The impact of sector concentration in loan portfolios on economic capital

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Introduction

The 1988 Basel Accord stipulated that a bank should hold minimum capital in the amount of eight percent of its risk-weighted assets. One of the key features of the computation of risk-weighted assets as specified by the Accord was that all loans to firms were assigned equal risk weights, independently of the actual riskiness of the loan. A second feature of the computation was that total risk-weighted assets were obtained by simple summation of the individual risk-weighted assets. In other words, no account was taken of concentration; banks with more concentrated loan portfolios did not have higher minimum capital requirements than banks with diversified portfolios.

The Basel II Framework aims to tailor banks' minimum regulatory capital requirements more closely to the riskiness of their loans. Pillar 1 of this Framework proposes new approaches for determining minimum capital requirements. Banks are able to choose between a standardised approach, which bases the risk weight for a firm on the rating assigned to the firm by an external rating agency, or two internal ratings-based (IRB) approaches, which assign a firm's risk weight on the basis of the bank's internally estimated probability of default for the firm (in addition to other variables). However, for reasons of tractability and feasibility, total risk-weighted assets are still to be computed by summing the individual risk-weighted assets. This implies that the additional capital requirements that banks need to hold when adding an exposure is the same whether the portfolio is well diversified or highly concentrated (this feature is called portfolio invariance).

In the internal ratings-based approaches of Pillar 1, the risk-weight functions, which map firms' probabilities of default to a risk weight, also have the property of being portfolio invariant. These risk-weight functions are based on a model that assumes that firms' returns on assets are affected by an idiosyncratic shock and a single systematic risk factor, which is the same for all firms. Correlations between firms' asset returns are determined by their sensitivity to this risk factor and depend on the probability of default and firm size. Hence, the risk-weight formulas used in Pillar 1 do not allow for correlations among firms' asset returns which depend upon the sectors in which the firms operate. The assumption that the performance of banks' loan portfolios is affected by one single systematic risk factor is appropriate only to the extent that the portfolio is perfectly diversified across industrial and regional sectors.

Concentration risk in banks' credit portfolios does not only arise from an excessive exposure to a single sector or to several highly correlated sectors (i.e. "sector concentration"), it can also arise from an excessive exposure to certain names (which is often referred to as "name concentration" or "granularity"). The Basel Committee recognises that the risk-weight functions do not explicitly account for name or sector concentration. Therefore, the Basel II Framework stipulates that credit risk concentration should be addressed in the context of Pillar 2, which involves the supervisory review process. To date, financial regulation and research have focused mainly on name concentration (1). The focus of this article is on sector

(1) See EU Directive 93/6/EEC, Joint Forum (1999), Gordy (2003).

concentration risk, where sectors are defined as business sectors. Although geographical regions can also be modelled as sectors, we do not consider that case here.

Sector concentration risk is an important issue; for instance, if a loan portfolio is excessively concentrated in credit to firms in a particular sector, a shock to the sector can have a significant impact on the entire portfolio. Indeed, the importance of prudently managing sector concentration risk in banks' credit portfolios is generally well recognised. However, existing literature does not provide much guidance on how to measure sector concentration risk, or on the levels of concentration that merit concern. From a regulatory and financial stability perspective, questions arise as whether or how particular levels of sector concentration should be translated into additional capital requirements.

We address these issues by simulating loss distributions of loan portfolios that have sectoral distributions that are similar to actual banks' portfolios, in order to measure the potential impact of concentration risk. In particular, we ask what effect increasing sector concentration will have on a bank's economic capital (*EC*), which is defined as the amount of capital a bank would need to cover losses up to a specified percentile of the portfolio loss distribution. In order to allow for differing inter-sectoral and intra-sectoral asset correlations, we allow firms' outcomes to depend upon multiple risk factors.

We construct a benchmark portfolio whose sectoral distribution of loans reflects the sectoral distribution of aggregate loans to corporates and SMEs in the German banking sector (and which is also similar to the aggregate sectoral distribution in several other European countries). After determining the economic capital for the benchmark portfolio, we construct a sequence of portfolios with increasing sector concentration and analyse the impact of this concentration on economic capital. We find that increasing sector concentration in loan portfolios does indeed cause a significant increase in a bank's economic capital, and this result holds for sectoral loan distributions similar to those actually observed in some individual banks' portfolios. This suggests the need for research aimed at developing simple quantitative tools that bank supervisors can use for measuring concentration risk in banks' loan portfolios.

