

## **Identifying European Industries with Extreme Default Risk: Application of CVaR Techniques to Transition Matrices**

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*Transition matrices help lenders to analyze credit risk by identifying the probability of a loan (or portfolio of loans) transitioning from one risk grade to another, including the risk of transitioning to a default grade. Traditionally, transition matrices have been used to measure credit Value at Risk (VaR), which is an estimate of losses below a selected threshold. Conditional Value at Risk (CVaR) measures the extreme risk beyond VaR. We use enhanced transition matrix CVaR techniques to measure the relative credit risk of ten European industries. This helps lenders identify those industries exposed to extreme default risk. The paper finds no correlation between VaR and CVaR metrics, meaning that VaR techniques fail to adequately identify the most risky industries which are most likely to experience defaults in times of extreme risk. The CVaR techniques, on the other hand, do identify this extreme industry risk. Over concentration in high risk industries can contribute to bank losses. The techniques in this study can assist lenders in identifying high risk industries which may need additional provisions, capital or industry exposure limits.*

**Field of Research:** Banking

**JEL Codes:** G01 and G21

### **1. Introduction**

The Global Financial Crisis (GFC) starkly highlighted the critical role that credit risk can play in regards to the soundness of financial institutions and economic stability. It is therefore essential that credit risk in extreme circumstances is accurately measured and understood. Essential to this process is an understanding of which industries are potentially the most risky in dynamic economic circumstances. Over-concentration of exposure in vulnerable industries can be a significant contributor to difficulties experienced by lenders in economic downturns. Understanding credit risk in an industry can assist a lender in setting credit policies and lending officer discretions, as well as ensuring adequate provisions and capital allocation for exposures to that industry.

This article aims, not only measure the relative credit risk of European industries, but also to improve the ability of current transition matrix techniques in measuring this risk. We will do this by first, through a literature survey, identifying the weaknesses of the traditional transition matrix Value at Risk (VaR) techniques, and then incorporating innovative Monte Carlo Conditional Value at Risk (CVaR) techniques into the model to better measure extreme risk. We explore two key research questions. Firstly, using a portfolio of S&P Euro entities spread among ten industries, we seek to identify which European industries are most (least) risky from a credit perspective, using both VaR

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and CVaR. Secondly, we examine whether there is significant difference between the VaR and CVaR measures of relative risk. The inclusion of CVaR addresses a key shortcoming of traditional transitional matrix methodology. Transition matrices measure the probability of a borrower transitioning from one credit rating to another, including the probability of transitioning to a default rating. Traditional modelling per the Creditmetrics approach, is used to measure VaR, a measure of risk below a specified threshold. The problem with VaR is that it says nothing of losses beyond VaR. CVaR, on the other hand, measures losses beyond VaR and is an increasingly popular method of measuring extreme insurance and market risk. It has also been incorporated into transition matrix methodology to optimise extreme credit risk portfolios as discussed in our literature survey. Using modified Monte Carlo CVaR methodology, as discussed in sections 2 and 3, we measure the relative extreme risk of European industries.

We find no correlation between traditional VaR measures and our modified CVaR measures in measuring relative industry risk. This is because VaR only measures risk below a specified threshold (such as 95% or 99%), and says nothing of the risks beyond that threshold. This means VaR fails to identify those industries which have the highest extreme risk and which are therefore most likely to experience defaults during extreme circumstances such as those seen during the GFC. Conversely, the CVaR model does measure this extreme risk. The lack of correlation between these two measures means that not all the industry portfolios are normally distributed, with some industries having higher tail risk, and that those industries which are the most (least) risky from a VaR perspective are not the same industries which are the most (least) risky from a CVaR perspective. Our study will show, for example, that the financial and consumer discretionary industries have a larger tail risk than other industries. The shortcomings of VaR are elaborated on in our literature survey.

To our knowledge, there are no other studies applying transitional matrix techniques to the measurement of relative CVaR among industries in Europe. This study addresses that gap and provides new insights into industry credit risk in Europe. The findings in this study can assist lenders in several facets of risk management, such as capital allocation, managing sector risk concentration, setting credit policies, pricing, and allocating lending discretions to officers according to industry. The study is arranged in the following order. Section 2 provides a review of the literature, including an overview of CVaR applications and transition matrices. Section 3 explains the data and methodology. Section 4 presents and analyses the results. Section 5 provides conclusions and recommendations for further studies.

