Crash Testing German Banks

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Abstract

In this paper we stress-test credit portfolios of 28 German banks based on a Merton-type multi-factor credit risk model. The stress scenario is an economic downturn in the automobile sector. Although the share of the credit exposure in the automobile sector is relatively low for all banks in the sample, the expected loss conditional on the stress event increases substantially by 70-80% for the total portfolio. This result mainly driven by correlation effects to related industry sectors confirms the need to adequately capture credit risk dependencies between sectors even if the stress scenario is confined to a single sector. Estimates of banks' economic capital increase between 8-20% in the stress scenario, far less than the expected loss. Finally, we calculate the impact on banks' own funds ratios which decrease on average from 12% to 11.4% due to the stress event, indicating that banks overall remain well-capitalized.

Keywords: Asset correlation, portfolio credit risk, stress test

JEL classification: G 21, G 33, C 13, C 15

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The views expressed herein are our own and do not necessarily reflect those of the Deutsche Bundesbank.

1. Introduction

In this paper we stress-test credit portfolios of large German banks based on a Merton-type multi-factor credit risk model. The stress scenario is an economic downturn in the automobile sector. The stress-test methodology is based on recent work by Bonti et al. (2006). Our study is set apart by the following five characteristics.

1. As the automobile sector is regarded as a key sector of the German economy, a downturn in this sector is expected to have severe repercussions in other business sectors. Therefore, inter-sector dependencies need to be accounted for, which is achieved by using a multi-factor portfolio risk model.
2. Our approach can also be used to identify hidden sectoral credit concentrations as it allows to identify risk concentrations under stress conditions across highly correlated sectors.
3. A common drawback of traditional stress tests is that they concentrate on a single-event scenario, which occurs only with a marginal probability. The sensitivity to deviations from this single event are rarely considered. In our set-up we consider instead a stress scenario comprising a range of stress events such that the probability of the stress scenario is quite significant.
4. The use of the German credit register allows us to apply our stress test methodology to a sample of 28 banks, taking into account their credit portfolios to the extent that loans are included in the credit register.
5. Traditionally the focus of stress tests is on the expected loss (EL) conditional on the stress event. We also consider the impact on economic capital (EC), defined as the difference between a 99.9% value-at-risk (VaR) and the EL. As a robustness check we also calculate the *Expected Shortfall* (ES) or tail conditional expectation. The impact on the solvency of the banks is measured by comparing banks' own funds ratios before and after stress.

The considered stress events are linked to an observable macroeconomic variable, the German automobile production index. They reflect an "exceptional but plausible"[3] stress scenario which captures a continuum of stress events which together occur with a probability of 33%.

For the stress tests we employ a default-mode, one-period version of a standard Merton-type portfolio model in the spirit of Gupton et al. (1997) and Finger (1999). This allows us to adequately capture credit concentrations and default dependencies between borrowers. Previous studies have found that name concentration, although less important than sectoral concentration, also has a material impact on economic capital.[4] Both types of credit concentration are captured by our methodology. Name concentration is automatically accounted for by using credit information aggregated to risk-oriented "borrower units" which is more appropriate for risk assessment than the facility level or the legal entity

[3] See CEBS, CP 12.

[4] See, for example, Düllmann and Masschelein (2007) or Heitfield et al. (2006).

level. Credit risk due to sectoral exposure concentrations is captured through empirically estimated inter-sector correlations.

A key challenge in any stress test design is how an adverse change in macroeconomic variables is incorporated into the model. In our case this is achieved by judiciously truncating the distribution of the risk factor that belongs to the automobile sector which is under stress. The cut-off point that defines the least adverse of all considered stress events is set such that the quantile of all risk factor realizations up to the cut-off point corresponds to the same quantile of the automobile production index. This quantile of the automobile index is defined such that the expected value of the production index, conditional on a drop below the cut-off point, equals the forecast of a downturn in the automobile sector.

