Beyond reasonable doubt: multiple tail risk measures applied to European industries

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Using a range of metrics, this article determines how relative market and credit risk changes among European sectors during times of extreme market fluctuations. Ten sectors comprising the S&P Euro index are compared prior to and during the Global Financial Crisis (GFC). Market risk is measured using Value at Risk (VaR) and Conditional Value at Risk (CVaR) which measures risk beyond VaR. Credit risk is measured using the Merton / KMV Distance to Default (DD) model, and our unique Conditional Distance to Default (CDD) model, which measures extreme credit risk. A range of methodologies (Parametric, Historical and Monte Carlo Simulation) are applied to the VaR, CVaR and Default measures, producing ten different metric combinations. Differences are found between conditional and non-conditional outcomes, and sectors which were most risky prior to the GFC are found to be different to the riskiest sectors during the GFC. These findings are consistent across the comprehensive range of metrics used. The insights into extreme sectoral risk provided by the study are important to investors in portfolio selection, to banks in setting sectoral concentration limits, and to economic policy makers in determining sectors vulnerable to downturn or corporate failures.

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Introduction

The extreme financial market volatility and severe bank stresses of the GFC have highlighted the importance of understanding and measuring extreme market and credit risk. In Europe, in particular, financial markets and the banking sector have experienced tremendous instability, with the GFC promptly followed by a sovereign debt crisis.

The inclusion of both market and credit risk in this article is due to the fact that understanding of sectoral risk is important to both investors in determining portfolio mix and to banks in setting policies such as credit concentration limits, pricing, and lending officers' loan approval authority limits for each industry. The interaction between market and credit risk is sufficiently important that the Bank for International Settlements (BIS) set up a task force to examine the link between the two. The BIS (2009) task force reported that market and credit risk are driven by the same underlying forces, which interact significantly in determining asset values, and that default may be affected by fluctuations in these asset values.

This study compares market risk prior to and subsequent to the onset of the GFC using VaR and CVaR (which measures risk beyond VaR). To measure credit risk we use the structural credit model of Merton (1974) and KMV (Crosbie & Bohn, 2003) which incorporates a combination of fluctuations in market asset values and the debt / equity structure of the borrower's balance sheet to measure DD. We also use CDD which is our unique measure applying CVaR methodology to the measurement of extreme credit risk.

There are three well known VaR methods. The parametric method estimates VaR on assumption of a normal distribution. The Historical method groups historical losses in categories from best to worse and calculates VaR on the assumption of history repeating itself. Monte Carlo Simulation simulates multiple random scenarios. To ensure a thorough investigation of industry rankings we apply all 3 methods to our VaR and CVaR/CPD metrics, creating ten different metric combinations many of which, notably the various CPD applications, are unique.

The main (first) question explored by this study is whether there is a difference between industry risk rankings using traditional credit measures such as VaR and DD as opposed to CVaR and CDD measures of extreme risk. To ensure this question is thoroughly explored across a range of circumstances, allied to the main question are three supporting questions. Therefore, secondly, the study examines whether these industry rankings change during the extreme conditions of the GFC as compared to pre-GFC. Thirdly, the study explores whether the outcomes are consistent across a range of metrics (using all ten methods). Finally, the study determines whether there is association between credit industry rankings and market industry rankings (i.e. whether those industries which are most/least risky from an investment perspective are the same as those industries which are risky from a credit perspective).

The study finds that European industry rankings change when using CVaR as compared to VaR. Similar results are obtained for credit risk when using CDD as compared to DD. In addition, those industries that were most risky prior to the GFC are not the same industries that were risky during the GFC. The above findings are found to be consistent across all ten metrics used in this article. Thus relative industry risk changes as economic circumstances change. It is precisely at times of extreme risk that companies are most likely to fail or default, causing losses to investors and lenders. This means that it is important for investors and lenders wishing to minimize extreme risk to include measures such CVaR and CDD in selecting portfolio mix. Finally, the study finds association between market and credit industry rankings, meaning that those industries which are most / least risky from a market (investment) perspective, also have the highest / lowest probability of default.

As background, Section 2 provides a brief overview of the risk climate in Europe brought about by the GFC and Sovereign Debt Crisis. Section 3 provides background to VaR, CVaR, DD and CDD. Data and Methodology are discussed in Section 4, followed by Results in Section 5 and Conclusions in Section 6.

I. The Risk Setting in Europe

A combination of the GFC and the Sovereign Debt Crisis has led to a prolonged period of financial instability in European markets. As happened in the US and other Global markets, the GFC led to a need in Europe for financial sector support programmes and macroeconomic stimulus to be provided by Central banks and Governments. Examples include the 2008 UK Government £500bn financial support package and liquidity support measures provided by the Bank of England (BOE) and European Central Bank (ECB), such as extension of maturity terms on refinancing operations and allowing banks to swap illiquid securities for liquid ones. Following an emergency Paris summit in 2008, Euro area governments provided co-ordinated support measures to banks such as increasing deposit insurance, providing guarantees on bank bond issues and making capital injections into banks. Asset relief measures were introduced to remove or insure toxic bank assets (European Central Bank, 2009).

2010 heralded a sovereign debt crisis in Europe amidst concern that a number of countries, including Greece, Portugal, Spain, Italy and Ireland would default on high debt levels. This led to the need for comprehensive rescue packages by the International Monetary Fund and other Eurozone countries. The ECB also introduced measures to reduce volatility in financial markets and improve liquidity such as commencing open market operations by buying government and private debt securities.

These events all provide a climate of extreme risk for investors and banks, leading to the need to for accurate measurement of extreme risk. Background to the measurements used in this study is provided in the following section.

