International Review of Business Research Papers
Vol. 9. No.1. January 2013 Issue. Pp. 22 – 37

Default Risk in the European Automotive Industry

D.E. Allen*, A. R. Kramadibrata*, R. J Powell* and A.K. Singh*

This paper examines credit risk in the European automotive industry. Distance to Default (DD) is calculated using the Merton structural credit model. In addition, we modify the Merton model to generate an innovative measure of credit risk at the extremes of the asset value fluctuations distribution, which we call Conditional Distance to Default (CDD). The credit risk of all listed automotive stocks on the S&P Euro Index is compared to all the other industries on this index, which comprises 180 stocks with geographic and sectoral diversity. The study spans the 10 years from 2000 to 2009 divided into pre-GFC and GFC periods. Our metrics find the automotive industry to be of high risk relative to other European industries, particularly during the GFC. We also find that our CDD metric is better able to capture the extreme credit risk prevalent in the industry during the GFC than traditional DD metrics.

Field of Research: Banking

JEL Codes: G01 and G21

1. Introduction

The extreme financial market volatility and severe bank stresses of the GFC highlighted the importance of understanding and measuring extreme credit risk. Understanding default risk in an industry is crucial to lenders in setting policies such as credit concentration limits, pricing, capital allocation and lending officers' loan approval authority limits for that industry.

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. Most prevailing credit models measure credit risk based on averages or standard deviations (including the Merton model) over time or in the case of Value at Risk (VaR), below a specified threshold. However credit losses are usually not normally distributed, and the problem with these approaches is that they do not cater for risk measurement at the extreme end of the scale, which is when firms are most likely to fail. We thus modify the Merton model to incorporate an extreme risk measurement which we call Conditional Distance to Default (CDD). This is our unique metric which measures credit risk above a selected threshold, in a similar vein to which Conditional Value at Risk (CVaR) is used to measure extreme insurance and market risk. These metrics are explained in Section 3.3. The conditional metrics have been used to examine industry risk in Europe (Allen, Powell, & Singh, 2011), but not in the automotive industry, making this study a first. The

* School of Accounting, Finance and Economics, Faculty of Business & Law, Edith Cowan University, Western Australia. *Email:* r.powell@ecu.edu.au

question explored by this study is the extent to which the automotive industry is more (less) risky than other European industries from a credit perspective using both traditional DD credit metrics as well as CDD measures of extreme risk. To ascertain this relative risk we compare the automotive industry to a range of other industries. We also examine whether the relative risk of the automotive industry changed during the extreme conditions of the GFC as compared to pre-GFC.

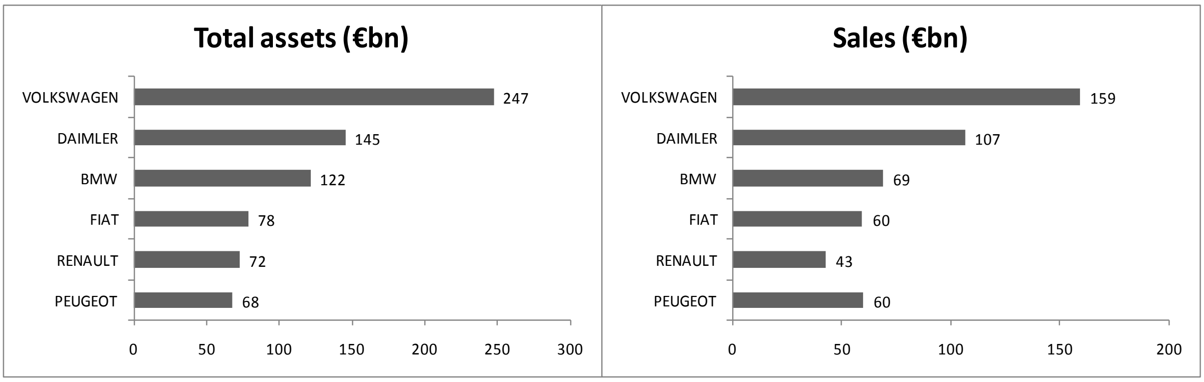
The study finds the automotive industry to be among the riskiest of the industries examined pre-GFC and that this relative risk increases even further during the GFC. This means that it is important for lenders wishing to minimize extreme risk to take care when lending to the automotive industry in volatile circumstances and to ensure sufficient provisions and capital to counter this risk.

As background, Section 2 provides an overview of the automotive industry, with a particular focus on Europe. Data and Methodology are discussed in Section 3, followed by results in Section 4 and conclusions in Section 5.