## **2. Literature Survey**

As per the introduction, identifying sectoral overconcentration is essential to managing portfolio credit risk. Several studies highlight the importance of this issue. Overconcentration of sectoral credit risk was found by Jackson (1996) to be a key contributor to past bank failures in the United Kingdom. Hibbeln (2010) examines risk concentrations as a primary cause of bank risk and reports that neglecting industry specific effects can lead to inappropriate capital requirements for credit risk. In a study of 13 banking crises, the Basel Committee on Banking Supervision (2004) cited risk concentration as a factor in nine of these. Basel II and Basel III (Bank for International Settlements, 2004, 2011) both direct banks to cover risk concentrations and risk rating systems in their assessment of capital adequacy for credit risk.

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Transition matrix VaR methodology was introduced and made popular as a credit risk tool by Creditmetrics (Gupton, Finger, & Bhatia, 1997) which is part of the Riskmetrics group who introduced and popularised VaR as a measure of market risk. Transition matrix methodology has been used for a number of credit related aspects such as bond pricing (Lando, 2004), business cycle sensitivity (Fei Fei & Kalotychou, 2012) consumer credit ratings (Malik & Thomas, 2012). Most often it is used to model corporate loans (e.g. Das, Duffie, Kapadia, & Saiata, 2007; Bajaj, 2010), either an individual corporate loan asset, or portfolio of loans. We discuss this model further in Section 2.1 and, given the importance of sectoral concentration risk discussed in the prior paragraph, we will go on to show how we can use the model to measure sectoral risk, using CVaR techniques.

Whilst CVaR is primarily used in the insurance industry, it is also gaining in the credit industry. This is because credit losses are characterised by large number of small earnings and a small number of large losses. Thus the distribution is heavily skewed. VaR does not provide any information on the excess / extreme losses. By contrast CVaR does quantify the losses experienced in the tail end of the distribution. Since CVaR is greater than or equal to VaR, portfolios with a high VaR also have a high CVaR. Another limitation of VaR is that it has been shown to not meet the requirements of 'coherent' risk measures such as subadditivity (Artzner, Delbaen, Eber, & Heath, 1997, 1999). Pflug (2000) proved that VaR is a coherent risk measure, not reflecting the undesirable characteristics of VaR.

CVaR applications, including credit risk, were largely pioneered in a series of studies which focus on portfolio optimisation (Andersson, Mausser, Rosen, & Uryasev, 2000; Rockafellar & Uryasev, 2002; Rockafellar, Uryasev, & Zabarankin, 2006; Uryasev & Rockafellar, 2000). The Andersson et al. (2000) study outlines the CVaR transition matrix approach used by these authors to calculate CVaR. For ease of reference, as Uryasev is the common denominator in these papers we shall hereafter refer to this CVaR credit approach as the 'Uryasev CVaR model'. Other papers which apply CVaR to portfolio optimisation problems include Alexander & Baptista (2003), and Alexander, Coleman & Li (2003). CVaR has also been used to measure credit risk using transition matrices in an Australian setting (Allen, Kramadibrata, Powell, & Singh, 2011, 2012b; Allen & Powell, 2009). Whilst CVaR techniques have been applied to structural models (which are based on market fluctuations) in a European study (Allen, Powell, & Singh, 2011), we are not aware of their application to transition matrices to measure European sectoral credit risk. The techniques used in this study are largely developed from the Creditmetrics VaR and Uryasev CVaR models mentioned above and we thus provide some detail of these approaches below.

### 2.1 Creditmetrics

The Creditmetrics model (Gupton, et al., 1997) calculates VaR using transition matrices which are based upon obtaining the probability ( $\rho$ ) of a bank customer transitioning from one grade to another as shown for the following BBB example:

BBB	$\rho_{AAA}$	$\rho_{AA}$	$\rho_A$	$\rho_{BBB}$	$\rho_{BB}$	$\rho_B$	$\rho_{CCC/C}$	$\rho_D$
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The model obtains forward zero curves for each rating category (based on the pricing spread between the bond rating and a risk free rate) expected to exist in a year's time. Using the zero curves, the model calculates the market value (V) of the loan, including