II. Background to Risk Measurements Used in this Study

Market Risk is measured in this study using VaR and CVaR. VaR, which measures potential losses over a specific time period within a given confidence level, is a well understood and widely used metric for measuring market risk. The concept has been incorporated into the Basel Accord as a required measurement for determining capital adequacy for market risk. VaR has also been applied to credit risk through models such as CreditMetrics (Gupton, Finger, & Bhatia, 1997), CreditPortfolioView (Wilson, 1998), and *i*Transition (Allen & Powell, 2009b)

Despite its wide use, VaR has undesirable mathematical properties; such as lack of sub-additivity (Artzner et al., 1999; 1997). Perhaps the biggest shortcoming of VaR is that it is focused on risks below a specified threshold and says nothing of the risks beyond VaR, giving rise to doubt as to whether the metric is adequately measuring relative risk between portfolio components. The measurement has been criticized by Standard and Poor's analysts (Samanta, Azarchs, & Hill, 2005) due to VaR being applied inconsistently across institutions, as well as lack of tail risk assessment.

Conditional Value at Risk (CVaR) measures extreme returns (those beyond VaR). Pflug (2000) proved that CVaR is a coherent risk measure with a number of desirable properties such as convexity and monotonicity, amongst other desirable characteristics. CVaR has been applied to portfolio optimization problems by several studies, including Rockafeller and Uryasev (2002; 2000), Andersson et.al (2000), Alexander et al (2003), Alexander and Baptista (2003) and Rockafellar et al (2006). Allen and Powell (2009a, 2009b) explored CVaR as an alternative method to VaR for measuring market and credit risk in an Australia.

Credit risk in this study is measured using the Distance to Default (DD) structural approach of Merton (Merton, 1974) and KMV (Crosbie & Bohn, 2003). The model measures DD based on a combination of fluctuating asset values and the debt / equity (leverage structure) of the borrower.

The importance of fluctuating asset values in measuring credit risk has been raised by the Bank of England (2008), who make the point that not only do asset values fall in times of uncertainty, but rising probabilities of default make it more likely that assets will have to be liquidated at market values. Examples of studies using structural methodology for varying aspects of credit risk include asset correlation (Cespedes, 2002; Kealhofer & Bohn, 1993; Lopez, 2004; Vasicek, 1987; Zeng & Zhang, 2001), predictive value and validation (Bharath & Shumway, 2008; Stein, 2007), fixed income modelling (D'Vari, Yalamanchili, & Bai, 2003), and effect of default risk on equity returns (Chan, Faff, & Kofman, 2008; Gharghori, Chan, & Faff, 2007; Vassalou & Xing, 2002).

Besides fluctuating assets, the other key component of structural modelling is the borrower's leverage ratio. Leverage ratios of banks have come under close scrutiny during the financial crisis, with many requiring additional capitalisation. The leverage ratios in this study range from 5.3% for Financials to 53% for Health Care. BOE (2008) report that during the GFC "system-wide vulnerabilities were exposed…rooted in uncertainties about the value of banks assets…amplified by excessive leverage". As probabilities of default increase, there is greater likelihood of assets needing to be liquidated at market prices, and BOE thus express a need for market participants need to revalue their assets with greater weight placed on mark to market values giving rise to reduced asset values and a need for increased capital.

Detailed methodology behind the above measurements is provided in the following section.

III. Methodology

Data

The study includes all S&P Euro stocks. This index represents the European region, including 180 stocks with geographic and sectoral diversity, and a total Market Cap of €2.1 trillion. We obtain daily returns for 10 years from Datastream, divided into two periods: pre-GFC and GFC. For the pre-GFC period we use the 7 years prior to 2007. 7 years aligns with Basel Accord advanced model requirements for measuring credit risk. The GFC period includes the 3 years from 2007 – 2009. The Merton KMV model requires balance sheet data for each entity (equity and debt) which we also obtain from Datastream.

Market risk measurement

Our methodology involves calculation of VaR and CVaR. To calculate VaR, we use all 3 well known methodologies, including parametric, historical, and Monte Carlo simulation. The parametric approach uses the methodology of RiskMetrics (J.P. Morgan & Reuters, 1996), who introduced and popularised VaR. This is the most commonly used VaR method. Following RiskMetrics, daily equity returns are calculated for our data sample using the logarithm of daily price relatives, for each company within each industry. From the standard deviation (σ) of these returns, VaR is calculated at a 95% confidence level, and based on standard tables, $VaR_x = 1.645\sigma_x$. To account for correlations between each entity in the industry, and calculate portfolio VaR for each of these industries, we use the RiskMetrics Variance-Covariance matrix multiplication method, details of which can also be found in Choudhry (2004). The historical (nonparametric) method makes no assumption about the distribution of returns. Daily returns are calculated for each entity as described for the parametric method. VaR is taken as the 95th percentile worst return. To obtain portfolio VaR for each industry, the daily weighted average returns of all the entities in the industry is calculated. As correlations across assets are naturally embedded in the historical weighted average time series, they require no separate estimation. The required confidence level (the 95% percentile worst return in our case) is then applied to these weighted average returns. For Monte Carlo Simulation, we generate 20,000 scenarios of returns, a similar number to that suggested by other prominent Monte Carlo Simulation studies (for example, Uryasev & Rockafellar, 2000). These simulations are generated by creating random numbers based on the distribution (mean and standard deviation) of historical returns. As per the historical method, the daily weighted average of returns is calculated, with VaR taken as the 95% percentile worst simulated return.