2. Background and Literature Review

Europe’s largest 6 car manufacturers have total assets of over €700bn with sales in 2011 of close to €700bn. Volkswagen (including Audi, Bentley, Bugatti, Lamborghini, Porsche, Scania and Skoda) is the largest manufacturer with a market share of around 20%, followed by Daimler (including Mercedes Benz), BMW (including Mini as well as being the outsourced manufacturer of Rolls Royce vehicles), Fiat (including Ferrari and Alpha Romeo), Renault and Peugeot (including Citroen). Other key players in the European market are Ford with a market share of around 10% and Asian car manufacturers (15%).

Figure 1: European Car Manufacturers: Assets and Sales



Source: Datastream

Sales have shrunk over the ten years to 2012 at an average of approximately 1% per annum.

Globally, the new car market suffered severe problems during the GFC with General Motors and Chrysler filing for bankruptcy in 2008, and many other manufacturers, including one of the world’s largest car manufacturers Toyota, posting losses in 2009. This led to many manufacturers downsizing their operations. In Europe, Volkswagen and BMW experienced significant profit reductions in 2009, with Daimler, Fiat, Renault and Peugeot all experiencing losses. Along with global trends, share prices in the European car market plunged 70% from its peak in 2007 to its trough in 2008. Globally, including Europe, the automotive industry was beset by downsizing, job losses and restructuring. GM sold Saab to Dutch manufacturer Spyker cars and closed Hummer. Ford sold Jaguar and Landrover to India's Tata and Volvo to China's Geely. The European company to buck the poor profitability trend during the crisis was Porsche, who maintained strong sales and profits over the GFC period. In 2007 and 2008 Porsche increased its stake in Volkswagen, giving it effective control over Volkswagen. However, in 2009 Porsche and Volkswagen agreed to form a Volkswagen led 'integrated automotive group' merger.

There are some key reasons why the new motor vehicle industry is particularly susceptible to economic downturns. Job losses cause reductions in discretionary purchases. Even employed consumers often put larger purchases such as vehicles on hold during difficult economic times. Sales are also highly reliant on motor vehicle finance being provided to purchasers. This latter issue was particularly prevalent during the GFC when the credit crunch following the sub-prime problems made it very difficult to obtain motor vehicle finance. A US congressional investigation (Cannis & Yacobucci, 2010) into the industry's performance during the GFC found that the global economy was already slowing prior to the GFC and consumers had been cutting back on their vehicle purchases even before the credit crunch began. The fear of unemployment during the GFC, coupled with rising fuel prices exacerbated these problems. When automakers started experiencing major problems they then it found it almost impossible to raise further finance to keep their companies afloat.

Blair and Freedman (2010) examine problems in the industry going back to the seventies and maintain that most of the problems arise from car manufacturers gearing their strategies to a particular business environment, as though that environment will continue indefinitely, and have no flexibility to change their strategy when the environment changes. Regassa and Ahmadian (2007) discuss the difficulties that inroads made by Asian car manufacturers have caused the US and European manufacturers, with the Asian firms having been successful at matching quality and price expectations of consumers.

Other than the studies mentioned above, there are not many studies specifically relating to credit risk in the European automotive industry. We provide some examples here of some more general studies on credit risk in Europe. A Bank of England study (Tudela & Young, 2003) found the probability of default derived from their Merton-model implementation for UK firms provides a strong signal of failure one year in advance of its occurrence. Geroski and Gregg (1997) find debt-to-assets ratio, employment, and certain profit measures to be significant determinants company default in the United Kingdom. Allen, Powell and Singh (2011), using a wide range of risk measures, found that European industries which were most (least) risky during the global financial crisis were not the same as those which were most (least) risky prior to the GFC. The authors found the Consumer Discretionary, Financials, Utilities and Energy industries showed more relative credit risk deterioration than other industries during the GFC. Bonfim (2009) finds that, though a firms' financial situation has a central role in explaining default probabilities, macroeconomic conditions are also very important when assessing default probabilities over time. Goddard, Molyneux, & Wilson (2009) find that under the regulatory framework in Europe that is being shaped in response to the crisis, banks are expected to become leaner, more strongly capitalised and less highly leveraged, and to develop improved risk management practices. None of the abovementioned prior studies, nor any other studies we are aware of, focus specifically on default risk in the European automotive industry, particularly using the metrics we use in this article, making this study unique.

Credit ratings applicable to European automotive companies are shown in Table 1. As mentioned in Section 3.3, credit ratings do not ratchet up or down with changing economic circumstances and remained fairly static over this period.

Table 1: European Car Manufacturers: Credit ratings

Credit ratings are by Moody's Investment Company at 2006 and 2009. A rating of A1 is broadly equivalent to Standard and Poor's A+, A2 to A, A3 to A-, Baa1 to BBB+, Ba1 to BB+ and Ba3 to BB-.