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the coupon, at the one year risk horizon. Effectively, this means estimating the change in credit spread that results from rating migration from one rating category to another, then calculating the present value of the loan at the new yield. The following example values a 5 year loan, paying a coupon of 6%, where  $r$  = the risk free rate (the rate on government bonds) and  $s$  = the spread between a government bond and corporate bonds of a particular category, say AA:

$$V = 6 + \frac{6}{(1+r_1+s_1)} + \frac{6}{(1+r_2+s_2)^2} + \frac{6}{(1+r_3+s_3)^3} + \frac{106}{(1+r_4+s_4)^4} \quad (1)$$

The above is calculated for each rating (yields for government and corporate bonds can be obtained from central bank websites). Transition probabilities, as obtained from the S&P European transition table (Standard and Poor's, 2012), are multiplied by  $V$  for each rating category to obtain a weighted probability. Based on the revised probability table, VaR is obtained by calculating the probability weighted portfolio variance and standard deviation ( $\sigma$ ), and then calculating VaR using a normal distribution (for example  $1.645\sigma$  for a 95% confidence level). Thus, the Creditmetrics model effectively comprises 3 core items, which act together to compute VaR: the underlying rating, the transition probability and the risk spread. The transition probabilities are updated by Standard and Poor's and Moody's (and usually published annually) based on the prevailing market circumstances. Thus the probabilities used in this model at 2009, when the market was just recovering from the worst of the GFC, should reflect the circumstances prevailing at that time. The risk spread is a market based yield and therefore effectively acts as a control for of all aspects affecting the risk of a rated entity in the model, such as economic circumstances. As circumstances change, the risk spread changes, and hence the VaR changes. Thus in the same way as the spread affects the price of a bond, it also affects the transition matrix VaR. However, despite this inbuilt control measure, it still has the weakness (which the CVaR model does not) of only measuring up to the VaR threshold. Creditmetrics also provide methodology for calculating VaR for diversified (correlated) multivariate portfolios which involves calculating the joint probabilities of each pair of assets in the portfolio and then calculating an overall portfolio standard deviation based on standard covariance and correlation formulae.

Creditmetrics use Monte Carlo modelling as an alternate approach to estimating VaR. This approach generates thousands (usually about 20,000) of random numbers based on a normal distribution assumption. These numbers are 'mapped' to credit ratings using asset thresholds ( $Z$ ) calculated for each rating category as follows:

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

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

and so on, where  $\Phi$  denotes the cumulative normal distribution, and

$$Z_{\text{Def}} = \Phi^{-1}\sigma \quad (2)$$

A return falling between thresholds receives the rating applying to threshold above it. To distinguish the two Creditmetrics approaches described above, we refer to them as the Creditmetrics standard method and the Creditmetrics Monte Carlo method.

### 2.2 The Uryasev Cvar Model

Conditional Value-at-Risk (CVaR) is closely related to VaR. CVaR is equal or greater than VaR. It is the conditional expected loss under the condition it exceeds VaR. CVaR is also called mean excess loss, mean shortfall, or tail VaR.  $\beta$ -VaR is a value with probability  $\beta$  the loss will not exceed  $\beta$ -VaR. CVaR is the mean value of the worst  $(1 - \beta) \times 100\%$  losses. For instance, if we are measuring VaR at a 95% confidence level ( $\beta=0.95$ ), CVaR is the average of the 5% worst losses (Uryasev & Rockafellar, 1999). The Uryasev study (Andersson, et al., 2000) sample included 197 bonds issued by 86 obligors in 29 countries. 20,000 scenarios were generated using Creditmetrics Monte Carlo methodology (as discussed in Section 2.1), with correlated CVaR then calculated based on the worst 5% returns. Each country's percentage contribution to total CVaR was then calculated. For example, their portfolio showed a total CVaR of \$1,320m USD. Venezuela's contribution to this was \$159m which is 12% of the portfolio. Venezuela was allocated a CVaR of 12% being their contribution to the portfolio. Venezuela's contribution was calculated as being the difference between the total portfolio risk, and the risk of the portfolio without Venezuela. Being a correlated CVaR, each country's contribution is less than their total exposure, and in Venezuela's case equated to 40% of their total CVaR exposure of \$398m, equalling \$159m. This 40% is termed marginal risk.