CVaR uses the same methodology as VaR, except we use the average returns beyond VaR (i.e. average of the worst 5% of returns). In the case of parametric CVaR, this is the average returns beyond parametric VaR, for historical CVaR, the average returns beyond historical VaR, and for Monte Carlo Simulation the average returns beyond the simulated VaR.

Credit risk

The Merton / KMV structural approach to estimating distance to default (DD) and probability of default (PD) is used. This model is then modified to incorporate an extreme risk component called Conditional Distance to Default (CDD) and Conditional Probability of Default (CPD). The structural 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 the leverage (the extent to which the assets are funded by borrowings as opposed to equity). The firm defaults when debt exceeds equity. DD and PD are measured as follows:

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

$$PD = N(-DD) \tag{2}$$

Where V is the market value of the firm, F = face value of firm's debt, and μ = an estimate of the annual return (drift) of the firm's assets.

Market value of assets is obtained using the approaches outlined by KMV (Crosbie & Bohn, 2003) and Bharath & Shumway (2008). Initial asset returns (for every day) in our data set are estimated from our historical equity data (obtained as per section 4.2) using the following formula, where *E* is the market capitalization of the firm:

$$\sigma_V = \sigma_E \left(\frac{E}{E+F} \right) \tag{3}$$

The daily log return is calculated and new asset values estimated every day following the KMV iteration and convergence procedure. We measure μ as the mean of the change in lnV as per Vassalou & Xing (2002). Following KMV, we define debt as current liabilities plus half of long term liabilities. Whereas VaR measurements are based on a specific quantile such as 95%, DD is based on standard deviation, therefore we do not compare 95% historical and Monte Carlo approaches to DD as the 95% quantile would not be comparable to the standard deviation based

DD. However, in our conditional distance to default (CDD) methodology which is based on the worst 5% of asset returns, we apply all 3 (parametric, historical and Monte Carlo methods). We do this in the same manner as we do for market returns, except we are now applying this to daily asset returns as opposed to daily share returns. For example, after the daily asset returns are calculated, parametric CCD is obtained by multiplying the asset σ by 1.645 to obtain the 95% threshold of asset returns, with CDD being the average asset returns (CStdev) beyond this threshold. Historical CStdev is based on those asset returns beyond the actual 95th worst historical returns. Monte Carlo CStdev is based on those asset returns beyond the 95th percentile of 20,000 simulated asset returns. The standard deviation of the worst 5% (CStdev) is substituted into formula 1 to obtain CDD:

$$CDD = \frac{\ln(V/F) + (\mu - 0.5\sigma_V^2)T}{CStdev_V \sqrt{T}} \tag{4}$$

and

$$CPD = N(-CDD) \tag{5}$$

Industry Ranking

We rank each industry according to risk for each of our risk measurements (Parametric VaR/CVaR/CDD, Historical VaR/CVaR/CDD, Monte Carlo VaR/CVaR/CDD, and DD) for the pre-GFC and GFC periods. A Spearman Rank Correlation Test is used to determine association between pre-GFC and GFC outcomes and between market and credit risk.

IV. Results

VaR and CVaR Results

Table 1. Comparison of Parametric, Historical, and Monte Carlo VaR and CVaR Outcomes

The table shows daily VaR and CVaR. Using methodology described in Section 4.2. VaR is calculated at a 95% confidence level. CVaR represents the average of the asset returns beyond VaR. The pre-GFC period incorporates the 7 years to 2006. The GFC period includes years 2007 – 2009. Rankings are from 1 (lowest risk) to 10 (highest risk). A negative change shows deterioration in risk ranking. A Spearman Rank Correlation Test is applied to determine correlation between parametric, historical and Monte Carlo Simulation rankings. Significance in ranking correlation at the 95% level is denoted by * and at the 99% level by **, with a '-' indicating no significance.

	Pre-GFC VaR									Pre GFC CVaR								
	Values			Ranking			Diff. in rank^2			Values			Ranking			Diff. in rank^2		
	Parametric	Historical	Monte Carlo	Parametric	Historical	Monte Carlo	Para / Hist	Para / Monte	Hist/Monte	Parametric	Historical	Monte Carlo	Parametric	Historical	Monte Carlo	Para / Hist	Para / Monte	Hist/Monte
Cons. Disc.	0.0239	0.0237	0.0286	7	6	7	1	0	1	0.0524	0.0592	0.0519	7	6	6	1	1	0
Cons. Stap.	0.0142	0.0140	0.0171	1	1	1	0	0	0	0.0441	0.0501	0.0455	3	4	4	1	1	0
Energy	0.0224	0.0223	0.0271	4	5	5	1	1	0	0.0389	0.0494	0.0405	1	3	2	4	1	1
Financials	0.0240	0.0267	0.0338	8	8	8	0	0	0	0.0496	0.0455	0.0435	4	1	3	9	1	4
Health Care	0.0235	0.0243	0.0284	6	7	6	1	0	1	0.0521	0.0584	0.0528	6	5	7	1	1	4
Industrials	0.0224	0.0217	0.0268	4	4	4	0	0	0	0.0543	0.0626	0.0530	8	8	8	0	0	0
IT	0.0431	0.0320	0.0424	10	9	10	1	0	1	0.0767	0.0607	0.0617	10	7	10	9	0	9
Materials	0.0200	0.0202	0.0239	3	3	3	0	0	0	0.0504	0.0699	0.0509	5	10	5	25	0	25
Telecomm.	0.0322	0.0343	0.0389	9	10	9	1	0	1	0.0590	0.0653	0.0605	9	9	9	0	0	0
Utilities	0.0168	0.0151	0.0198	2	2	2	0	0	0	0.0392	0.0463	0.0391	2	2	1	0	1	1
Total	0.0243	0.0234	0.0287				5	1	4	0.0517	0.0567	0.0499				50	6	44
						n	10	10	10						*n*	10	10	10
						r	0.970	0.994	0.976						*r*	0.697	0.964	0.733
						t	11.226	25.574	12.610						*t*	2.749	10.200	3.051
						critical value 95%	2.306	2.306	2.306						*critical value 95%*	2.306	2.306	2.306
						critical value 99%	3.355	3.355	3.355						*critical value 99%*	3.355	3.355	3.355
						significance	**	**	**						*significance*	*	**	*