Company	Pre-GFC (2006)	GFC (2009)
BMW	A1	A2
Daimler	Baa1	A3
Fiat	Ba3	Ba1
Peugeot	Ba1	Ba1
Renault	Ba1	Ba1
Volkswagen	A3	A3

Despite the losses and problems mentioned earlier, only one company (BMW) shows a downgrade over this period. Neither of the two companies which were bailed out by the French government (Peugeot and Renault as mentioned in Section 4) received any rating change since 2006, when their credit rating of Baa1 had an associated probability of default (PD) of less than 0.0001%. Indeed, the aggregate Moody's PD risk associated with the above six companies based on their ratings at 2009 was less than 1%. On the other hand, our CDD measure of 0.87 during the GFC shown in the results section of this paper has an associated Conditional PD (CPD) exceeding 20% per equations 4 and 5. This is because the DD and CDD models used in this paper are based on daily asset fluctuations and therefore respond far more rapidly to changing economic circumstances than credit ratings. The higher PD shown by the CDD model seems much more consistent than the static ratings with the fact that the industry as a whole suffered losses and downsizing and two out of six automotive companies needed to be bailed out.

3. Methodology

3.1 Data

The study includes all listed automotive stocks on the S&P Euro index, which is all the major six European vehicle manufacturing companies. We compare the automotive industry to all other industries in this index, which comprises 180 stocks with geographic and sectoral diversity, and a total market cap of €2.3 trillion. Industries are classified according to the Global Industry Classification System (GICS). We obtain 10 years of daily returns from Datastream, divided into pre-GFC and GFC periods. The pre-GFC period is 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. We do not include data later than this as the market improved from 2010 onwards, and inclusion of this would defeat the object of isolating the extreme risk during the GFC. The Merton KMV model requires balance sheet data for each entity (equity and debt) which we also obtain from Datastream. Descriptive statistics of our data sample are shown in Table 2.

Table 2: Descriptive Statistics

The table provides a sector breakdown of the S&PEuro index used in this study. The market leader shown in the final column is based on market cap.

Sector	Number of Companies	Total Sector Market Cap (€bn)	Average Market Cap. (€bn)	Market Cap. of Largest Company in Sector (€bn)	Market Leader
Automotive	**6**	**134**	**22.34**	**74**	**Volkswagen**
Consumer discretionary	21	68	3.23	24	LVMH
Consumer staples	15	205	13.69	48	Unilever
Energy	7	187	26.77	87	Total
Financials	38	484	12.72	54	Banco Santander
Health care	9	130	14.47	59	Sanofi-Aventis
Industrials	30	236	7.86	57	Siemens
Information technology	8	95	11.84	41	Nokia
Materials	18	144	8.01	25	BASF
Telecommunication services	9	229	25.41	73	Telefonica
Utilities	16	375	23.47	76	EDF
Total S&P Euro	177	2,287	12.92	87	Total

3.2 Hypotheses

In line with our research questions outlined in section 1, we formulate the following hypotheses:

H_1: Credit risk of the automotive industry, as measured by DD, deteriorated relative to other industries during the GFC as compared to pre-GFC.

H_2: Credit risk of the automotive industry, as measured by CDD ranking, deteriorated relative to other industries during the GFC as compared to pre-GFC.

We will measure absolute DD and CDD values as well as ranking the credit risk of the automobile industry relative to other industries.

3.3 Credit Risk Measurement

The Merton / KMV structural approach to estimating distance to default (DD) and probability of default (PD) is used. The KMV model is one of the most widely used credit risk models in the banking industry. 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 assets. 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 firm's market value, F is the face value of firm's debt, σ_V is the standard deviation of market asset returns over period T (which we set to 1 year per usual practice), and μ is an estimate of 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 daily equity returns data (obtained from Datastream) 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 (2004). Following KMV, we define debt as current liabilities plus half of long term liabilities.

A key advantage that the structural model has over other prevailing models is that it incorporates fluctuating asset values thus enabling the model to respond rapidly to changing economic circumstances, whereas most other credit models are based on accounting or ratings methods which do not automatically ratchet up or down when circumstances change. The importance of fluctuating asset values in measuring credit risk has been raised by the Bank of England (2008), who make makes 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, 2004) and quantile regression (Allen, Boffey, & Powell, 2011).

Besides fluctuating assets, the other key component of structural modelling is the borrower's leverage ratio. Excessive leverage ratios by many companies, most notably banks and motor vehicle manufacturers, led to many requiring additional capitalisation during the GFC. The equity ratios for automotive companies in this study range from 40.6% (BMW) to 64.0% (Fiat).

A shortfall of the Merton / KMV model is that it is based on the standard deviation of fluctuating assets over the period measured. This does not tell us how close the borrower came to default at the most extreme points of the period being measured. In the measurement of share market risk, Conditional Value at Risk (CVaR) is becoming an increasingly popular risk measure as it measures risk at the extremes of the distribution, which is ignored by more traditional measures such as Value at

Risk (VaR). CVaR measures the average risk beyond a determined threshold, such as the average of the worst 5% of returns.

