures corporate credit risk for capital adequacy purposes by applying risk weightings to customers on the basis of their external credit rating.

Other models use Value at Risk (VaR), which is one of the most widely used approaches for measuring credit and market risk by banks, on the basis of risks falling below a pre-determined threshold at a selected level of confidence, such as 95% or 99%. A key shortfall of this approach is that it says nothing of risk beyond VaR and it is usually based on a normal distribution Gaussian approach which does not adequately capture tail risk. Critics have included Standard and Poor’s analysts (Samanta, Azarchs, & Hill, 2005) due to inconsistency of VaR application across institutions and lack of tail risk assessment. Artzner, Delbaen, Eber, & Heath (1999; 1997) found VaR to have undesirable mathematical properties (most notably lack of sub-additivity), whereas Pflug (2000) proved that Conditional Value at Risk (CvaR), which looks at losses beyond VaR does not have these undesirable properties. In

assessing why existing credit models failed in the credit crisis, Sy (2008) finds that most existing credit models are based on a reduced form linear approach which have typical reliance on having large amounts of statistical data coming from a quasi-equilibrium state, and that this approach is ineffective in making even short-term forecasts in rapidly changing environments such as in a credit crisis. The study finds that such inductive models have failed to predict what would happen just when they were most needed to. Hedge fund returns have also been found to deviate from the VaR Gaussian approach (Bali, Gokcan, & Liang, 2007; Gupta & Liang, 2005). Jackson, Maude & Perraudin (1998) found that VaR estimates based on a simulation approach outperformed VaR estimates based on a Gaussian approach. Ohran and Karaahmet (2009) found that VaR works well when the economy is functioning smoothly, but fails during times of economic stress, because VaR is ignorant of the extreme losses beyond VaR.

The Merton / KMV model (Crosbie & Bohn, 2003; Merton, 1974), does measure fluctuating risk over time using a combination of the structure of the customer's balance sheet and movements in market asset values to calculate default probabilities. However, again this is based on an 'average' over the time period measured, and does not highlight the extreme quantiles within the measured period.

Credit models which do not adequately measure tail risk for corporates could lead to banks having underprovisions or capital shortages during extreme economic circumstances. During the GFC, many global banks were not adequately prepared to deal with the extent of defaults and increased impaired assets occurring during this time, and were left scrambling for capital and funding just when it was most difficult to obtain. Per the International Monetary Fund (Caruana & Narain, 2008), "it (Basel) does emphasize that banks should address volatility in their capital allocation and define strategic plans for raising capital that take into account their needs, especially in a stressful economic environment". The Basel Committee on Banking Supervision (2008) stated that capital adequacy requirements should include "introducing a series of measures to promote the build-up of capital buffers in good times that can be drawn upon in periods of stress". Indeed, recently announced changes to Basel II (i.e. Basel III) include requirements for such capital buffers.

Whereas existing models focus on 'average risk' or risk below a defined threshold, we use quantile regressions to divide the data into different tranches, enabling the researcher to isolate and model the most risky tranches. Quantile regression, as introduced by Koenker and Bassett (1978) has successfully measured extreme market risk (share prices) as it is more

robust to the presence of outliers than other prediction methods such as Ordinary Least Squares. Quantile regression has been applied to a range of market risk models, notably by Nobel economics laureate Robert Engle, who together with Manganelli (Engle & Manganelli, 2004) applied them to a suite of CAViaR (Conditional Autoregressive Value at Risk) models. The authors make the point that modelling techniques must be responsive to financial disasters, and that existing VaR techniques are inadequate as they only focus on one particular quantile. By not properly estimating risk, financial institutions can underestimate (or overestimate) the risk, consequently maintaining excessively high (low) capital. Their CaViaR models are unique in that instead of modelling a single distribution, they can directly model different quantiles, including the tail of the distribution.

Section 2 discusses the Merton / KMV model (and its associated Distance to Default and Probability of Default measures). Section 3 explains the quantile regression techniques used. Section 4 includes Data and Methodology. Results are presented in Section 5, followed by Conclusions in Section 6.