The article is organised as follows. In Section 1 we present the CreditMetrics model, which is used to simulate the portfolio loss distributions. The loan portfolios on which the simulations are based are described in Section 2. In Section 3 we analyse the impact of sector concentration on economic capital. We conclude in Section 4.

1. Measuring concentration risk in a multi-factor model

To simulate portfolio loss distributions, we use the well-known CreditMetrics model, which is a highly stylised version of a Merton-type model[1]. In this model default happens when a variable X_i, which we denote as firms' asset returns[2], falls below a default threshold (DD_i) over the considered time horizon. In what follows we will assume that the variables X_i have a standard normal distribution. The probability of default of firm i (PD_i) is defined by

$$(1) \quad PD_i = Pr\ (X_i < DD_i) = \Phi(DD_i),$$

where Φ is the cumulative standard normal distribution function. Conversely, the value of DD_i can be determined from this relation if the PD_i is known.

In order to capture sectoral dependencies among firms and to examine the effects of differing levels of sector concentration in loan portfolios on the bank's economic capital, we use a multi-factor version of the CreditMetrics model. More specifically, we assume that each firm can be uniquely assigned to a single sector[3]. We also assume that the asset return over the risk horizon of one year can be decomposed into a sector-specific (systematic) and a firm-specific (idiosyncratic) component

$$(2) \quad X_i = r_s\, Y_s + \sqrt{1 - r_s^2}\, \varepsilon_i$$

where Y_s is an industry sector risk factor and ε_i an idiosyncratic risk factor which are both assumed to have a standard normal distribution. The coefficient r_s, referred to as the sector factor loading, measures the sensitivity of firm i's asset return to the sector factor Y_s.

We further assume that the sector risk factor Y_s can be expressed as a linear combination of independent risk factors $Z_1,\ldots,Z_S$, each of which is assumed to have a standard normal distribution, and where the number of factors corresponds to the number of sectors. That is,

$$(3) \quad Y_s = \sum_{j=1}^{S} \alpha_{s,j}\, Z_j \quad \text{for } 1 \le s \le S,$$

where coefficients $\alpha_{s,j}$ must satisfy the relation $\sum_{j=1}^{S} \alpha_{s,j}^2 = 1$ to ensure that Y_s has unit variance. As can

(1) See also Gupton et al. (1997), Gordy (2000), and Bluhm et al. (2003) for more detailed information on these types of models. The origin of these models can be found in the seminal work by Merton (1974).

(2) Technically, the variables X are unobservable variables that drive asset returns, however it is standard procedure to use the term asset return.

(3) In practice (large) firms often comprise business lines from different industry sectors. However, we pose this assumption here for practical and presentational purposes.

be seen from this equation, the sector factors are correlated through their mutual dependence on the independent risk factors $Z_1,\ldots,Z_S$ via these coefficients $\alpha_{s,j}$. Sector factor correlations are defined as correlations between the sector factors Y_s and Y_t and are given by $\sum_{n=1}^{S} \alpha_{s,n}\alpha_{t,n}$.

In our simulations, the coefficients $\alpha_{s,j}$ are estimated from the correlation matrix of industry equity indexes using a Cholesky decomposition (1).

The asset correlation for each pair of borrowers i and j in sectors s and t can be shown to be given by:

$$(4) \quad cor\,(X_i, X_j) = r_s\, r_t \sum_{n=1}^{S} \alpha_{s,n}\,\alpha_{t,n} \quad .$$

Given that $\sum_{j=1}^{S} \alpha_{s,j}^{2} = 1$, equation (4) implies that the intra-sectoral asset correlation for each pair of borrowers is simply r_s^2 . For the simulations in this paper, we assume that r_s = 0.5 for each sector. This implies that the intra-sectoral asset correlations are equal to 0.25.

We use the above model of firm asset returns and the default condition to simulate a portfolio loss distribution. To compute the losses for firms in default, we assume a loss given default (LGD) of 45 p.c. for each firm, which is also the supervisory value set for senior unsecured corporate loans in the Foundation IRB approach of the Basel II Framework. Our measure of risk is economic capital, which covers only the unexpected loss and which is defined as the difference between the 99.9 p.c. percentile of the loss distribution and the expected loss. The Monte Carlo approach used for the simulation of the portfolio loss distribution is described in Box 1.

(1) If C is an NxN correlation matrix, the Cholesky matrix is the NxN symmetric positive definite lower triangular matrix A, such that $C = AA^T$. A lower triangular matrix has zeros on the upper right corners above the diagonal. The superscript "T" denotes the "transpose" of the matrix.