The idea behind calculating each country's CVaR as a percentage of the portfolio is to maximize returns by suppressing obligors with higher risk exposures. Whilst this is useful in optimising a portfolio, this portfolio contribution method does not tell us about the relative risk of the portfolio components. This is because the portfolio contribution is impacted by size. Thus in a portfolio with two equally risky countries (or industries) but one's size is twice as large as the other, the larger portfolio will have double the contribution of the smaller. As we are more interested in a measure of riskiness of an industry, rather than their contribution based on size, we modify the Uryasev approach per the methodology in Section 3.

### 3. Methodology

Data includes the 180 companies comprising the S&P Euro index (Standard & Poor's, 2012), which has a market cap exceeding 2.2 trillion. Twelve countries (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxemburg, Netherlands, Portugal and Spain) are included in the index. We compare the relative credit risk of the ten sectors in the index, based on the General Industry Classification System (GICS), including consumer discretionary, consumer staples, industrials, energy, financials, healthcare, information technology, materials, telecommunication services, and utilities. We use the Standard & Poor's (S&P) European transition probabilities at 2009 (Standard & Poor's, 2012). The most critical years of the Global Financial Crisis are 2007-2009 and we use 2009 default ratings because this is the final of these 3 GFC years and credit ratings should capture the GFC events. We obtain ratings from S&P and Moody's websites at 2009. For consistency we use S&P ratings where available and map Moody's ratings to S&P, using mapping provided by the Bank for International Settlements (2011). Unrated entities are classified as BB, consistent with Basel II (Bank for International Settlements, 2004) where BB ratings have the same weighting as unrated entities.

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Table 1 summarises the rating spread of our data at 2009. For simplicity, ratings are grouped into bands, with the AA band incorporating AA+, AA and AA-, the A band incorporating A+, A, and A- and so on. The CC band incorporates everything from CCC to C. These bands are consistent with the bands in which the S&P and Moody's transition matrix default probabilities are reported. We see that no entities have AAA ratings, and only Consumer Discretionary, Financials and Telecommunications have ratings from B downwards.

**Table 1: Rating spread**

	Number	Debt Percentage								Total
		AAA	AA	A	BBB	BB	B	CC	D	
Energy	7	0.0%	0.0%	45.7%	37.1%	17.2%	0.0%	0.0%	0.0%	100.0%
Materials	18	0.0%	13.2%	53.2%	19.8%	13.8%	0.0%	0.0%	0.0%	100.0%
Industrials	29	0.0%	9.0%	12.4%	31.4%	47.2%	0.0%	0.0%	0.0%	100.0%
Consumer Discretionary	30	0.0%	1.4%	37.8%	40.6%	18.0%	1.2%	1.0%	0.0%	100.0%
Consumer staples	15	0.0%	9.4%	42.3%	23.5%	24.8%	0.0%	0.0%	0.0%	100.0%
Health Care	8	0.0%	0.0%	17.8%	35.4%	46.8%	0.0%	0.0%	0.0%	100.0%
Financials	37	0.0%	0.3%	52.9%	10.9%	33.4%	1.4%	1.2%	0.0%	100.0%
Information Technology	8	0.0%	29.5%	17.7%	14.9%	37.9%	0.0%	0.0%	0.0%	100.0%
Utilities	16	0.0%	0.0%	45.3%	14.1%	40.6%	0.0%	0.0%	0.0%	100.0%
Telecommunications	9	0.0%	24.7%	46.6%	4.2%	22.6%	1.9%	0.0%	0.0%	100.0%
Probability of Default		0.00%	0.00%	0.18%	0.56%	0.83%	10.16%	48.97%	100%	

Industry, based on the Global Industry Classification System (GICS), is shown in column 1. The total number of entities (included in the S&P Euro index) in each industry, is shown in Column 2. Percentage of total debt (per rating) for entities in each industry is shown in the remaining columns. Debt is based on the total liabilities (obtained from Datastream) of each entity in that industry. The S&P 2009 European probability of default for each rating band is shown at the bottom of the table.

The S&P probabilities of default in the table are calculated by Standard and Poor's based on their database of actual defaults of European companies in 2009. These figures show that there is negligible default associated with AAA and AA rated industries. Default levels increase dramatically from B downwards.