Our stress test set-up has the following conceptual advantages. It it is *plausible* in the sense that the stress scenario should be believable and have a certain probability of actually occuring. It is *consistent* with the existing quantitative framework since we employ the same model which is also used under "normal" circumstances and we make use of all information contained in the parameter estimates of this model. Finally it is *adapted to the portfolio and reporting* as it examines a relevant part of a bank's portfolio and allows for drawing clear conclusions from the results.

The need to take into account the reaction of other risk factors if one or a few risk factors are stressed in order to avoid a material underestimation of the stress impact has been recognized already in Kupiec (1998). Our stress test design and the underlying credit risk model draw heavily from the work by Bonti et al. (2006) but differ in important ways. Since we have access to the German central credit register we can apply it to 28 different banks instead of only a single institute. This allows conclusions for the stress impact on a cross-section of banks. Secondly, we extend our analysis by additionally considering the impact on banks' capitalization, in this case measured by the own funds ratio. Thirdly, since we do not have access to borrower-specific default probabilities we have to revert to sector-dependent average default probabilities, which we consider to be one of the most severe limitations of our analysis.[5] A related methodology was also applied by Elsinger et al. (2006) with a stronger focus on financial stability aspects.

Our results can be useful from a risk manager's, a central bank's and a supervisor's perspective. From a risk management perspective they provide an empirical implementation of the stress testing methodology invented by Bonti et al. (2006). From a financial stability perspective, which is typically the domain of central banks, it gives valuable information as to the resiliency of a major part of the German banking system (in terms of asset size) against an external shock to the automobile sector. Although the number of banks considered is relatively low compared to the total number of German banks – 28 compared with 2301 – their total credit exposure nevertheless amounts to 75% of the total credit exposure of German banks to non-financial firms, measured in terms of banks' credit volume captured by the credit register. Finally, the performance of individual banks, particularly the change of their own funds ratios may be useful information for supervisory purposes.

Our main results are the following:

[5]This restriction will be lifted in future work when the German credit register is extended to include PD estimates of all banks adopting the internal ratings based approach of Basel II.

1. The expected loss (EL) increases under stress conditions by 70-80% for all banks in the sample. As a consequence, the own funds ratio decreases on average from 12% to 11.6%. Therefore, the German banks in the sample overall could sustain losses from a stress event in the automobile sector, at least up to the extent captured by our stress test.
2. EC increases under stress by between 8% and 20%. Although the increase of 12% to 22% is somewhat stronger with ES as risk measure. In both cases it is still significantly lower than the increase in EL.
3. The significant impact on EC and the even stronger impact on EL is mainly driven by the effect of inter-sector correlations. If only the impact on the automobile sector is considered, EL of the total portfolio increases in the sample by less than 2.5%. This low number is explained by the relatively low share of the automobile sector relative to the total exposure of the portfolio. Therefore, the results underline the need to account carefully for inter-sector dependencies also if a stress scenario in a single sector is analyzed.
4. The absolute level of EC is substantially, i.e. on average about 16% higher for portfolios of real banks compared with highly fine-grained or *infinitely granular* portfolios with otherwise the same risk characteristics. The relative increase in EC due to the stress scenario, however, is similar in both cases. This finding suggests that the computationally more tractable case of an infinitely granular portfolio can provide a reasonable proxy of the stress impact on the VaR, at least if PDs are homogenous in every sector.
5. A robustness check with higher inter-sector correlations shows a materially higher relative increase in EL of up to 16.4 percentage points whereas the relative increase in EC is slightly lower. Therefore, good estimates of the asset correlations are a key prerequisite for meaningful stress test results.

The paper is structured as follows. Section 2 describes the data on banks' credit portfolios and the correlation estimates. The design of the stress scenario and the portfolio credit risk model are presented in Section 3. The impact of the stress scenario on banks' portfolios is measured and discussed in Section 4. Section 5 contains a sensitivity analysis with respect to the granularity of the exposures in the portfolio and the level of inter-sector correlations. Section 6 summarizes and concludes.