2. Distance to Default (DD) and Probability of Default (PD)

The Merton / KMV approach (which we use in this study, but modify to incorporate quantiles) provides an estimate of distance to default (DD) and probability of default (PD). The model holds that there are 3 key determinants of default: the asset values of a firm, the risk of fluctuations in those asset values, and leverage (the extent to which the assets are funded by borrowings as opposed to equity). The firm defaults when debt exceeds assets, and DD measures how far away the firm is from this default event. KMV (Crosbie & Bohn, 2003), in modelling defaults using their extensive worldwide database, find that firms do not generally default when asset values reach liability book values, and many continue to service their debts at this point as the long-term nature of some liabilities provides some breathing space. KMV finds the default point to lie somewhere between total liabilities and current liabilities and therefore use current liabilities plus half of long term debt as the default point.

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

$$PD = N(-DD) \quad (2)$$

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 $\ln V$ of the period being modelled as per Vassalou & Xing (2004))

N = cumulative standard normal distribution function.

To estimate asset volatilities and arrive at DD, we follow an intensive estimation, iteration and convergence procedure, as outlined by studies such as Bharath & Shumway (2009), Vassalou & Xing (2009), and Allen and Powell (2009).

3. Quantile Regression.

Quantile regression per Koenker & Basset (1978) and Koenker and Hallock (2001) is a technique for dividing a dataset into parts. Minimising the sum of symmetrically weighted absolute residuals yields the median where 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 3. This makes quantile regression robust to the presence of outliers.

$$\min_{\varepsilon \in R} \sum p_r(y_1 - \varepsilon) \quad (3)$$

where $p_r(\cdot)$ is the absolute value function, providing the τ th sample quantile with its solution.

Figure 1 Illustrative Quantile Regression Example

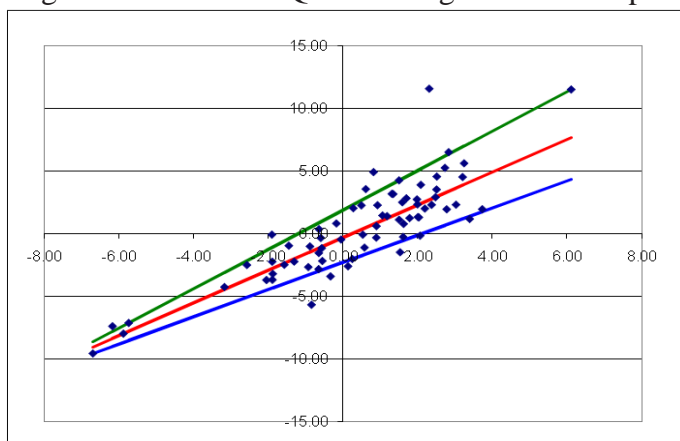


Figure 1 (Andreas Steiner, 2006) illustrates the quantile regression technique. The x and y axes represent any two variables being compared (such as age and height; or market returns and individual asset returns).

The 50 percent quantile (middle line) is the median, where 50 percent of observations fall below the line and 50 percent above. Similarly, the 90 percent quantile (top line) is where 10 percent of observations lie above the line, and 10 percent quantile (bottom line) has 90 percent of observations above the line. The intercept and slope are obtained by minimising the sum of the asymmetrically weighted residuals for each line. Quantile Regression allows direct modelling of the tails of a distribution rather than ‘average’ based techniques such as ordinary least squares or credit models which focus on ‘average’ losses over a period of time. The technique has enjoyed wide application such as investigations into wage structure (Buschinsky, 1994; Machado & Mata, 2005), production efficiency (Dimelis & Lowi, 2002), and educational attainment (Eide & Showalter, 1998). Financial applications include Engle & Manganelli (2004) and Taylor (2008) to the problem of VaR and Barnes and Hughes (2002) who use quantile regression analysis to study CAPM in their work on stock market returns.

In a stock market context Beta measures the systematic risk of an individual security with CAPM predicting what a particular asset or portfolio’s expected return should be relative to its risk and the market return. The lower and upper extremes of the distribution are often not well fitted by OLS. Allen, Gerrans, Singh, & Powell (2009), using quantile regression, show large and sometimes significant differences between returns and beta, both across quantiles and through time. These extremes of a distribution are especially important to credit risk measurement as it is at these times when failure is most likely. We therefore expand these quantile techniques to credit risk by measuring Betas for fluctuating assets across time and across quantiles, and the corresponding impact of these quantile measurements on DD. This is shown in Figures 1 and 2 in the results section, where our y axis depicts the asset returns for the quantile being measured (we measure the 50 percent quantile which corresponds roughly to the standard Merton model, and the 95 percent quantile), and the x axis represents all the asset returns (all quantiles) in the dataset.