In a similar vein, we have developed a credit risk measure called Conditional Distance to Default (CDD), which is defined as DD based on the worst 5% of asset returns. The standard deviation of the worst 5% (CStdev) is substituted into equation 1 to obtain a conditional DD:

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

And

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

4. Findings and Discussion

Table 3: DD and CDD Results

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 11 (highest risk).

DD:

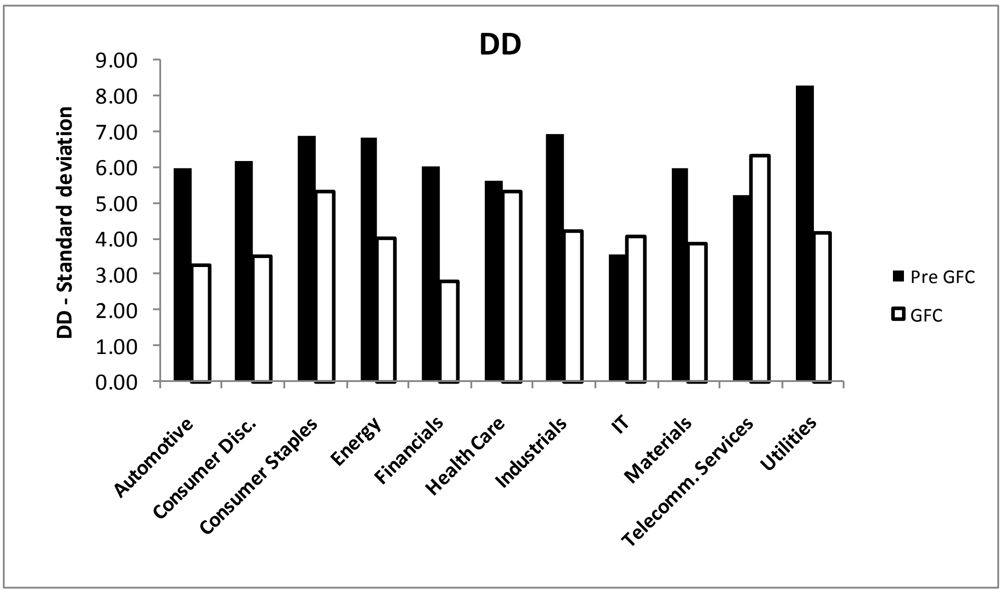
Sector	DD Pre GFC	DD GFC	Rank Pre GFC	Rank GFC
Automotive	**5.99**	**3.27**	**7**	**10**
Consumer Disc.	6.15	3.48	5	9
Consumer Staples	6.88	5.30	3	2
Energy	6.82	3.98	4	7
Financials	6.00	2.77	6	11
Health Care	5.62	5.30	9	3
Industrials	6.94	4.19	2	4
IT	3.56	4.07	11	6
Materials	5.98	3.88	8	8
Telecomm. Services	5.20	6.32	10	1
Utilities	8.31	4.15	1	5
	6.15	4.34		
Motor Vehicles	1.44	0.85	7.00	10.00

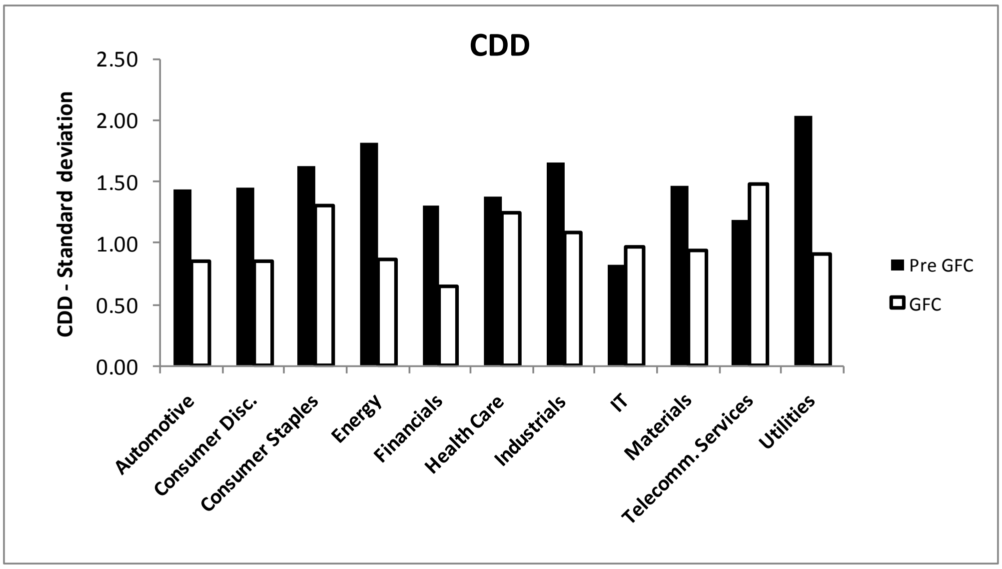
CDD:

Sector	CDD Pre GFC	CDD GFC	Rank Pre GFC	Rank GFC
Automotive	**1.44**	**0.85**	**7**	**10**
Consumer Disc.	1.45	0.86	6	9
Consumer Staples	1.62	1.31	4	2
Energy	1.81	0.87	2	8
Financials	1.31	0.65	9	11
Health Care	1.38	1.25	8	3
Industrials	1.65	1.09	3	4
IT	0.83	0.96	11	5
Materials	1.46	0.94	5	6
Telecomm. Services	1.20	1.48	10	1
Utilities	2.04	0.91	1	7
	1.48	1.03		

Not unexpectedly, given the well known problems experienced by the Finance industry as a leading player during the GFC downturn, this industry is the highest risk during the GFC, with a strong downward shift in relative ranking from the pre-GFC period. However, the automotive industry is not far behind, ranking 10 out of 11 industries during the GFC in line with the automotive industry problems outlined in Section 2 (see Allen, Powell & Singh (2011) for industries excluding automotive, and for other risk metrics). Figure 2 illustrates differences between pre-GFC and GFC outcomes.

Figure 2: DD and CDD Values





The completely different pattern in solid and non-solid bars illustrates how relative risk has changed between the industries. This is certainly the case with the motor vehicle industry, dropping 3 rankings on both DD and CDD measurements. Some industries show a difference between DD and CDD rankings. For example Utilities have a GFC DD ranking of 5, but a CDD ranking of 7 meaning they have a relatively fatter left tail than the other industries. For the automotive industry, there is consistency between DD and CDD rankings. However, both metrics drop 3 rankings during the GFC, a finding consistent with the studies mentioned in section 2, which showed the industry to be highly susceptible to problems in downturn times. Table 4 presents a correlation analysis between DD/CCD and pre-GFC/GFC outcomes and tests for whether differences are significant.

Table 4: Correlation – All Industries

The upper table correlates pre-GFC rankings with GFC rankings for both DD (on the left of the table) and CDD (on the right). The lower table correlates DD rankings with CDD rankings for both the pre-GFC (on the left of the table) and GFC (on the right). Rankings are taken from Table 3 and range from 1 (lowest risk) to 11 (highest risk). A Spearman Rank Correlation Test is applied to determine correlation between the rankings. Significance in ranking correlation at the 95% level is denoted by * and at the 99% level by **, with a '-' indicating no significance.

Correlation between pre-GFC and GFC

Sector	DD Rank pre-GFC	DD Rank GFC	Difference in rank^2	CDD Rank pre-GFC	CDD Rank GFC	Difference in rank^2
Automotive	**7**	**10**	**9**	**7**	**10**	**9**
Consumer Discretionary	5	9	16	6	9	1
Consumer Staples	3	2	1	4	2	4
Energy	4	7	9	2	8	36
Financials	6	11	25	9	11	4
Health Care	9	3	36	8	3	25
Industrials	2	4	4	3	4	1
IT	11	6	50	11	5	50
Materials	8	8	0	5	6	1
Telecomm. Services	10	1	81	10	1	81
Utilities	1	5	16	1	7	36
			247			248
		n	11			11
		r	-0.123			-0.127
		t	-0.371			-0.385
		critical value 95%	2.262			2.262
		critical value 99%	3.250			3.250
		significance	-			-

Correlation between DD and CDD

Sector	DD Rank pre-GFC	CDD Rank pre-GFC	Difference in rank^2	DD Rank GFC	CDD Rank GFC	Difference in rank^2
Automotive	**7**	**7**	**0**	**10**	**10**	**0**
Consumer Discretionary	5	6	1	9	9	0
Consumer Staples	3	4	1	2	2	0
Energy	4	2	4	7	8	1
Financials	6	9	9	11	11	0
Health Care	9	8	1	3	3	0
Industrials	2	3	1	4	4	0
IT	11	11	50	6	5	50
Materials	8	5	9	8	6	4
Telecomm. Services	10	10	0	1	1	0
Utilities	1	1	0	5	7	4
			76			59
		n	11			11
		r	0.655			0.732
		t	2.597			3.222
		critical value 95%	2.262			2.262
		critical value 99%	3.250			3.250
		significance	*			*

The Spearman rank correlation coefficient is a useful nonparametric measure for testing correlation when variables have been ranked, as it tests for relative changes between items rather than absolute numbers. Nonparametric tests are more suitable for smaller data sets where we are not making assumptions about distribution (for example where we are concerned about rankings rather than actual statistics such as means and standard deviations). In our case, we have a relatively small dataset as there are eleven variables and credit risk is often characterized by large losses in the tail of the distribution rather than by normality. We are also not overly concerned with absolute numbers as we already know that the GFC period was riskier than pre-GFC and we also already know that mathematically CDD will always exceed DD, so we are more interested with the performance of the automotive industry relative to other industries than in actual changes in numbers. The r value shown in the table above provides a correlation between -1 and 1, and the t value is compared to the critical value to determine the level of significance.