Box 1 – Monte Carlo approach to simulating the portfolio loss distribution

Assume there are N firm borrowers in the portfolio, each borrower can be assigned to a sector s, and C_i denotes the loan amount of borrower i.

Determine the default probability PD_i for each of the N firms in the portfolio. (For the simulations of this paper, we assume that each firm's PD_i is initially equal to 2 p.c. (1)).

Compute the default threshold DD for each of the N firms, using relation (1): $\Phi^{-1}(PD_i) = DD_i$, where Φ^{-1} is the inverse of the cumulative standard normal function.

Generate a vector of the uncorrelated, standard normally distributed factors Z_j (which appear on the right-hand side of equation (3)).

Use the Cholesky matrix $(\alpha_{s,t})_{1\leq s,t\leq S}$ obtained from the sector factor correlation matrix (As mentioned in the text, the correlation matrix of sectoral equity indices is used as a proxy for the sector factor correlation matrix, whose elements are $\sum_{n=1}^{S} \alpha_{s,n}\alpha_{t,n}$).

Multiply the Cholesky matrix with the independent risk factors Z_j to obtain the correlated sector risk factors Y_s (see equation (3)).

For each firm i construct the value X_i, using the sector risk factor Y_s, the sector sensitivities r_s, and an idiosyncratic shock ε_i generated from a standard normal distribution (see equation (2)). (Our simulations assume that the sector sensitivities are equal to 0.5 for each sector.)

(1) This assumption is relaxed in a robustness check.

For each firm i, determine whether it is in default by comparing X_i with DD_i. If $X_i < DD_i$, firm i is in default. The loss for each firm in default is by multiplying LGD, with the exposures size C_i. (In our simulations LGD is set at 45 p.c. for each firm.)

Compute the losses L for the entire portfolio by summing the losses for each firm in default. Label this value L_m where m represents the number of this simulation run.

Repeat the above steps until the desired number M of simulation runs has been completed.

Arrange the loss values L_m, for $m = 1$ to M, in ascending order. This gives the empirical portfolio loss distribution, from which values such as expected loss, value at risk, and economic capital can be computed.

2. Portfolio composition

2.1 Data set and sectoral definitions

Our analyses are based on portfolios that reflect characteristics of real portfolios, obtained from German credit register data. Our benchmark portfolio represents the overall sector concentration of the German banking system as it was constructed by aggregating the exposure values of loan portfolios of 2224 German banks in September 2004. The portfolio includes exposures to firms borrowing from branches of foreign banks located in Germany. Credit exposures to foreign borrowers, however, are excluded. We deem this to be a reasonable approximation of a well-diversified portfolio based on the intuition that a portfolio cannot be more diversified than in the case in which it represents the average relative sector exposures of the national banking system. In principle, we could also have created a more diversified portfolio in the sense of having a lower VaR. However, such a portfolio would be specific to the credit risk model used and would not be obtainable for all banks.

All credit institutions in Germany are required by the German Banking Act (*Kreditwesengesetz*) to report quarterly exposure amounts of those borrowers whose indebtedness to them amounts to at least 1.5 millions of euro or more at any time during the three calendar months preceding the reporting date. Individual borrowers are summarised to *borrower units* which are linked, for example, by investments and constitute an entity sharing roughly the same risk. The aggregation of exposures on a business sector level was carried out on the basis of borrower units. Therefore, the credit register includes not only exposures above 1.5 millions of euro but also smaller exposures to individual borrowers belonging to a borrower unit that exceeds this exposure limit. This characteristic also increases its coverage which is around 90 p.c. of the German credit market, including inter-bank exposures.

The industry classification chosen by CreditMetrics is the Global Industry Classification Standard (GICS), which was launched jointly by Standard & Poor's and Morgan Stanley Capital International (MSCI) in 1999. The classification scheme was developed to establish a global standard for categorising firms into broad sectors and into more detailed industry groups according to their principal business activities (see Table 8 in the Appendix). In the following we use the broad sector classification scheme (1). Because some of the industry groups that form the broad sector "Industrial" are very heterogeneous, we decided to split this sector into the three industry groups: Capital goods (including construction), Commercial services and supplies, and Transportation.