2. Data and Descriptive Analysis

In order to base our stress test results on realistic input parameters, we employ information on credit portfolios of German banks that was extracted from the credit register maintained in the Deutsche Bundesbank. The reference date is September 2006. The credit register recognizes bank loans exceeding € 1.5 million, i.e. smaller loans are not considered. Credit information is available only at borrower level, not at facility level. As a particularity, the credit register aggregates borrowers to *borrower units* which are treated as single credit entities because of business ties or legal linkages.[6] Companies not belonging to a borrower unit are treated as single entities. Loans granted within borrower units are omitted in this exercise. Credit mitigation techniques in the form of guarantees and plain-vanilla credit default swaps are recognized in the exposure amount.

The analysis requires every borrower to be assigned to one industrial sector. For single firms, the sector can be assigned directly according to their field of business. In the case of borrower units, the industrial sector covering the highest share of the borrower unit's total exposure is used. This assignment is reasonable since for all borrower units the share of the largest industrial sector amounts to 88.9% on average.

Since the credit register does not contain information on the credit quality of single borrowers, we have to revert to sector-dependent average probabilities of default (PDs) which are deduced from historical insolvency rates, available from the German Federal Statistical Office.[7] In order to calculate PDs, the ratio of average default events in 2005 and 2006 to the number of existing companies is used. The definition of sectors follows the *Industry Classification Benchmark* (ICB) which is convenient for the estimation of inter-sector correlations.

The ICB classification was originally developed by the Financial Times Stock Exchange and Dow Jones to create a standard for trading and investment decisions. It distinguishes four hierarchical sector levels which comprise ten sectors at the top level and 104 subsectors at the base level. For this study we use the second aggregation level that comprises 18 sectors. For the analyses, the ICB classification has two main advantages; firstly, additional stock indices are readily available which can be directly mapped to the ICB. Secondly, the industrial sectors used in the credit register of the Bundesbank can be easily matched to the ICB.

The banking sector is excluded from the study due to its specific characteristics, e.g. the monitoring by banking supervisors and the particularities of the inter-bank market which constitutes a major section of inter-bank exposures. Furthermore, since no German company is listed in the sector *oil and gas*, the analyses are limited to 16 sectors instead of 18.

The inter-sector correlations are estimated from weekly log-returns of stock indices over a time frame of two years. In order to differentiate between industry sectors, Dow Jones Eurostoxx sub-indices are used which can be matched to the 16 ICB sectors. The correlation matrix was estimated from index returns during 2005/2006 and is shown in Table 4 of the Appendix.

Figure 1 illustrates the correlations between the sector *automobiles and parts* and the 15 remaining sectors. Figure 11 and Figure 12 of the Appendix show similar diagrams for the sectors *financial services* and *industrial goods and services.* Figure 1 points out that the fluctuations of the correlations over time strongly depend on the respective pair of sectors. As an example, the correlations between the sector *automobiles and parts*

[6] A borrower unit comprises e.g. companies which are formally independent but which are considerably influenced or controlled by one of these companies.

[7] See Table 3 of the Appendix.

and *chemicals* are relatively stable over time whereas the correlations with the sector *telecommunications* fluctuate considerably. Between 1999 and 2001, almost all observed correlations are remarkably low, which can be explained by a sharp decline in stock prices during this period.

Figure 1. Correlations Between Sector Index *Automobiles And Parts* And Other Sectors

This figure shows the empirical pairwise correlations between the sector index *automobiles and parts* and the sector indices of the 15 remaining sectors of the ICB sector classification.