Using actual returns provides us with only a limited number of extreme returns with which to model the quantiles. To increase the richness of the data we use Monte Carlo simulation to generate 20,000 simulated asset returns for every company in our dataset. This is done by generating 20,000 random numbers based on the standard deviation and mean of historical asset returns.

4. Data

Data is divided into two periods: Pre-GFC (2000 – 2006, 7 years aligning with Basel Accord advanced model credit risk requirements) and GFC (2007 – 2009).

We obtain daily prices from Datastream (approximately 250 observations x 10 years = 2500 observations per company). Required balance sheet data, which includes asset and debt values, is also obtained from Datastream. To ensure a mix of investment and speculative entities for both Australia and the US, we use two data sources for each market. US data includes entities from the S&P500 index as well as Moody's Speculative Grade Liquidity Ratings list (Moody's Investor Services, 2010). For Australia, we use entities from the ASX200 and from S&P/ASX Emerging Companies Index. In each case we only include rated entities, for which equity prices and Worldscope balance sheet data are available in Datastream. Entities with less than 12 months data in either of the 2 periods are excluded. This results in 378 US entities consisting of 208 S&P 500 companies and 170 speculative companies, and 234 Australian Entities consisting of 118 ASX200 companies and 116 emerging entities.

5. Results

Results are summarised in Figure 1 (Australia) and Figure 2 (US). The graphs show the asset value fluctuations (σ), the associated Beta (β) and DD. The graphs show large differences in DD between the quantiles for both countries, although the spread is somewhat lower for Australia than the US. For example, the 95% GFC quantile has a DD more than 3x lower than the US 10 year 50% quantile DD. The difference between asset value fluctuations at the 95% quantile compared to the 50% quantile is significant for both countries at the 99 percent confidence level using F tests for changes in volatility. This has significant implications for banks. Provisions and capital calculated on 'average' or below the threshold measurements for a portfolio of corporate assets will clearly not be adequate during periods of extreme downturn. .

Figure 1. Australian Quantile Results

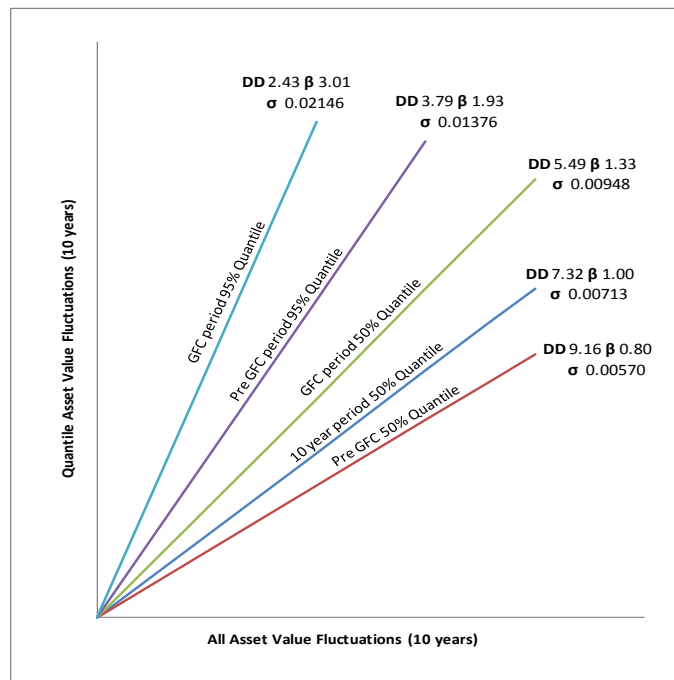
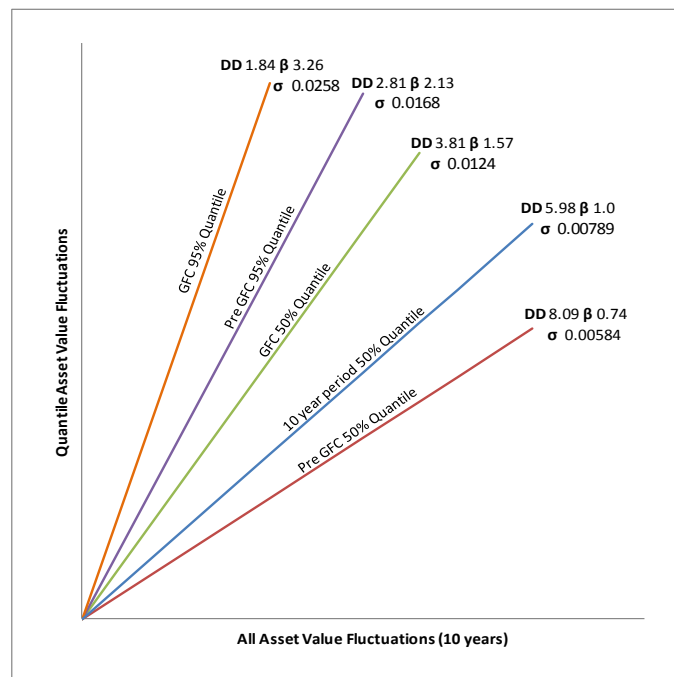