Credit register data sets, however, use the NACE industry classification system, which is quite different from the GICS system. In order to use the information from the credit register, we have performed a mapping (2) from the NACE codes to the GICS codes. We have excluded exposures to financials because of the specificities of this sector. Exposures to the real estate sector are heavily biased as it comprises a large number of exposures to borrowers that are related to the public sector. Finally, we also have disregarded exposures to households since a representative equity index does not exist for them. In sum, we distinguish between 11 sectors, which can be considered as broadly representing the asset class corporate and SMEs.

(1) Unreported simulations have shown that results are not affected when using the more detailed classification scheme.

(2) This mapping function is presented in the appendix in Düllmann and Masschelein (2006).

2.2 Comparison with French, Belgian and Spanish banking systems

A rough comparison of the sectoral composition of aggregate exposures in the German, French, Belgian and Spanish banking systems is shown in Table 1. This table reveals that the distributions are relatively similar. The only noticeable differences are the greater importance of the Capital goods sector (33 p.c.) in Spain compared to Germany and Belgium, and the lesser importance of the Commercial services and supplies sector in Spain compared to Germany and Belgium. In general, however, the average sector concentrations are very similar across the four countries, which suggests that our results are to a large extent transferable to these countries.

2.3 Description of benchmark portfolio

The sectoral distribution of exposures in the benchmark portfolio is shown in Table 2 assuming that the total portfolio has a volume of 6 millions of euro. As mentioned above, this portfolio represents the sectoral distribution of aggregate exposures in the German banking system. It is possible for banks to use a more detailed sector classification scheme. We consider it more conservative to use a broad sector classification scheme rather than a very detailed scheme. In a broad sector classification scheme, a larger proportion of exposures is attached to a sector. Therefore, correlations between exposures of the same sector, which are typically greater than the correlations between exposures of a different sector, will play a larger role.

In order to focus on the impact of sector concentration we assume an otherwise homogeneous portfolio by requiring that all other characteristics of the portfolio are uniform across sectors. We further assume that the total portfolio volume of 6 millions of euro consists of 6,000 exposures of equal size which have a uniform probability of default of 2 p.c. We set a uniform LGD of 45 p.c., which is the supervisory value for a senior unsecured corporate loan in the Foundation IRB approach of the Basel II Framework [1].

2.4 Sequence of portfolios with increasing sector concentration

In order to measure the impact on *EC* of more concentrated portfolios than the benchmark portfolio, we construct a sequence of six portfolios, each with increased sector concentration relative to the previous portfolio in the sequence.

(1) See BCBS (2005).

TABLE 1 COMPARISON OF BANKS' AVERAGE SECTOR CONCENTRATIONS IN GERMANY, FRANCE, BELGIUM AND SPAIN
(Percentages)

Sector	Germany	France	Belgium	Spain
A. Energy	0.18	0.88	0.05	1.05
B. Materials	6.01	3.97	7.45	9.34
C. *Industrials* [1]	*52.36*	*63.82*	*54.77*	*48.53*
1. Capital goods	11.53	n.	9.89	32.90
2. Commercial services and supplies	33.69	n.	37.74	10.20
3. Transportation	7.14	n.	7.14	5.43
D. Consumer discretionary	14.97	11.91	15.77	18.60
E. Consumer staples	6.48	7.21	7.05	10.20
F. Health care	9.09	5.00	5.64	1.85
H. Information technology	3.20	1.47	1.86	1.99
I. Telecommunication services	1.04	1.91	0.54	2.67
J. Utilities	6.67	3.82	6.87	5.77

(1) Aggregate of C1, C2 and C3 only used for comparison with French data, not used in the analysis.

TABLE 2 COMPOSITION OF THE BENCHMARK PORTFOLIO

(Using the GICS sector classification scheme)

Sector	Total exposure (thousands)	Number of exposures	Exposure (percentages)
A. Energy	11	11	0.18
B. Materials	361	361	6.01
C. *Industrials*			
1. Capital goods	692	692	11.53
2. Commercial services and supplies	2,020	2,020	33.69
3. Transportation	429	429	7.14
D. Consumer discretionary	898	898	14.97
E. Consumer staples	389	389	6.48
F. Health care	545	545	9.09
H. Information technology	192	192	3.20
I. Telecommunication services	63	63	1.04
J. Utilities	400	400	6.67
Total	**6,000**	**6,000**	**100.00**