The upper section of Table 4 shows that there is no significant association between those industries that were risky pre-GFC and those that were risky during the GFC. The lower section of Table 4 confirms that there is some correlation between DD and CDD rankings, but only significant at a 95% level of confidence. We have also undertaken F tests, which measure changes in volatility, and these tests show that the increase in volatility experienced by the automotive industry is significantly higher than that experienced by the S&P Euro as a whole. Table 5 shows the individual automobile entity DD and CDD rankings both pre-GFC and during the GFC and the change in rankings is illustrated in Figure 3.

Table 5: Automotive manufacturer DD and CDD

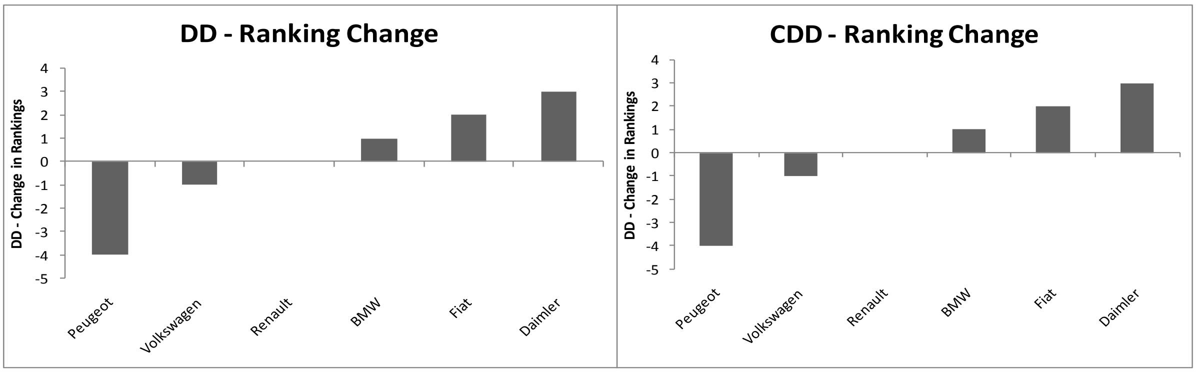
DD (measured by number of standard deviations) is calculated using equation 1. CDD is based on the worst 5% of asset returns and is calculated using equation 4. Pre-GFC incorporates the 7 years to 2006. GFC includes 2007 – 2009. Rankings are from 1 (lowest risk) to 10 (highest risk). Equity is measured as book value of shareholder funds to book value of total assets at 2009.

	Equity	DD Pre-GFC	DD GFC	Rank Pre-GFC	Rank GFC
BMW	40.6%	6.42	6.46	2	1
Daimler	54.7%	5.00	4.54	5	3
Fiat	64.0%	5.44	5.09	4	2
Peugeot	54.3%	6.45	2.87	1	5
Renault	52.9%	4.57	2.49	6	6
Volkswagen	57.8%	5.82	3.15	3	4
	53.8%	5.99	3.27		

	Equity	CDD Pre-GFC	CDD GFC	Rank Pre-GFC	Rank GFC
BMW	40.6%	1.52	1.77	2	1
Daimler	54.7%	1.20	1.07	5	3
Fiat	64.0%	1.22	1.34	4	2
Peugeot	54.3%	1.62	0.80	1	5
Renault	52.9%	1.17	0.65	6	6
Volkswagen	57.8%	1.45	0.81	3	4
	53.8%	1.44	0.85		

Both Peugeot and Renault suffered losses during the GFC and this, coupled with the difficulty in raising finance during the GFC, led to both requiring bailout packages from the French Government. These two manufacturers occupy the bottom two rankings on both a DD and CDD basis during the GFC. Peugeot, which was operating well prior to the GFC, fell 5 rankings. Renault was ranked bottom both prior to and during the GFC, so the company showed no change in rankings.

Figure 3: Automotive manufacturer ranking changes



Volkswagen, who avoided losses during the GFC, nonetheless moved down two rankings, primarily because of increased volatility associated with the takeover bid triggered by Porsche. Up until mid 2008, Volkswagen's volatility was among the lowest of the automotive manufacturers and increased substantially thereafter. BMW, Daimler and Fiat, who all experienced profitability problems during the GFC but not to the same extent as Renault and Peugeot, improved their rankings relative to the others.