	GFC VaR									GFC CVaR								
	Values			Ranking			Diff. in rank^2			Values			Ranking			Diff. in rank^2		
	Parametric	Historical	Monte Carlo	Parametric	Historical	Monte Carlo	Para / Hist	Para / Monte	Hist/Monte	Parametric	Historical	Monte Carlo	Parametric	Historical	Monte Carlo	Para / Hist	Para / Monte	Hist/Monte
Cons. Disc.	0.0341	0.0324	0.0402	5	6	5	1	0	1	0.1070	0.0935	0.0967	10	10	10	0	0	0
Cons. Stap.	0.0210	0.0209	0.0251	1	1	1	0	0	0	0.0538	0.0548	0.0532	3	3	5	0	4	4
Energy	0.0363	0.0318	0.0432	7	5	7	4	0	4	0.0655	0.0557	0.0530	5	5	4	0	1	1
Financials	0.0424	0.0401	0.0507	10	10	10	0	0	0	0.0816	0.0749	0.0715	9	9	9	0	0	0
Health Care	0.0264	0.0260	0.0314	3	3	2	0	1	1	0.0534	0.0506	0.0497	2	2	2	0	0	0
Industrials	0.0368	0.0363	0.0446	8	8	8	0	0	0	0.0699	0.0669	0.0651	7	7	7	0	0	0
IT	0.0355	0.0326	0.0431	6	7	6	1	0	1	0.0669	0.0637	0.0647	6	6	6	0	0	0
Materials	0.0390	0.0394	0.0456	9	9	9	0	0	0	0.0743	0.0721	0.0654	8	8	8	0	0	0
Telecomm.	0.0260	0.0231	0.0317	2	2	3	0	1	1	0.0496	0.0425	0.0434	1	1	1	0	0	0
Utilities	0.0329	0.0289	0.0386	4	4	4	0	0	0	0.0641	0.0549	0.0507	4	4	3	0	1	1
	0.0330	0.0311	0.0394				6	2	8	0.0686	0.0630	0.0614				0	6	6
						n	10	10	10						*n*	10	10	10
						r	0.964	0.988	0.952						*r*	1.000	0.964	0.964
						t	10.200	18.000	8.749						*t*	-	10.200	10.200
						critical value 95%	2.306	2.306	2.306						*critical value 95%*	2.306	2.306	2.306
						critical value 99%	3.355	3.355	3.355						*critical value 99%*	3.355	3.355	3.355
						significance	**	**	**						*significance*	**	**	**

The Spearman Rank Correlation Coefficient shows rank correlation at a 99% level of confidence for almost all the comparisons between 3 methods (Parametric, Historical, and Monte Carlo) in Table 1. The only exception is during the pre-GFC period, where Historical CVaR still shows a correlation with the other methods, but at the 95% level. This is mainly due to Materials having a higher historical CVaR than that estimated by parametric and Monte Carlo methods. Overall it can be said that there is association between all the methods in measuring VaR and CVaR.

We next consider whether there is association in industry rankings between pre-GFC and GFC periods. For expediency we have only shown the parametric method in Table 2, however very similar results are obtained for the Historical and Monte Carlo methods (as would be expected given the high ranking association between all three methods shown in Table 1).

As per Table 1, using VaR, Consumer Staples in Table 2 is shown to have a lowest risk both prior to and during the GFC. From a CVaR perspective, the lowest risk industry rankings are different, with lowest risk accorded to Energy pre-GFC and Telecommunication Services during the GFC. The Spearman rank correlation test shows no association between those industries that had the highest market risk pre-GFC and those that were riskiest during the GFC. This means that those industries that were riskiest pre-GFC are not the same as those that were riskiest during the GFC.

Table 2. VaR and CVaR Ranking Shifts

The table shows daily VaR and CVaR. VaR is calculated at a 95% confidence level, being the standard deviation of daily returns multiplied by 1.645 as per normal distribution tables. CVaR represents the average of the worst 5% of asset returns. The pre-GFC period incorporates the 7 years to 2006. The GFC period includes years 2007 – 2009. Rankings are from 1 (lowest risk) to 10 (highest risk). A negative change shows deterioration in risk ranking. A Spearman Rank Correlation Test is applied to determine correlation between pre-GFC and GFC rankings. Significance in ranking correlation at the 95% level is denoted by * and at the 99% level by **, with a '-' indicating no significance.