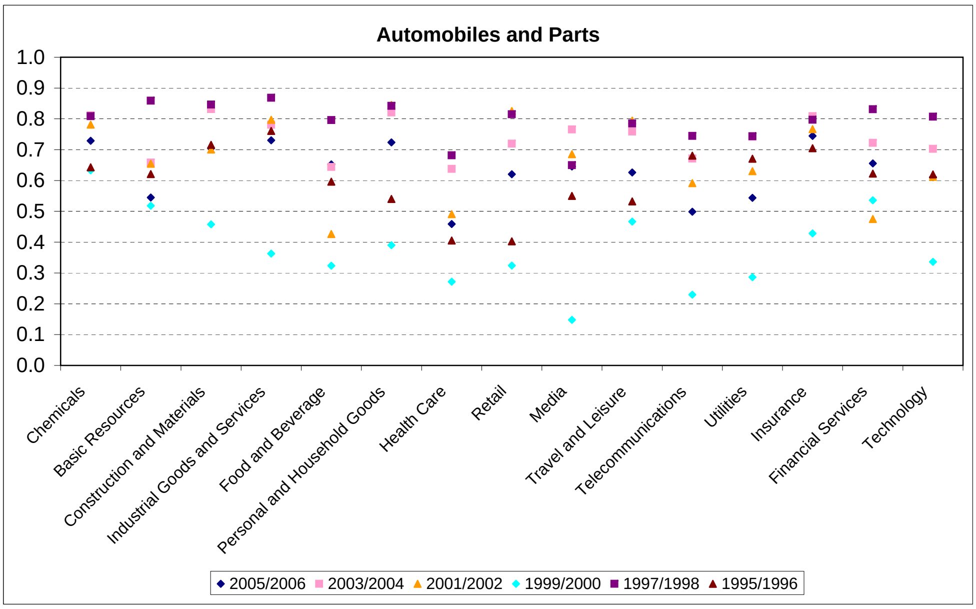


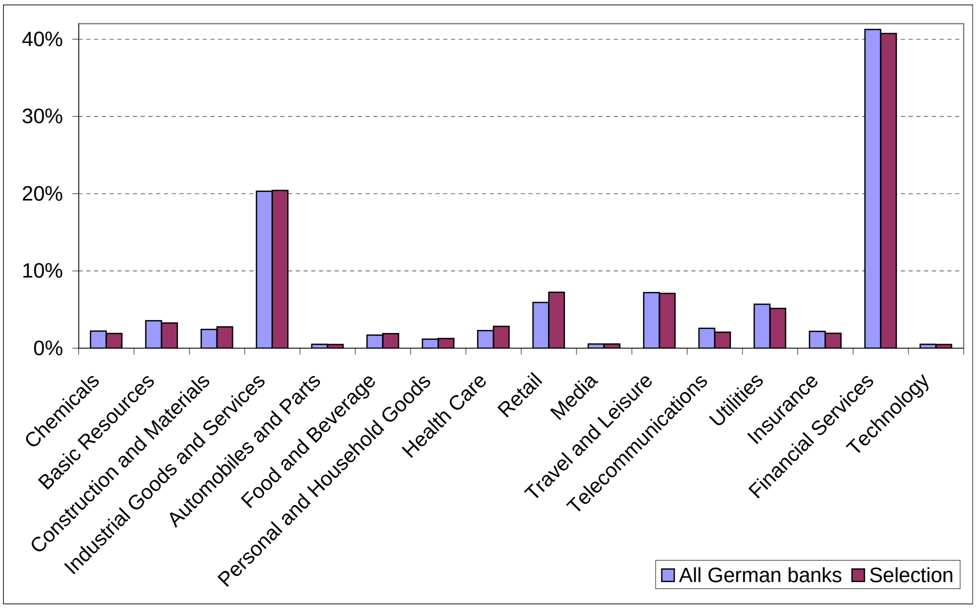
Figure 2 shows the distribution of the aggregated credit claims among the sectors, both for the 28 selected banks and for all domestic banks. Since the 28 chosen banks cover approximately 75% of the claims granted to non-financial companies included in the credit register, their credit distributions among the different sectors are quite similar to those of all domestic banks. The distribution indicates high concentrations in two sectors, *financial services* (approx. 40%) and *industrial goods and services* (approx. 20%). Since banks in their function as borrowers are excluded from our analyses and since insurance firms are assigned to a separate sector, the considerable loan share of financial services is to other financials, in particular to capital investment companies.

The share of the sector *automobiles and parts* appears relatively small. Yet it has to be considered that due to the sector correlation matrix the stress event also affects other branches with economic ties to this sector. In order to draw conclusions on the contribution of a specific sector to the entire portfolio risk, both the credit exposure *and* the correlations with other sectors have to be considered.