Whilst there are a different number of companies in each industry, this is how the S&P Euro is made up, and the industry split is broadly representative of the entire European market, with the companies in the S&P Euro representing approximately 40% of the entire European market by market cap. We see that the financial industry has the highest percentage of entities by number on the index, followed by Consumer Discretionary and Industrials. The top ten largest entities on the index by Market Capitalisation (in order of size, starting from the largest) are Total SA (Energy), Sanofi Aventis (Health Care), Siemens AG (Industrials), BASF SE (Materials), ENI SpA (Energy), Anheuser Busch Inbev NV (Consumer Staples), Unilever NV (Consumer Staples), Banco Santander SA, Telefonica SA (Telecommunication Services), and SAP AG (Information Technology).

To calculate VaR, we use the Creditmetrics standard approach per Section 2.1. The standard approach is not appropriate for CVaR given the small number of returns (5%) and we thus use the Creditmetrics Monte Carlo approach (which Creditmetrics applied to measure VaR and which we now apply to CVaR) per Section 2.1 to generate 20,000 return scenarios based on random numbers. Unlike the Uryasev approach, instead of mapping the *total* 5% of worst returns to ratings per equation 2, we map the 5% of worst returns for *each industry* to ratings per equation 2. We illustrate this with

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an example. Assume 2 industries, X (debt \$5m) and Y (debt \$10m) form a portfolio of \$15m. Assume the 5% of worst ratings for both industries are all 'C'. Under our approach, both industries will have an identical CVaR, allowing us to compare their relative risk. Under the Uryasev approach Y will have double the CVaR of B as it double the size, thereby contributing more to total portfolio risk. Therefore the Uryasev approach is more useful for measuring overall contribution to a portfolio, whereas our method is more useful when comparing the relative risk between industries.

Our two research questions, as outlined in the introduction, related firstly to the identification of which industries were the most (least risky). To measure this, we first calculate VaR and CVaR as above, and then rank the industries from best to worst on each of these two metrics. The second question was whether there was a difference in the VaR and CVaR rankings. In answering this research question, we provide the following hypothesis:

**H<sub>1</sub>:** There is no association between VaR and CVaR rankings.

We test for significance in ranking difference using the Spearman rank correlation coefficient (explained further in Table 2). As a robustness check, we will also undertake correlation on the actual values, not just the rankings.

### 4. Results and Analysis

**Table 2: VaR and CVaR Results**

Industry	Number of Companies	VaR	CVaR
Consumer Discretionary	30	0.0867	0.1499
Consumer Staples	15	0.0621	0.1091
Energy	7	0.0666	0.1109
Financials	37	0.0719	0.1671
Health Care	8	0.0856	0.1327
Industrials	29	0.0749	0.1448
Information Technology	8	0.0635	0.1260
Materials	18	0.0544	0.1105
Telecommunication Service	9	0.0532	0.1140
Utilities	16	0.0701	0.1110
Total	177	0.0716	0.1223

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Industry	VaR	CVaR	Diff in ranks	Diff in ranks <sup>2</sup>
Consumer Discretionary	2	2	0.00	0.00
Consumer staples	8	10	-2.00	4.00
Energy	6	8	-2.00	4.00
Financials	4	1	3.00	9.00
Health Care	1	4	-3.00	9.00
Industrials	3	3	0.00	0.00
Information Technology	7	5	2.00	4.00
Materials	9	6	3.00	9.00
Telecommunication Service	10	7	3.00	9.00
Utilities	5	9	-4.00	16.00
			Sum	64.00
			<i>N</i>	10
			<i>R</i>	0.612
			<i>T</i>	2.189
			<i>critical value</i> 95%	2.306
			<i>critical value</i> 99%	3.355
			<i>significance</i>	-

The top half of the table shows VaR and CVaR by amount. VaR is calculated at the 95% level of confidence using Creditmetrics standard methodology. CVaR uses Monte Carlo methodology and is based on the worst 5% of simulated rankings. Transitions are based and S&P European 2009 transition probabilities. The bottom half shows VaR and CVaR rankings, with 1 being the highest risk and 10 being the lowest. A positive ranking change indicates risk has increased. A negative ranking change means risk has decreased. A Spearman ranking correlation test for association between VaR and CVaR ranking shows no significance in association. This test is shown below the table, with *N* being the number of industries, *R* being the correlation coefficient, and *T* being the test value which will exceed the critical value if it is significant.