We see from Table 6 that there is no significant association between the individual company rankings pre-GFC and rankings during the GFC, meaning that those automotive companies that were most / least risky pre-GFC are not the same as those that were most / least risky during the GFC. As already discussed, this comes through ranking improvements by BMW, Daimler and Fiat, with deterioration by Peugeot and Volkswagen. Although there are large differences between absolute DD and CDD values in Table 6, these metrics are perfectly correlated in their ranking of the relative credit risk of the individual automobile companies.

Table 6: Correlation – automotive industry

The upper table correlates pre-GFC rankings for the automotive industry with GFC rankings for both DD (on the left of the table) and CDD (on the right). The lower table correlates DD rankings with CDD rankings for both the pre-GFC (on the left of the table) and CDD (on the right). Rankings for both the upper and lower tables are taken from Table 3 and range from 1 (lowest risk) to 11 (highest risk). A negative change shows deterioration in risk ranking. A Spearman Rank Correlation Test is applied to determine correlation between the rankings. Significance in ranking correlation at the 95% level is denoted by * and at the 99% level by **, with a '-' indicating no significance.

Correlation between pre-GFC and GFC

	DD Rank pre-GFC	DD Rank GFC	Difference in rank^2	CDD Rank pre-GFC	CDD Rank GFC	Difference in rank^2
BMW	2	1	1	2	1	1
Daimler	5	3	4	5	3	4
Fiat	4	2	4	4	2	4
Peugeot	1	5	16	1	5	16
Renault	6	6	0	6	6	0
Volkswagen	3	4	1	3	4	1
			26			26
	n		6			6
	r		0.257			0.257
	t		0.532			0.532
		critical value 95%	2.776			2.776
		critical value 99%	4.604			4.604
		significance	-			-

Correlation between DD and CDD

	DD Rank pre-GFC	CDD Rank pre-GFC	Difference in rank^2	DD Rank GFC	CDD Rank GFC	Difference in rank^2
BMW	2	2	0	1	1	0
Daimler	5	5	0	3	3	0
Fiat	4	4	0	2	2	0
Peugeot	1	1	0	5	5	0
Renault	6	6	0	6	6	0
Volkswagen	3	3	0	4	4	0
			0			0
	n		6			6
	r		1.000			1.000
	t		null			null
		critical value 95%	2.776			2.776
		critical value 99%	4.604			4.604
		significance	**			**

We end this section with some final remarks on the findings, and how these relate to our hypotheses. The differences between the standard DD measures as captured by the Merton model and our unique CDD measures are highly significant (<1% using an F test for differences in volatility). The GFC DD measure of 3.27 has an associated PD of 0.05%, whereas the CDD of 0.85 has an associated PD of 29%. Given that two out of the six companies (33%) needed government bailout during this time and others suffered severe profitability problems, our CDD measure seems to be far more realistic in its magnitude than DD. This is because our measure focuses on extreme tail risk, which is not adequately captured by the DD measure. Overall, the rank correlation and F tests presented in this section have confirmed that, for both DD and CDD, relative risk between industries has changed for the GFC period as compared to pre-GFC, with automotive industry risk deteriorating relative to other industries, and supporting the following hypotheses as formulated in our methodology section:

H_1: Credit risk of the automotive industry, as measured by DD, deteriorated relative to other industries during the GFC as compared to pre-GFC.

H_2: Credit risk of the automotive industry, as measured by CDD, deteriorated relative to other industries during the GFC as compared to pre-GFC.

5. Conclusions

The study has shown that the credit risk of the automotive industry increased relative to other European industries during the GFC, with the industry shifting down three ranking positions. This supported our research hypotheses of deterioration in credit risk relative to other industries using both DD and CDD. These metrics showed the automotive industry to have the second highest credit risk during the GFC, just behind the highly volatile financial industry over this period. Leading causes of this were consumers putting discretionary purchases on hold and a credit crunch which affected both the ability of consumers to raise motor vehicle finance and the ability of manufacturers to raise finance to bide them over this period. In particular, this increase in credit risk was evident among the French motor automotive companies of Peugeot and Renault, both requiring bailout from the French government.

This high level of credit risk in the automotive industry has implications for lenders in considering portfolio composition and credit policies. Relative to most other industries, additional provisions and capital buffers will need to be held for the automotive industry in downturn times. Our CDD measure showed a much higher default likelihood that the traditional DD measure, and was more closely aligned than DD with the problems experienced by European automotive manufacturers during the GFC. This is due to CDD’s focus on default at the extreme loss end of the credit distribution, which is precisely when firms are most likely to fail. We therefore recommend CDD as a useful measure to lenders in assessing credit risk in dynamic economic circumstances. Potential further study on the automotive industry could involve analysis of the industry using our CDD metrics in other large automobile manufacturing regions such as Asia and the US, as well as associated entities such as automotive parts suppliers. The study also showed how the DD and CDD measures appeared far more responsive to dynamic economic circumstances than credit ratings, and it would be useful to further explore credit ratings as a measure of automotive industry credit risk in times of high volatility.