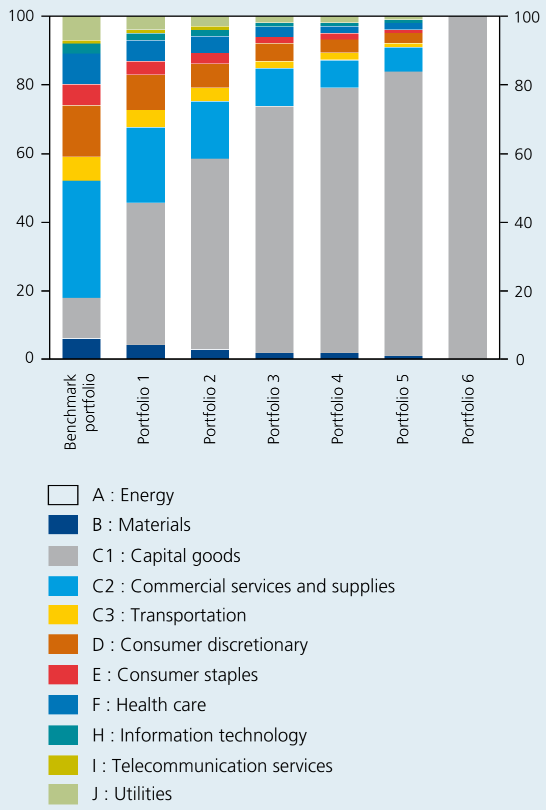
TABLE 3 SEQUENCE OF PORTFOLIOS WITH INCREASING SECTOR CONCENTRATION (1)

(Percentages)

	Benchmark portfolio	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6
A. Energy	0	0	0	0	0	0	0
B. Materials	6	4	3	2	2	1	0
C. *Industrials*							
1. Capital goods	12	41	56	71	78	82	100
2. Commercial services and supplies	34	22	17	11	8	7	0
3. Transportation	7	5	4	2	2	1	0
D. Consumer discretionary	15	10	7	5	4	3	0
E. Consumer staples	6	4	3	2	2	1	0
F. Health care	9	6	5	3	2	2	0
H. Information technology	3	2	2	1	1	1	0
I. Telecommunication services	1	1	1	0	0	0	0
J. Utilities	7	4	3	2	2	1	0
HHI	17.6	24.1	35.2	51.5	61.7	68.4	100.0

(1) Portfolio 2 and portfolio 5 reflect real bank portfolios.

CHART 1 SEQUENCE OF PORTFOLIOS WITH INCREASING SECTOR CONCENTRATION (1)



(1) Portfolio 2 and portfolio 5 reflect real bank portfolios.

Table 3 and Chart 1 illustrate the sequence of portfolios. The increase in sector concentration is also reflected in the Herfindahl-Hirschman-Index (HHI) (1), which is calculated at sector level. Portfolio 1 has been constructed from the benchmark portfolio by re-allocating one third of each sector exposure to the sector Capital goods. The more concentrated portfolios 2, 3, 4 and 5 have been created by a repeated application of this rule. The sector Capital goods and the algorithm have been chosen in such a way that portfolios 2 and 5 are similar to real portfolios of existing banks (2). They are similar insofar as the sector with the largest exposure size has a similar share of the total portfolio. Furthermore, the HHI is similar to what is observed in real-world portfolios. Finally, we created portfolio 6 with the highest degree of concentration as a one-sector portfolio by shifting all exposures to the Capital goods sector.

2.5 Intra- and inter- sectoral correlations

The sector factor correlations are estimated from historical equity index correlations. Table 4 shows the equity correlation matrix of the relevant MSCI EMU industry indices (3). The sector factor correlations are based on weekly return data covering the period from November 2003 to November 2004. Sectors that are highly correlated with other sectors (i.e. sectors that have an average inter-sector equity correlation greater than 65 p.c.) are: Materials (B), Capital goods (C1), Transportation (C3) and Consumer discretionary (D). Sectors that are moderately correlated with other sectors, i.e. sectors that have an average inter-sector equity correlation of between 45 p.c. and 65 p.c., are Commercial services and supplies (C2), Consumer staples (E), and Telecommunication (I). Sectors that are the least correlated with other sectors, i.e. sectors that have an average inter-sector equity correlation of less than 45 p.c., are: Energy (A) and Health care (F). The relative order of these sectors is broadly in line with results reported in other empirical papers (4). The heterogeneity between the sectors Capital goods, Commercial services and supplies and Transportation is confirmed by noticeable differences in correlations. The intra-sector correlations and/or inter-sector correlations between exposures are obtained by multiplying these sector factor correlations of Table 4 with the factor weights of the exposures.