Figure 2. US Quantile Results



The figures show the results of the Quantile Regression Model for the 50 percent and 95 percent quantiles for pre- GFC and GFC periods. The pre-GFC period is the 7 years from 2000 – 2006 whereas the GFC period is the 3 years between 2007 – 2009. The y axis is calculated on the asset fluctuations (σ), using the Merton model, for the quantile in question. The x axis is the median σ for the entire 10 year period. Thus the Beta (β) for the 50 percent Quantile for the 10 year period is one. Where σ for a particular quantile is less (greater) than the median for the 10 year period, $\beta < (>) 1$, and DD increases (reduces) accordingly.

The above graph shows that the ‘median’ DD (based on how the standard Merton structural model calculates DD) over the 10 year study period was 5.98 for US banks (7.32 for Australia) with an asset value standard deviation (σ) of 0.00789 (0.00713 for Australia). As asset value σ is the denominator of the DD equation (equation 1), as σ 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 assets and liabilities) needs to increase to restore DD for these Corporates back to the same level, i.e. capital will need to increase by the same proportion as the change in DD (approximately 3x for both Australia and the US).

Of course, the capital buffer needed by banks will depend on how much capital banks held in relation to problem loans in the first place. US collective bank capital ratios at the start of the GFC were 7.1% (calculated from Datastream) against impaired assets of 2.4% per table 1 (3:1 ratio). With a threefold increase in market asset values fluctuations and a fivefold increase in impaired assets, any existing capital buffer is eliminated. Australian Bank capital on the other hand was 6.2% against impaired assets of 0.19% (32:1 ratio). This is why Australian bank capital could much more easily weather the fivefold increase in impaired assets and trebling market asset value fluctuations of corporate borrowers than the US.

6. Conclusions

This paper demonstrated how Monte Carlo simulation and Quantile Regression can be applied to credit risk models to measure extreme risk in the Australian and US markets, as well as measure the extent of capital buffers required to deal with that risk. The US and Australia both showed significant (and similar) increases in asset value fluctuations and impaired assets. However, Australian banks had a much lower impaired asset position (and thus in-built capital buffer) to start with and were therefore much better placed to weather the storm than their US counterparts. Therefore Australian banks required no additional capital buffer, whereas the US banks did.