VaR:

Sector	VaR Pre GFC	VaR GFC	Change	VaR Rank Pre GFC	VaR Rank GFC	Diff in ranks	Diff in ranks^2
Consumer Discretionary	0.0239	0.0341	-0.0102	7	5	2	4
Consumer Staples	0.0142	0.0210	-0.0068	1	1	0	0
Energy	0.0224	0.0363	-0.0139	4	7	-3	9
Financials	0.0240	0.0424	-0.0184	8	10	-2	4
Health Care	0.0235	0.0264	-0.0029	6	3	3	9
Industrials	0.0224	0.0368	-0.0144	5	8	-3	9
Information Technology	0.0431	0.0355	0.0076	10	6	4	16
Materials	0.0200	0.0390	-0.0190	3	9	-6	36
Telecomm. Services	0.0322	0.0260	0.0062	9	2	7	49
Utilities	0.0168	0.0329	-0.0161	2	4	-2	4
	0.0242	0.0330	-0.0088				140.00
						n	10
						r	0.152
						t	0.434
						critical value 95%	2.306
						critical value 99%	3.355
						significance	-

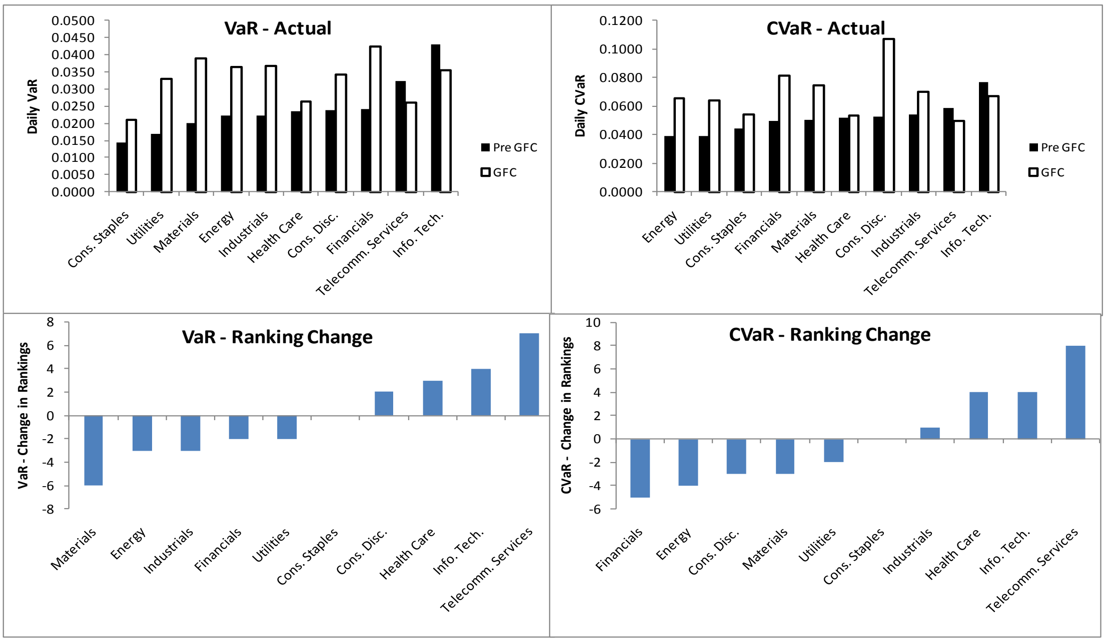
CVaR:

Sector	CVaR Pre GFC	CVaR GFC	Change	CVaR Rank Pre GFC	CVaR Rank GFC	Diff in ranks	Diff in ranks^2
Consumer Discretionary	0.0524	0.1070	-0.0546	7	10	-3	9
Consumer Staples	0.0441	0.0538	-0.0097	3	3	0	0
Energy	0.0389	0.0655	-0.0265	1	5	-4	16
Financials	0.0496	0.0816	-0.0320	4	9	-5	25
Health Care	0.0521	0.0534	-0.0013	6	2	4	16
Industrials	0.0543	0.0699	-0.0156	8	7	1	1
Information Technology	0.0767	0.0669	0.0097	10	6	4	16
Materials	0.0504	0.0743	-0.0240	5	8	-3	9
Telecomm. Services	0.0590	0.0496	0.0094	9	1	8	64
Utilities	0.0392	0.0641	-0.0249	2	4	-2	4
	0.0517	0.0686	-0.0169				160.00
						n	10
						r	0.030
						t	0.086
						critical value 95%	2.306
						critical value 99%	3.355
						significance	-

The industry showing the greatest improvement in ranking between the two periods is Telecommunications. The Financial sector showed the greatest ranking deterioration on a CVaR basis, and the Materials sector on a VaR basis. Whilst eight out of ten sectors showed deterioration in VaR and CVaR during the GFC, two industries (Telecommunications and Information Technology) showed an improvement. This is due to the pre-GFC period including the burst of the dot-com bubble, which severely affected these high-tech sectors. The deterioration in Financial sector rankings is expected, given that banks led the GFC, and the problems that were experienced by this sector as outlined in the Section 2 of this study.

The upper two graphs in Figure 1 show actual VaR and CVaR as per Table 2. The solid bar (pre-GFC) goes from lowest to highest risk, showing a steady progression in risk. The non-solid bar (post-GFC) shows a completely different pattern, illustrating the difference between the pre-GFC and the GFC outcomes. The bottom two graphs in Figure 1 illustrate those industries which had the greatest shift in rankings, notably Materials, Energy, and Financials on the downside (due to aspects such as volatile commodity prices and the well known poor performance of the banking sector during the GFC) and Health Care, IT and Telecommunication Services on the upside (due to less volatility among essential services and the high volatility of the Technology sector during the early pre-GFC period).