Acknowledgements

The authors would like to thank the Australian Research Council for funding support.

References

Allen, DE, Boffey, RR & Powell, RJ 2011, ‘A quantile Monte Carlo approach to measuring extreme credit risk’, *Proceedings of World Business Economics and Finance Conference*, World Business Institute Australia, Bangkok.

Allen, DE, Powell, RJ, & Singh, AK 2011, 'Beyond reasonable doubt: Multiple tail risk measures applied to European industries', *Applied Economics Letters,* vol. 19, no.7, pp. 671-676.

Bank of England 2008. *Financial stability report*, issue no. 24, viewed 16 April, 2012, <http://www.bankofengland.co.uk/publications/fsr/2008/fsrfull0810.pdf>.

Bharath, ST & Shumway, T 2008, 'Forecasting default with the Merton distance-to-default model', *The Review of Financial Studies,* vol. 21, no. 3, pp. 1339-1369.

Blair, A & Freedman, C 2010, 'Seeds of destruction: The decline and fall of the US car industry ', *Economic and Labour Relations Review,* vol. 21, no. 1, pp. 105 - 126.

Bonfim, D 2009, 'Creditrisk drivers: Evaluating the contribution of firm level information and of macroeconomic dynamics', *Journal of Banking and Finance,* vol. 33, no. 2, pp. 281-299.

Cannis, B & Yacobucci, Y 2010, *The US motor vehicle industry: Confronting a new dynamic in the global economy*, Congressional Research Service report no . R41154, viewed 16 April 2012, <http://www.fas.org/sgp/crs/misc/R41154.pdf>.

Cespedes, JCG, 2002. 'Credit risk modelling and Basel II', *ALGO Research Quarterly,* vol. 5, no. 1, pp. 57-66.

Chan, H, Faff, R & Kofman, P 2008, *Default risk, size and the business cycle: Three decades of Australian pricing evidence*, viewed 1 April 2012, <http://ssrn.com/abstract=1097444>.

Crosbie, P & Bohn, J 2003, *Modelling default risk*, viewed 20 July 2011, <http://www.defaultrisk.com/pp_model_35.htm>.

D'Vari, R, Yalamanchili, K & Bai, D 2003, *Application of quantitative credit risk models in fixed income portfolio management*, viewed 16 April 2012, <http://www.rondvari.com/CIEF%202003_Final.pdf>.

Geroski, PA & Gregg, G 1997, *Coping with recession: Company performance in adversity*, Oxford University Press, Oxford.

Gharghori, P, Chan, H & Faff, R 2007, 'Are the Fama-French factors proxying default risk?', *Australian Journal of Management,* vol. 32, no. 2, pp. 223-249.

Goddard, J, Molyneux, P & Wilson, J 2009, 'The financial crisis in Europe: Evolution, policy responses and lessons for the future', *Journal of Financial Regulation and Compliance,* vol. 17 no. 4, pp. 362-380.

Kealhofer, S & Bohn, JR 1993, *Portfolio management of default risk, viewed* 11 April 2012, <http://www.moodysanalytics.com>.

Lopez, J A 2004, 'The empirical relationship between average asset correlation, firm probability of default and asset size', *Journal of Financial Intermediation,* vol. 13, no. 2, pp. 265-283.

Merton, R 1974, 'On the pricing of corporate debt: The risk structure of interest rates', *Journal of Finance,* vol. 29, no. 2, pp. 449-470.

Regassa, H & Ahmadian, A 2007, 'Comparative study of American and Japanese auto industry: General Motors versus Toyota Motors corporations'. *The Business Review, Cambridge,* vol. 8, no. 1, pp. 1-11.

Stein, RM 2007, 'Benchmarking default prediction models: Pitfalls and remedies in model validation', *Journal of Risk Model Validation,* vol.1, no. 1, pp. 77-113.

Tudela, M & Young, G 2003, *A Merton-model approach to assessing the default risk of UK public companies*, Bank of England Working paper no.194, viewed 16 April 2012, <http://www.repec.org/res**2003**/**Tudela**.pdf>.

Vasicek, OA 1987, *Probability of loss on loan portfolio*, viewed 16 April 2012, <http://www.moodysanalytics.com>.

Vassalou, M & Xing, Y 2004, 'Default risk in equity returns', *Journal of Finance,* vol. 59 no. 2, pp. 831-868.

Zeng, B & Zhang, J 2001. *An empirical assessment of asset correlation models*, viewed 16 April 2012, <http://www.moodysanalytics.com>.