The stress test analysis is carried out for a sample of 28 German banks. Table 6 in the Appendix gives an overview of external ratings by Standard & Poor's and Fitch. 80% or

Figure 2. Sectoral Distribution of Credit Exposures

This figure shows the relative share of sectors measured in credit volume, both for banks in the sample and all German banks.



4/5 of the 28 banks have an A rating. Table 5 provides some more detailed balance sheet information on the sample of banks. Four banks are large commercial banks, eight "other" commercial banks, i.e. excluding large commercial banks, 13 belong to the savings bank sector which comprises also the *Landesbanken* and the remaining three are cooperative banks.

Figure 3 suggests that any relation between rating grades and sector concentrations measured by the HHI is weak at best. The same holds for a modified HHI^* which captures also the borrowers' credit risk

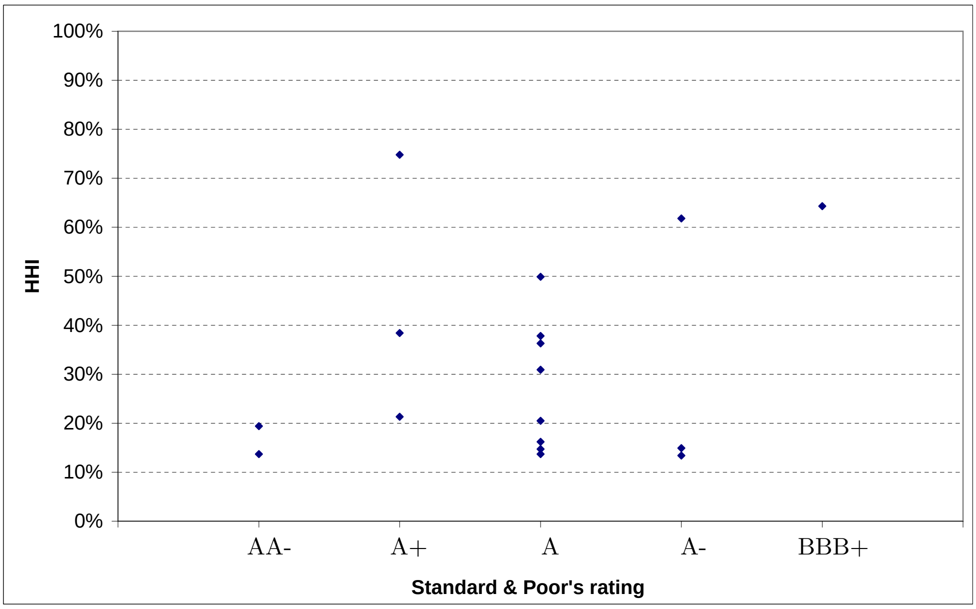
$$HHI^* = \sum_i \frac{PD_i}{\overline{PD}} w_i^2 \tag{1}$$

where PD_i denotes the default probability in the $i-$th sector, $\overline{PD}$ the average default probability of all sectors and all banks in the sample and w_i the percentage share of the $i-$th sector in the total portfolio exposure. Comparisons between the capital ratio and both HHI indices as well as PDs and HHI indices do not suggest any strong interrelation either. The missing relation between the concentration indices and the banks' risk ratings (or other risk indicators) could be either because sectoral concentrations have only a negligible impact on risk, or because more concentrated banks have a higher capital buffer possibly combined with more efficient risk management systems. It could also be explained by an inability of the sectoral HHI index to capture the effect of inter-sector correlations which are a driver of sectoral concentration risk.

Section 4 will provide further insight suggesting that it is rather the limited explanatory power of the simple measures HHI and modified HHI than a missing impact of sectoral concentration on the VaR that explains the missing link between concentration index and risk. Even in cases in which the exposure amount to a specific sector is relatively low, there can be a "hidden" concentration risk if this sector is highly correlated with another in which the bank has a substantial exposure. Such effects are not captured by a concentration index but by a portfolio model for credit risk which is introduced in the following section.