Figure 1. VaR and CVaR Values and Ranking Changes



DD and CDD

Table 3 shows DD and CDD values and sector ranking changes for pre-GFC as compared to GFC. Again, for expediency, we only show the parametric CDD method in Table 3. However similar results were obtained for Historical and Monte Carlo methods as expected given the high correlation between each of the CVaR methods shown in Table 4. Consumer Discretionary, Financials, Utilities and Energy had the worst ranking movement. The Consumer Discretionary (discretionary products are more affected during downturns) and Financials (well known problems during GFC) Sectors both illustrate how rankings change during extreme circumstances. Pre-GFC, both groups show worse CDD rankings than DD rankings, and both show deterioration in rankings during the GFC. During the GFC, Financials rank worst for DD and CDD. Entities in this sector come precariously close to default during the worst 5% of the GFC, with a CDD of 0.65 equating to a PD of

25% using equation 5, due to a combination of high volatility and high leverage.

Financials have capital ratios of approximately 5%, much lower than other sectors.

Table 3. DD and CDD Ranking Shifts

DD (measured by number of standard deviations) is calculated using equation 1. CDD is based on the worst 5% of asset returns and is calculated using equation 4. Pre-GFC incorporates the 7 years to 2006. GFC includes 2007 – 2009. Rankings are from 1 (lowest risk) to 10 (highest risk). A negative change shows deterioration in risk ranking. A Spearman Rank Correlation Test is applied to determine correlation between pre-GFC and GFC rankings. Significance in ranking correlation at the 95% level is denoted by * and at the 99% level by **, with '-' indicating no significance. The equity ratio is the total equity as per the firm's balance sheet as a percentage of total assets.

DD:

Sector	DD Pre GFC	DD GFC	Change	DD Rank Pre GFC	DD Rank GFC	Diff in ranks	Diff in ranks^2	Equity
Consumer Discretionary	6.13	3.48	-2.66	5	9	-4.00	16.00	28.0%
Consumer Staples	6.88	5.30	-1.58	3	2	1.00	1.00	31.3%
Energy	6.82	3.98	-2.84	4	7	-3.00	9.00	36.4%
Financials	6.00	2.77	-3.23	6	10	-4.00	16.00	5.3%
Health Care	5.62	5.30	-0.33	8	3	5.00	25.00	53.0%
Industrials	6.94	4.19	-2.75	2	4	-2.00	4.00	26.6%
Information Technology	3.56	4.07	0.51	10	6	4.00	16.00	44.0%
Materials	5.98	3.88	-2.10	7	8	-1.00	1.00	43.2%
Telecomm. Services	5.20	6.32	1.12	9	1	8.00	64.00	29.4%
Utilities	8.31	4.15	-4.16	1	5	-4.00	16.00	26.6%
	6.14	4.34	-1.80				168.00	
						n	10	
						r	-0.018	
						t	-0.051	
						critical value 95%	2.306	
						critical value 99%	3.355	
						significance	-	

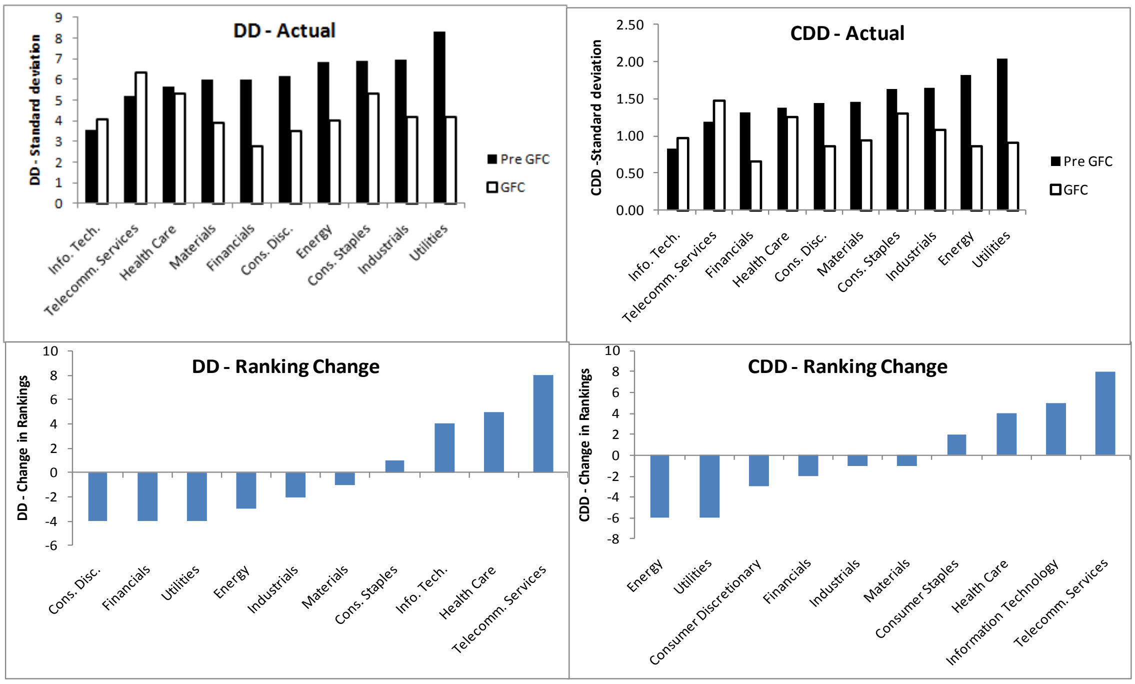
CDD:

Sector	CDD Pre GFC	CDD GFC	Change	CDD Rank Pre GFC	CDD Rank GFC	Diff in ranks	Diff in ranks^2
Consumer Discretionary	1.45	0.86	-0.58	6	9	-3.00	9.00
Consumer Staples	1.62	1.31	-0.32	4	2	2.00	4.00
Energy	1.81	0.87	-0.95	2	8	-6.00	36.00
Financials	1.31	0.65	-0.66	8	10	-2.00	4.00
Health Care	1.38	1.25	-0.13	7	3	4.00	16.00
Industrials	1.65	1.09	-0.57	3	4	-1.00	1.00
Information Technology	0.83	0.96	0.14	10	5	5.00	25.00
Materials	1.46	0.94	-0.52	5	6	-1.00	1.00
Telecomm. Services	1.20	1.48	0.28	9	1	8.00	64.00
Utilities	2.04	0.91	-1.12	1	7	-6.00	36.00
	1.47	1.03	-0.44				196.00
						n	10
						r	-0.188
						t	-0.541
						critical value 95%	2.306
						critical value 99%	3.355
						significance	-

Note, for simplicity, in Table 3 we only show DD and CDD figures (not PD and CPD figures) given that this will have no impact on rankings (the worst/best ranked DD will also have the worst/best ranked PD per formulas 1,2,4 and 5).