References

- Allen, D. E., Gerrans, P., Singh, A. K., & Powell, R. (2009). Quantile Regression: Its Application in Investment Analysis. *Jassa*(4), 7 -12.
- Allen, D. E., & Powell, R. (2009). Structural Credit Modelling and its Relationship to Market Value at Risk: An Australian Sectoral Perspective. In G. N. Gregoriou (Ed.), *The VaR Implementation Handbook* (pp. 403-414). New York: McGraw Hill.
- Andreas Steiner. (2006). Available at <http://www.andreassteiner.net/performanceanalysis>.
- Artzner, P., Delbaen, F., Eber, J., & Heath, D. (1999). Coherent Measures of Risk. *Mathematical Finance*, 9, 203-228.
- Artzner, P., Delbaen, F., Eber, J. M., & Heath, D. (1997). Thinking Coherently. *Risk*, 10, 68-71.
- Bali, T. G., Gokcan, S., & Liang, B. (2007). Value-at-Risk and the Cross-section of Hedge Fund Returns. *Journal of Banking and Finance*, 31(4), 1135-1166.
- Barnes, M. L., & Hughes, A. W. (2002). A Quantile Regression Analysis of the Cross Section of Stock Market Returns. *Working Paper 02-2, Federal Reserve Bank of Boston*.
- Basel Committee on Banking Supervision. (2008). *Consultative Proposals to Strengthen the Resilience of the Banking Sector Announced by the Basel Committee, 17 December, 2008*.
- Buschinsky, M. (1994). Changes in the US Wage Structure 1963 - 1987: Application of Quantile Regression. *Econometrica*, 162(2), 405 - 458.
- Caruana, J., & Narain, A. (2008). Banking on More Capital. *International Monetary Fund, Finance & Development*, 45(2).
- Crosbie, P., & Bohn, J. (2003). *Modelling Default Risk: Moody's KMV Company*.
- Dimelis, S., & Lowi, H. (2002). Oxford Economic Papers. *Oxford University Press*, 20(4), 445 - 465
- Eide, E., & Showalter, M. H. (1998). The effect of school quality on student performance: a quantile regression approach. *Economics Letters, Elsevier*, 58(3), 345 - 350.
- Engle, R., & Manganelli, S. (2004). CAViaR: Conditional Autoregressive Value at Risk by Regression Quantiles *Journal of Business & Economic Statistics*, 22(4), 367-381.
- Federal Reserve Bank. (2009). *Federal Reserve Statistical Release. Charge-off and Delinquency Rates*. Retrieved 27 December 2009. Available at www.federalreserve.gov
- Gupta, A., & Liang, B. (2005). Do hedge funds have enough capital? A Value-at-Risk approach. *Journal of Financial Economics*, 77(1), 219-253.
- Jackson, P., Maude, D. J., & Perraudin, W. (1998). Bank Capital and Value at Risk, *Working paper Series No 79, Bank of England*.
- Koenker, R., & Bassett, G., Jr. (1978). Regression Quantiles. *Econometrica*, 46(1), 33-50.
- Koenker, R., & Hallock, K. (2001). Quantile Regression. *Journal of Economic Perspectives*, 15(4), 143 - 156.
- Machado, J., & Mata, J. (2005). Counterfactual Decomposition of Changes in Wage Distributions Using Quantile Regressions. *Journal of Applied Econometrics*, 20(4), 445 - 465.
- Merton, R. (1974). On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance*, 29, p.p. 449-470.
- Moody's Investor Services. (2010). *Moody's Speculative Grade Liquidity Ratings*. Retrieved 31/10/10. Available at www.moody's.com

- Ohran, M., & Karaahmet, M. (2009). Risk Evaluation of Sectors Traded at the ISE with VaR Analysis. In G. N. Gregoriou (Ed.), *The VaR Implementation Handbook*. New York: McGraw Hill.
- Pflug, G. (2000). Some Remarks on Value-at-Risk and Conditional-Value-at-Risk. In R. Uryasev (Ed.), *Probabilistic Constrained Optimisation: Methodology and Applications*. Dordrecht, Boston: Kluwer Academic Publishers.
- Powell, R., & Allen, D. (2009). CVaR and Credit Risk Management. In *Anderssen, R.S., R.D. Braddock and L.T.H. Newham (eds) 18th World IMACS Congress and MODSIM09 International Congress on Modelling and Simulation. Modelling and Simulation Society of Australia and New Zealand and International Association for Mathematics and Computers in Simulation, July 2009, pp. 1508-1514.*
- Reserve Bank of Australia. (2009). *Statistics*. Retrieved 28 August 2009. Available at <http://www.rba.gov.au/statistics/>
- Samanta, P., Azarchs, T., & Hill, N. (2005). Chasing Their Tails: Banks Look Beyond Value-At-Risk. , *RatingsDirect*.
- Sy, W. (2008). *Credit Risk Models: Why They Failed in the Financial Crisis*: APRA, wp0803.
- Taylor, J. W. (2008). Using Exponentially Weighted Quantile Rergression to Estimate Value at Risk and the Expected Shortfall. *Journal of Financial Econometrics*, 6(3), 282 - 406.
- Vassalou, M., & Xing, Y. (2004). Default Risk in Equity Returns. *Journal of Finance*, 59, 831-868.