Figure 3. Rating of Standard & Poor's and Herfindahl-Hirschman-Index

This figure shows the rating of Standard & Poor's against the Herfindahl-Hirschman-Index at sector level for all rated banks in the sample.



3. Stress Scenarios and Methodology

3.1. Credit Risk Model

In order to capture all aspects of credit risk, including the impact of credit dependencies, a CreditMetrics-type portfolio model is applied which is frequently used in the banking business for credit risk modelling. Our implementation of this model-type considers a one-period time horizon and differentiates between two states of a default-trigger variable, default and non-default at the end of a one-year risk horizon.[8] An obligor defaults if the

[8] A generalization of the model framework towards a mark-to-market valuation which considers migration risk in addition to default risk would be possible, however, is not implemented in the current approach

default trigger – corresponding to the asset value in the classic Merton model – falls below an exogenously determined default barrier.

The portfolio losses due to credit defaults are described by the following loss function L_N:

$$L_N = \sum_{i=1}^{N} w_i \cdot LGD_i \cdot 1_{\{Y_i \leq c_i\}} \tag{2}$$

L_N denotes the total loss of the bank portfolio which is composed of credit claims to N borrowers or borrower units. The relative share of a single loan in the entire portfolio is indicated by w_i whereas the corresponding probability of default and the expected loss severity are described by PD_i and LGD_i. Since we do not have information on the ratings or PDs of individual borrowers, the PDs are estimated from historical default rates on a sector basis. Table 3 in the Appendix shows the PDs sector by sector which were calculated as average default rates over two years. The LGDs of all borrowers are set to 45% which is the value set by supervisors for senior unsecured corporate exposures in the internal ratings-based foundation approach of Basel II. The indicator function $1_{\{...\}}$ denotes a binary random variable which takes the value of one if a loan defaults and zero otherwise. A default event occurs if the default trigger Y_i falls below the default barrier c_i. Since Y_i has a standard normal distribution by construction (see below), the default barrier $c_i = \Phi^{-1}(PD_i)$ can be directly derived from the probability of default where $\Phi()^{-1}$ denotes the inverse of the cumulative normal distribution function.

The default trigger Y_i economically represents the change in the unobservable and appropriately normalized asset value of the company at the end of the risk horizon. It is composed of two risk components:

$$Y_i = r \cdot X_{s(i)} + \sqrt{1 - r^2} \cdot \epsilon_i. \tag{3}$$

The first risk component is the sector-dependent systematic risk factor $X_{s(i)}$ and the second component is the borrower-dependent (or idiosyncratic) risk factor ϵ_i. Both components are pairwise independent and have a joint standard normal distribution. As initially assumed, each loan is uniquely assigned to one out of S business sectors. Let $s : \{1, ..., N\} \to \{1, ..., S\}$ denote a mapping of the borrower to a sector. The empirically estimated correlations between the sector factors $X_{s(i)}$ are summarized in the correlation matrix Ω given by Table 4 in the Appendix. For simulating the loss distribution of the portfolio it is convenient to express $X_{s(i)}$ as a linear combination of independent standard normal systematic factors Z_k

$$X_{s(i)} = \sum_{k=1}^{S} \alpha_{s(i),k} \, Z_k. \tag{4}$$

The linear coefficients $\alpha_{s,k}$ are obtained from a Cholesky decomposition of the correlation matrix Ω.

due to data constraints.

The coefficient r determines the relative weight of the systematic and non-systematic risk factor, i.e. the closer its value is to one, the higher the systematic risk. Since the asset correlation of any pair of borrowers i and j is given by

$$\rho_{i,j} \equiv cor(Y_i, Y_j) = r^2 \, \omega_{s(i),s(j)}, \tag{5}$$

the parameter r can be determined if the asset correlation and the correlation between the two sector factors are known. For practical purposes we take the average asset correlation $\overline{\rho}$ of small and medium-sized German companies[9], an empirical value of 0.09, and the mean value $\overline{\omega} = 0.648$ of the correlation matrix given by Table 4 in the Appendix. With these values r is calculated by $\sqrt{\overline{\rho}/\overline{\omega}}$ and equals 0.373.