Figure 1 illustrates differences between pre-GFC and GFC outcomes as shown in Table 3. The completely different pattern in solid and non-solid bars in the top 2 graphs illustrates how relative risk has changed between the industries, and the bottom two graphs illustrate how this impacts on industry rankings.

Figure 2. DD and CDD Values and Ranking Changes



The less discretionary sectors such as Consumer Staples and Health Care fare well on all measures. Health Care's improvement in rankings during the GFC is due to a combination of relatively lower volatility and a stronger equity ratio. Telecommunications and Technology show significant improvement in credit rankings due to the lower volatility noted in the earlier discussion on VaR and CVaR.

Table 4. Comparison of Parametric, Historical, and Monte Carlo CDD and CVaR outcomes

The table shows CDD using methodology described in Section 4.3. The pre-GFC period incorporates the 7 years to 2006. The GFC period includes years 2007 – 2009. Rankings are from 1 (lowest risk) to 10 (highest risk). A Spearman Rank Correlation Test is applied to determine correlation between parametric, historical and Monte Carlo Simulation rankings. Significance in ranking correlation at the 95% level is denoted by * and at the 99% level by **, with a '-' indicating no significance.

	Pre-GFC CDD									GFC CDD								
	Values			Ranking			Diff. in rank^2			Values			Ranking			Diff. in rank^2		
	Parametric	Historical	Monte Carlo	Parametric	Historical	Monte Carlo	Para / Hist	Para / Monte	Hist/Monte	Parametric	Historical	Monte Carlo	Parametric	Historical	Monte Carlo	Para / Hist	Para / Monte	Hist/Monte
Cons. Disc.	1.45	1.31	1.52	6	6	4	0	4	4	0.86	0.97	0.90	9	8	9	1	0	1
Cons. Stap.	1.62	1.41	1.49	4	4	6	0	4	4	1.31	1.34	1.38	2	2	2	0	0	0
Energy	1.81	1.47	1.74	2	2	3	0	1	1	0.87	1.07	1.05	8	5	7	9	1	4
Financials	1.31	1.36	1.49	8	5	5	9	9	0	0.65	0.69	0.71	10	10	10	0	0	0
Health Care	1.38	1.28	1.35	7	7	8	0	1	1	1.25	1.31	1.29	3	3	3	0	0	0
Industrials	1.65	1.46	1.76	3	3	2	0	1	1	1.09	1.17	1.15	4	4	4	0	0	0
IT	0.83	1.07	0.99	10	9	10	1	0	1	0.96	1.01	1.02	5	7	8	4	9	1
Materials	1.46	1.07	1.37	5	8	7	9	4	1	0.94	0.93	1.09	6	9	6	9	0	9
Telecomm.	1.20	1.03	1.18	9	10	9	1	0	1	1.48	1.80	1.76	1	1	1	0	0	0
Utilities	2.04	1.73	2.11	1	1	1	0	0	0	0.91	1.07	1.12	7	6	5	1	4	1
Total	1.48	1.32	1.50				20	24	14	1.03	1.14	1.15				24	14	16
						n	10	10	10						*n*	10	10	10
						r	0.879	0.855	0.915						*r*	0.855	0.915	0.903
						t	5.209	4.654	6.421						*t*	4.654	6.421	5.946
						critical value 95%	2.306	2.306	2.306						*critical value 95%*	2.306	2.306	2.306
						critical value 99%	3.355	3.355	3.355						*critical value 99%*	3.355	3.355	3.355
						significance	**	**	**						*significance*	**	**	**

The table shows very high correlation (99% confidence level) between all 3 methods, supporting the CDD outcomes for the parametric rankings shown in Table 3 and Figure 2.

Market versus Credit Outcomes

The final aspect considered by this study is whether there is association between market and credit risk rankings. Whilst some association is expected (due to share price fluctuations, being a component of both), there are also differences between the key components of the models (i.e. the balance sheet components of the credit model) which could affect the outcomes. To test for association, DD rankings are correlated with each of the 3 Market VaR methods (parametric, historical and Monte Carlo Simulation) for both the pre-GFC and GFC periods. CVaR rankings are compared to corresponding CDD rankings (parametric CVaR compared to parametric CDD, historical CVaR to historical CDD, Monte Carlo CVaR Monte Carlo CDD). Results are presented in Table 5 in Appendix 1. In every instance, correlation is found at either the 95% or 99% level, meaning there is a high degree of similarity between those industries which are risky from a market perspective and those which are risky from a credit perspective. Where a lower level of correlation is found (95% as opposed to 99%), it is primarily due to Financials and Industrials, both of which have low equity levels as per Table 3.