The value of the sector factor weights r_s in (1) is calibrated to the corresponding IRB regulatory capital charge. More precisely, we use a sector factor loading $r_s = 0.50$ for all sectors, which ensures that the *EC* equals the IRB capital charge for corporate exposures, assuming a default probability of 2 p.c., an LGD of 45 p.c., and a maturity of one year. This value is slightly more conservative than empirical results for German companies suggest (5).

Intra-sector asset correlations between exposures are thus fixed at 25 p.c. Inter-sector asset correlation can be calculated by multiplying the factor weights of both sectors by the inter-sector equity correlation. The lowest equity correlation between the Energy equity index and the Information technology index of 10 p.c. translates into an inter-sector asset correlation between exposures

(1) The HHI is calculated by summing the squares of the shares of each sector in the portfolio.
(2) Due to confidentiality requirements, we cannot reveal more detailed information.
(3) The correlation matrix based on MSCI US data is similar.
(4) See, for example, De Servigny and Renault (2001), FitchRatings (2004) and Fu et al. (2004). It is very hard to compare the absolute inter-sector correlation values as different papers report different types of correlations. De Servigny and Renault (2001) report inter-sector default correlation values, FitchRatings (2004) reports inter-sector equity correlations while Fu et al. (2004) provides correlation estimates inferred from co-movements in ratings and asset correlation estimates. Furthermore, the different papers distinguish between a different number of sectors.
(5) See Hahnenstein (2004).

TABLE 4 CORRELATION MATRIX OF MSCI EMU INDUSTRY INDICES

(Based on weekly log return data covering the November 2003 until November 2004 period; in percentages)

	A	B	C			D	E	F	H	I	J
			1	2	3						
A. Energy	100	50	42	34	45	46	57	34	10	31	69
B. Materials		100	87	61	75	84	62	30	56	73	66
C. *Industrials*											
1. Capital goods			100	67	83	92	65	32	69	82	66
2. Commercial services and supplies				100	58	68	40	8	50	60	37
3. Transportation					100	83	68	27	58	77	67
D. Consumer discretionary						100	76	21	69	81	66
E. Consumer staples							100	33	46	56	66
F. Health care								100	15	24	46
H. Information technology									100	75	42
I. Telecommunication services										100	62
J. Utilities											100

of 2.5 p.c. The highest equity index correlation occurs between the Commercial services and supplies and the Consumer discretionary sector index. At 92 p.c., it translates into an inter-sector asset correlation between exposures of 23 p.c.

As mentioned before, the model underlying the Basel II Framework assumes that all systematic risk is driven by a single risk factor model and therefore takes no account of the fact that asset correlations can vary across sectors. Asset correlations are defined as a decreasing function of the probability of default. More specifically, these correlations vary between 12 p.c. for low quality exposures and 24 p.c. for high quality exposures. In our analysis we allow for a variation between 2.5 p.c. (which is the lowest inter-sector asset correlation) and 25 p.c. (which is the highest intra-sector asset correlation).

3. Impact of sector concentration on economic capital

3.1 Main results

The results for the *EC* of the seven portfolios are given in Table 5. We observe that, for our corporate benchmark portfolio, *EC* is estimated at 7.8 p.c. Economic capital increases when we gradually increase sector concentration. From the benchmark portfolio to portfolio 2, *EC* increases by more than 20 p.c. *EC* for the relatively concentrated portfolio 5 increases by a substantial 37 p.c. relative to the benchmark portfolio. These results demonstrate the importance of taking sector concentration into account when calculating *EC*.

Typically, the corporate portfolio comprises only a fraction of the total loan portfolio (which also contains loans to sovereigns, other banks and private retail clients). Although the increase in sector concentration may have a significant impact on the *EC* for the corporate credit portfolio, it may have a much smaller impact in terms of a bank's total credit portfolio. For a meaningful comparison, we assume that the corporate credit portfolio comprises 30 p.c. of the total portfolio and that the banks need to hold capital amounting to 8 p.c. of the outstanding exposure for their total portfolio which also comprises, for example, retail exposures. By assuming that there are no diversification benefits between corporate exposures and the bank's other assets, the *EC* of the total portfolio can be determined as the sum of the *EC* for the corporate exposure and the *EC* for the remaining exposures.

Table 5 compares *EC* for a corporate portfolio with *EC* for the total portfolios. For the total portfolios 1 to 6, *EC* increases only because the sector concentration in the corporate portfolio increases, whereas *EC* for other assets remains constant at 8 p.c. As expected, the impact of an increase in sector concentration is much less severe when looking at the *EC* for the total portfolio. Total *EC* increases in portfolio 2 by 6 p.c. relative to the benchmark portfolio and in portfolio 5 by 11 p.c.