On a VaR basis, Health Care shows the highest risk and Telecommunications the lowest risk. On a CVaR basis Financials shows the highest risk and Consumer Staples the lowest risk. Industries which remain fairly mid table on both measurements are Industrials and Information Technology. A Spearman rank correlation coefficient shows that, at a 95% level of confidence, there is no association between VaR and CVaR. This means that the portfolios are not normally distributed, with some industries having higher tail risk, and that those industries which are the most (least) risky from a VaR perspective are not the same industries which are the most (least) risky from a CVaR perspective.

In volatile times, the spread between the ratings of riskier industries tends to increase to a greater extent than less riskier industries. The 'Difference in Ranks' column in Table 2 shows which industries have the greatest difference between VaR and CVaR. These differences indicate that a lender who optimised this portfolio according to VaR, would have greater weightings of Financials, Telecommunications and IT stocks and lesser weightings of Consumer Staples, Energy, Health Care and Utilities, than if they optimised it using CVaR. Looking at the spread of ratings in Table 1, we see that the lowest 5% of ratings for the two industries with a highest CVaR (Financials and Consumer Discretionary) are spread between BBB, BB and CCC/C, whereas the two lowest CVaRs (Consumer Staples and Materials) have nothing lower than BB. This lower 5% is ignored by VaR, yet it is precisely these firms which are most likely to fail

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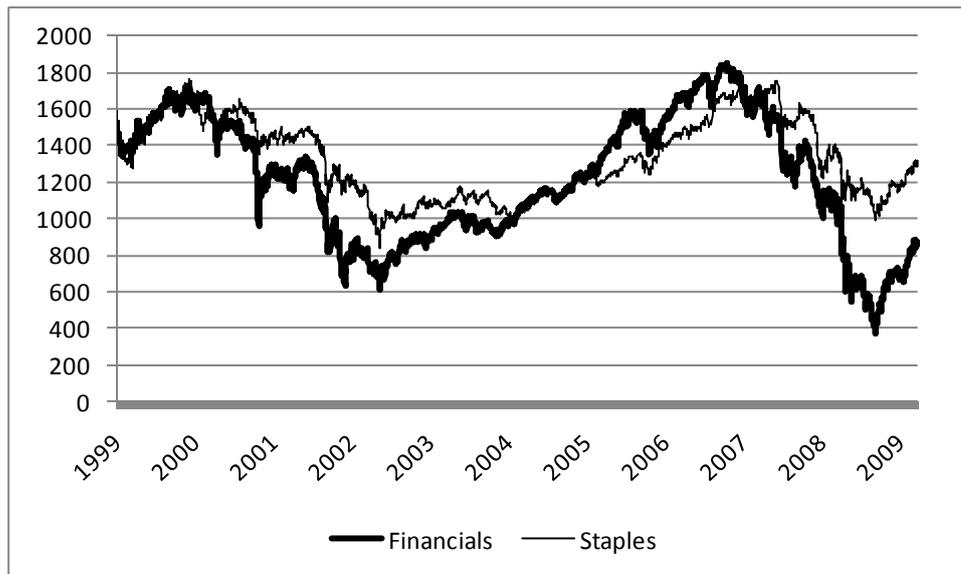
and therefore the industries which are of key importance to lenders in managing and providing for their credit risk.

It is not surprising that Financials have the highest CVaR as at 2009 given the problems experienced by this industry during the GFC. Yet VaR ranks it as only the fourth highest risk. Globally, and in Europe, the industry was at the forefront of the crisis. Problems experienced by the industry required government and Central bank support, with examples being 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 summit in Paris in 2008, Euro area governments provided co-ordinated support measures to banks such as increasing deposit insurance, providing guarantees on new bank bond issues and making capital injections into banks. Asset relief measures were also introduced to remove or insure toxic bank assets (European Central Bank, 2009).

In contrast, the Consumer Staples industry has the lowest CVaR, yet it is only ranked third lowest by VaR. During crisis times, consumers generally put larger discretionary purchases on hold (as seen by the relatively high CVaR of the Consumer Discretionary industry), but continue to purchase staple items. An example of this is the high risk experienced in the European Motor Vehicle industry (Allen, Kramadibrata, Powell, & Singh, 2012a), with severe reduction in profitability and some entities such as Citroen and Renault requiring (French) Government support. Staples include items such as food and beverage, supermarkets and household items as compared to discretionary items such as motor vehicles, high fashion clothing and expensive hotels.