V. Conclusions

The study has shown how relative sector risk changes during extreme circumstances for both market and credit risk. Those industries that were riskiest pre-GFC are not the same industries that were riskiest during the GFC, and even within each of the two periods, there are changes in risk rankings using conditional as compared to non-conditional metrics. The study has also shown that these findings hold across a range of metrics, ten of which were used in this study (Parametric VaR/CVaR/CDD, Historical VaR/CVaR/CDD, Monte Carlo VaR/CVaR/CDD, and DD). This has important implications for investors or lenders. Portfolio decisions made on non-conditional measures such as VaR may not accurately identify the highest risk sectors. Conditional measures such as CVaR and CDD will assist in identifying those sectors having the highest risk during the most extreme circumstances, which is when firms are most likely to fail.

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VI. Appendix 1

Table 5. Market and Credit Risk Comparison

The top segment of the table shows market risk industry rankings for all VaR and CVaR metrics as per Table 1. The second segment shows credit risk industry rankings for all DD and CDD rankings for all metrics as per Tables 3 and 4. The third segment compares each market risk column in the top segment with the corresponding credit risk column in the second segment (for example Parametric CVaR is compared with Parametric CDD, Historical CVaR with Historical CDD and so on.) As there is only one DD metric, (as compare to 3 metrics for each of VaR CVaR and CDD), this is termed standard DD and compared to each VaR metric. The pre-GFC period incorporates the 7 years to 2006. The GFC period includes years 2007 – 2009. Rankings are from 1 (lowest risk) to 10 (highest risk). A Spearman Rank Correlation Test is applied to determine correlation between parametric, historical and Monte Carlo Simulation rankings. Significance in ranking correlation at the 95% level is denoted by * and at the 99% level by **, with a '-' indicating no significance.

	Parametric	Parametric	Parametric	Parametric	Historical	Historical	Historical	Historical	Monte Carlo	Monte Carlo	Monte Carlo	Monte Carlo
Market Risk	Pre VaR	Pre CVAR	GFC Var	GFC CVaR	Pre VaR	Pre CVAR	GFC VaR	GFC CVaR	Pre VaR	Pre CVAR	GFC Var	GFC CVaR
Cons. Disc.	7	7	5	10	6	6	6	10	7	6	5	10
Cons. Stap.	1	3	1	3	1	4	1	3	1	4	1	5
Energy	4	1	7	5	5	3	5	5	5	2	7	4
Financials	8	4	10	9	8	1	10	9	8	3	10	9
Health Care	6	6	3	2	7	5	3	2	6	7	2	2
Industrials	4	8	8	7	4	8	8	7	4	8	8	7
IT	10	10	6	6	9	7	7	6	10	10	6	6
Materials	3	5	9	8	3	10	9	8	3	5	9	8
Telecomm.	9	9	2	1	10	9	2	1	9	9	3	1
Utilities	2	2	4	4	2	2	4	4	2	1	4	3
	Standard	Parametric	Standard	Parametric	Standard	Historical	Standard	Historical	Standard	Monte Carlo	Standard	Monte Carlo
Credit Risk	Pre DD	Pre CDD	Post DD	Post CDD	Pre DD	Pre CDD	Post DD	Post CDD	Pre DD	Pre CDD	Post DD	Post CDD
Cons. Disc.	5	6	9	9	5	6	9	8	5	4	9	9
Cons. Stap.	3	4	2	2	3	4	2	2	4	6	3	2
Energy	4	2	7	8	4	2	7	5	3	3	7	7
Financials	6	8	10	10	8	5	10	10	8	5	10	10
Health Care	8	7	2	3	7	7	3	3	7	8	2	3
Industrials	2	3	4	4	2	3	6	4	2	2	4	4
IT	10	10	6	5	9	9	5	7	10	10	6	8
Materials	7	5	8	6	6	8	8	9	6	7	8	6
Telecomm.	9	9	1	1	10	10	1	1	9	9	1	1
Utilities	1	1	5	7	1	1	4	6	1	1	5	5
Difference[2]	Pre VaR / DD	Pre CVAR / CDD	GFC Var / DD	GFC CVaR / CDD	Pre VaR / DD	Pre CVAR / CDD	GFC VaR / DD	GFC CVaR / CDD	Pre VaR / DD	Pre CVAR / CDD	GFC Var / DD	GFC CVaR / CDD
Cons. Disc.	4	1	16	1	1	0	9	4	4	4	16	1
Cons. Stap.	4	1	1	1	4	0	1	1	9	4	4	9
Energy	0	1	0	9	1	1	4	0	4	1	0	9
Financials	4	16	0	1	0	16	0	1	0	4	0	1
Health Care	4	1	1	1	0	4	0	1	1	1	0	1
Industrials	4	25	16	9	4	25	4	9	4	36	16	9
IT	0	0	0	1	0	4	4	1	0	0	0	4
Materials	16	0	1	4	9	4	1	1	9	4	1	4
Telecomm.	0	0	1	0	0	1	1	0	0	0	4	0
Utilities	1	1	1	9	1	1	0	4	1	0	1	4
	37	46	37	36	20	56	24	22	32	54	42	42
n	10	10	10	10	10	10	10	10	10	10	10	10
r	0.776	0.721	0.776	0.782	0.879	0.661	0.855	0.867	0.806	0.673	0.745	0.745
t	3.477	2.945	3.477	3.547	5.209	2.489	4.654	4.914	3.852	2.572	3.163	3.163
critical val. 95%	2.306	2.306	2.306	2.306	2.306	2.306	2.306	2.306	2.306	2.306	2.306	2.306
critical val. 99%	3.355	3.355	3.355	3.355	3.355	3.355	3.355	3.355	3.355	3.355	3.355	3.355
significance	**	*	**	**	**	*	**	**	**	*	*	*