TABLE 5 IMPACT OF SECTOR CONCENTRATION ON ECONOMIC CAPITAL FOR THE SEQUENCE OF CORPORATE PORTFOLIOS AND FOR THE SEQUENCE OF TOTAL PORTFOLIOS OF A BANK

(Percentages)

	Benchmark portfolio	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6
Corporate portfolio	7.8	8.8	9.5	10.1	10.3	10.7	11.7
Total portfolio	8.0	8.3	8.5	8.7	8.8	8.9	9.2

These results are in line with the empirical paper on US data by Burton et al. (2005), who simulated the distribution of portfolio credit losses for a number of real US syndicated loan portfolios. They find that, although name concentration can meaningfully increase *EC* for smaller portfolios (with exposures of less than 10 billions of dollar), sector concentration risk is the main contributor to *EC* for portfolios of all sizes.

3.2 Robustness checks

The procedure for generating a sequence of portfolios with increasing sector concentration is by no means unique. Therefore, we employ two alternative rules to generate these portfolios. The idea is that each new sequence of portfolios is generated by assigning exposures to the sector, which exhibits the highest (the "High-*MEC* rule") or by assigning exposures to the sector with the lowest marginal economic capital[1] (the "Low-*MEC* rule"). The sector with the highest *MEC* appears to be Commercial services and supplies. This is an intuitive result, because this is not only a large sector, it is also moderately correlated with other sectors. The sector with the lowest *MEC* is the Energy sector which is a small sector and one of the least correlated with other sectors.

We find that economic capital increases in a similar way under these alternative rules of portfolio generation. Results are presented in detail in Düllmann and Masschelein (2006). As expected, the economic capital increases at the fastest pace for the sequence of portfolios which are generated by the "High-*MEC*"-rule. Economic capital for the sequence of portfolios generated by the "Low-*MEC*"-rule increases at the slowest pace. The difference between *EC* under the three construction rules, however, diminishes as sector concentration increases.

In order to verify how robust our results are in relation to the input parameters, we have carried out the following four robustness checks (labelled RC1 – RC4 in Table 7):

- a lower uniform PD of 0.5 p.c. instead of 2 p.c. for all sectors (RC1),
- heterogeneous sector-level PDs which were estimated from historical default rates of the individual sectors (RC2) and given in Table 6,
- a sector factor correlation matrix representing the correlation matrix with the highest average annual correlation over the period 1997-2005 (RC3),
- a uniform intra-sector asset correlation of 15 p.c. and a uniform inter-sector asset correlation of 6 p.c. (RC4), which are values also used by Moody's for the risk analysis of synthetic collateralised debt obligations (CDOs)[2].

Although the absolute level of *EC* varied between these robustness checks, the relative increase in *EC* compared with the benchmark portfolio is similar to previous results in this section. The results are summarised in Table 7. For Moody's correlation assumptions in RC4, the increase in

TABLE 6 AVERAGE DEFAULT RATES 1990-2004

(Percentages)

A. Energy	1.50
B. Materials	2.80
C. *Industrials*	
1. Capital goods	2.90
2. Commercial services and supplies	3.70
3. Transportation	2.90
D. Consumer discretionary	3.20
E. Consumer staples	3.50
F. Health care	1.60
H. Information technology	2.40
I. Telecommunication services	3.60
J. Utilities	0.60

Source: Own calculation, based on S&P (2004).

(1) The marginal economic capital of a sector is defined as the difference between the *EC* of the whole portfolio including the sector and the *EC* of the portfolio excluding the sector.

(2) See Fu et al. (2004).

TABLE 7 ECONOMIC CAPITAL AS PERCENTAGE OF TOTAL EXPOSURE FOR THE BENCHMARK PORTFOLIO AND ITS PERCENTAGE INCREASE FOR THE MORE CONCENTRATED PORTFOLIOS

	Using "Real-rule"	RC1: PD = 0.5 p.c.	RC2: Heterogeneous PD	RC3: Higher correlation	RC4: Moody's
	(EC, percentages)				
Benchmark portfolio	7.8	3.3	10.0	8.7	4.0
	(Change of EC, percentages)				
Portfolio 1	13	12	11	6	6
Portfolio 2	20	21	15	13	18
Portfolio 3	30	29	25	22	39
Portfolio 4	35	37	27	24	46
Portfolio 5	36	42	32	24	51
Portfolio 6	49	52	42	33	77

EC is stronger than for the other robustness checks. This can be explained by the bigger difference between intra-sector and inter-sector asset correlations, which leads to a stronger *EC* increase when the portfolio becomes more and more concentrated in a single sector. We conclude that the observed substantial relative increase in *EC* due to introducing sector concentration is robust against realistic variation of the input parameters. Furthermore, this increase in *EC* may even be stronger, depending on the underlying dependence structure.