Indeed, there are only four ranking differences in VaR between Financials and Consumer Staples. Given the difference in risk profiles between the two industries during a crisis as mentioned above, we would expect this to be much higher. CVaR captures this spread, showing nine ranking differences. The share price indices of the highest (Financials) and lowest (Consumer Staples) CVaR industries are shown in Figure 1. We see that Staples have a flatter trend than financials, in particular during the GFC when Financials have a much sharper downturn.

Figure 1: Share Price Trends: Financial and Consumer Staples Industries



Data is sourced from Datastream. Indices are based on 1 Jan 1998 at 1000.

During upturns, Financials growth outpaces Consumer Staples and during downturns, Financials falls further. During the financial crisis period, the gap between these two industries widened considerably, which is more consistent with the spread in our CVaR rankings than the much smaller spread in VaR rankings.

The correlation coefficient in Table 2 is based on rankings. This test is suitable when the researcher wants to test for ranking differences between two variables, such as in our case where our hypothesis relates to ranking differences between VaR and CVaR. As a robustness check we also correlated the actual VaR and CVaR values shown in Table 2, which yields a correlation coefficient of 0.626, not very different from the ranking correlation coefficient of 0.612 shown in Table 2. Table 3 below is a further illustration of how an industry with a relatively high VaR does not necessarily have a relatively high CVaR, which can result in low correlation between these two measures. The table shows how the upper 95% of Financials has a greater weighting towards better credit ratings than Health Care, giving Financials a better VaR than Health Care (as shown in Table 2). Yet, in the lower 5%, Financials has a greater weighting towards worse credit ratings than Health Care, giving Financials a worse CVaR than Health Care, thus showing negative correlation between VaR and CVaR values for these two industries.

Table 3: Example of VaR / CVaR Spread

	AAA	AA	A	BBB	BB	B	CC	VaR/CVaR Spread
Financials	0.0%	0.3%	52.9%	10.9%	33.4%	1.4%	1.2%	2.3 x
Health Care	0.0%	0.0%	17.8%	35.4%	46.8%	0.0%	0.0%	1.6 x

The table shows percentage of total debt (per rating) for entities in each of the two example industries, as taken from Table 1. The VaR/CVaR spread is the number of times that CVaR exceeds VaR, using the VaR and CVaR figures in Table 2.

Whilst the transition matrix method includes other variables than the ratings (such as transition probabilities and forward values), the ratings in the matrix itself are

nonetheless a key component of the credit risk of a sector. The least risky industries by CVaR (Consumer Staples, Utilities and Energy as per Table 2) have no ratings BB and lower. The most risky industries by CVaR (Financials and Consumer Discretionary as per Table 2) are those industries which have the highest percentage of poor risk ratings (BB and lower). The industries with the lowest rated entities are the ones most likely to experience corporate failures, yet as we have seen from Table 2 these are not necessarily the ones rated the most risky by VaR. This is because the VaR transition matrix method ignores the extreme end of the tail, whereas our CVaR transition matrix methodology improves on the traditional VaR matrix by capturing these extreme values.

### 5. Conclusions

The study has shown significant differences between the VaR transition matrix and CVaR transition matrix outcomes. In particular, the well documented severe stresses experienced by the financials industry during the GFC, were captured by the CVaR transition matrix, but not the VaR transition matrix. Our study found that on a CVaR basis, Financials had the highest risk and Consumer Staples the lowest. In comparison, VaR showed Healthcare to be the highest risk and Telecommunications to be the lowest. These differences exist because the VaR transition matrix does not capture extreme tail risk. It ignores risk beyond a specified threshold. On the other hand, our improved (CVaR) transition matrix method does capture tail risk as it specifically focuses on the highest risk entities, which are precisely those which are most likely to fail in a crisis. We therefore recommend CVaR as a useful tool for lenders in identifying industry risk. In saying that, we caution that a limitation of transition matrix modelling (which applies to VaR and CVaR) is that it is only as good as the underlying credit ratings. Credit ratings do not ratchet up or down with changing economic circumstances and ratings changes may therefore lag economic events. Potential for further study includes applying the techniques in this study to industries in other countries, as well as more in depth analysis of specific high risk industries such as Financials and Consumer Discretionary.

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