4. Summary and policy implications

The minimum capital requirements for credit risk in the IRB approach of Basel II implicitly assume that banks' portfolios are well diversified across business sectors. Potential concentration risk in certain business sectors is covered by Pillar 2 of the Basel II Framework which comprises the supervisory review process [1]. To what extent the regulatory minimum capital requirements may understate the required capital is an empirical question. In this paper we approached this question by using data from the German central credit register. The loss distribution is simulated in the default-mode version of the CreditMetrics multi-factor model, and credit risk is measured by economic capital.

In order to measure the impact of concentration risk on *EC* we start with a benchmark portfolio that reflects average sector exposures of the German banking system. Since the exposure distributions across business sectors were similar in Belgium, France, and Spain, we expect that our main results also hold for other European countries.

Starting with the benchmark portfolio, we have successively increased sector concentration in six steps, considering degrees of sector concentration which are observable in real banks. The last and most concentrated portfolio contained only exposures to a single sector. Compared with the corporate benchmark portfolio, *EC* for the concentrated real portfolios can increase by 37 p.c. and is even higher in the case of a single-sector portfolio. Under the assumption that the corporate credit portfolio comprises 30 p.c. of the total portfolio, *EC* for the total portfolio resembling a real portfolio increases by 11 p.c. relative to the benchmark portfolio. These results clearly underline the necessity to take inter-sector dependency into account for the measurement of credit risk.

We have subjected our results to various robustness checks, first with a lower uniform PD and sector-dependent PDs, based on historical default rates provided by S&P. We have also calculated *EC* for our portfolios using a correlation matrix with the highest observed average factor correlations since 1997. Finally, similarly to the assumptions adopted by Moody's for valuing synthetic CDOs, we have applied a uniform intra-sector asset correlation of 15 p.c. and an inter-sector asset correlation of 6 p.c. In all cases our results remain qualitatively the same. The increase in *EC* may even be stronger than in our original analysis, depending on the underlying dependence structure.

(1) See BCBS (2005), paragraphs 770-777.

In addition to the individual bank level, sector concentration can also play a role from a system-wide risk perspective, if banks' loan portfolios reflect the sectoral concentration within a country and if the degree of this sectoral concentration is high. Furthermore, indicative comparisons, based on the credit registers of four European countries, show similarities in the sectoral distributions of aggregate loan exposures across countries. These similarities imply that diversification across countries generally need not improve the sectoral diversification of a bank.

In our analysis we have used Monte Carlo simulations to measure *EC* in a multi-factor setting, which is computationally burdensome. Approaches that avoid the use of Monte Carlo simulations would in this respect be very helpful. Research on analytic approximations, however, is still in progress (1).

We conclude that sector concentration in individual banks' corporate credit portfolios merits careful attention in banks' internal risk management, since sectoral concentration appears to have a strong impact on credit risk.

(1) See for example Pykhtin (2004), Cespedes et al. (2005), Düllmann (2006) and Düllmann and Masschelein (2006).

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Appendix

TABLE 8 GICS CLASSIFICTION SCHEME: BROAD SECTORS AND INDUSTRY GROUPS

A. Energy

B. Materials

C. *Industrials*

   1. Capital goods
   2. Commercial services and supplies
   3. Transportation

D. *Consumer discretionary*

   1. Automobiles and components
   2. Consumer durables and apparel
   3. Hotels, restaurants and leisure
   4. Media
   5. Retailing

E. *Consumer staples*

   1. Food and drug retailing
   2. Food, beverage and tobacco
   3. Household and personal products

F. *Health care*

   1. Health care equipment and services
   2. Pharmaceuticals and biotechnology

G. *Financials*

   1. Banks
   2. Diversified financials
   3. Insurance
   4. Real estate

H. *Information technology*

   1. Software and services
   2. Technology hardware & equipment
   3. Semiconductors & semiconductor equipment

I. Telecommunication services

J. Utilities