In order to calculate the risk measures, the loss distribution is determined by Monte Carlo-simulation. In every simulation run, $S + N$ independent and standardized normally distributed random numbers are generated. The sector factors can be calculated as linear combinations of the first S random numbers whereas the idiosyncratic risk factors are determined by the remaining N realizations of the random numbers. The portfolio loss can subsequently be calculated by means of equations 2 and 3. *Expected loss. Economic capital* and expected shortfall are used as risk measures for the credit portfolio before and after stress. Both EC and ES refer to the 99.9% quantile of the loss distribution. Following common industry practice, both risk measures are defined after subtraction of EL.

3.2. Design of the Stress Scenario

In the "normal" scenario, i.e. before the stress event occurred, a standard normal distribution is assumed for all sector factors. In this case, EL can be calculated analytically whereas EC has to be determined by Monte-Carlo simulations. In order to consider the stress scenario, adverse realizations of the sector factor, i.e. only realizations below a scenario-specific threshold, are generated. Technically speaking, the marginal distribution associated with the sector factor is restricted to a lower half-space limited by the upper threshold of the scenario.

In principle, this scenario threshold can be derived from a macroeconomic model. Our stress test follows a pragmatic approach which only requires as input the expectation value of an observable macroeconomic variable which is closely related to the risk factor associated with the stressed industry sector. In order to determine the threshold value of the corresponding risk factor, we also need the distribution function of the macroeconomic variable. This distribution function can be approximated by the empirical distribution of the production index. Accordingly, all paths of the risk factor considered in the stress test already reflect realistic stress conditions observed in the past.

Concerning the choice of the industry sector that needs to be stressed, we take into account forecasts that, due to stricter environmental regulations, the demand for cars could increasingly shift towards less petrol-consuming and less expensive models over the coming

[9] See Hahnenstein (2004).

years.[10] The German car industry which is traditionally mostly present in the segment of powerful cars in the upper price range would be particularly affected by such developments which could trigger a drop in German automobile production. Yet it depends on its ability to adapt to these emerging trends how strongly it will be affected.

A sudden decline in automobile production, however, can also have other explanations. Market disturbances such as the sub-prime crisis starting in summer 2007 could also negatively affect the automobile industry. A declining demand for cars due to stricter credit conditions could cause the situation of an already fragile US car market to deteriorate.[11] Since car exports have made an increasingly important contribution to the economic success of German car producers over the preceding years, this could have material repercussions also for the German car industry.

In light of these economic considerations, we assess the impact of a stress scenario in the automobile sector, more specifically of a sudden decline in automobile production, on the credit portfolios of our sample of 28 banks. Our stress scenario refers to an expected decline in automobile production by 10%. This figure is motivated by historical data. The de-trended log-returns of the underlying automobile production index between 1996 and 2007 are illustrated in Figure 4. The values can be used as an empirical frequency distribution of the yearly index variations. The horizontal line at the ordinate value of -0.1 indicates the 10% decline in the index value subsequently assumed as reference point for the stress scenario. Since various more pronounced drops in the index value occurred during the observation period (e.g. in autumn 2003), a decrease of 10% is not regarded as an extreme scenario.

In order to consider the stress scenario within the portfolio model, the expected decrease in the index value induced by the stress event needs to be transferred to the systematic and unobservable risk factor of the automobile sector. For this purpose, the empirical distribution of the historical yearly log-returns of the index is restricted by an upper threshold in such a way that the log-returns of the remaining distribution average 10%. Given an expected drop in the index value by -10%, the upper threshold of the log-returns equals the 33% quantile of the frequency distribution. This quantile is transferred to the risk model, i. e. to the unobservable systematic risk factor of the automobile sector. By assuming a standard normal distribution of the sector factor (before stress), the scenario threshold amounts to -0.44.

As a crucial advantage of the underlying multi-factor risk model, the impact of the stress event is also reflected in the remaining sectors (e.g. *industrial goods and services*). Since the sector factors are correlated with one another, the stress event is also transferred to other sectors and affects the distributions of the remaining sector factors.

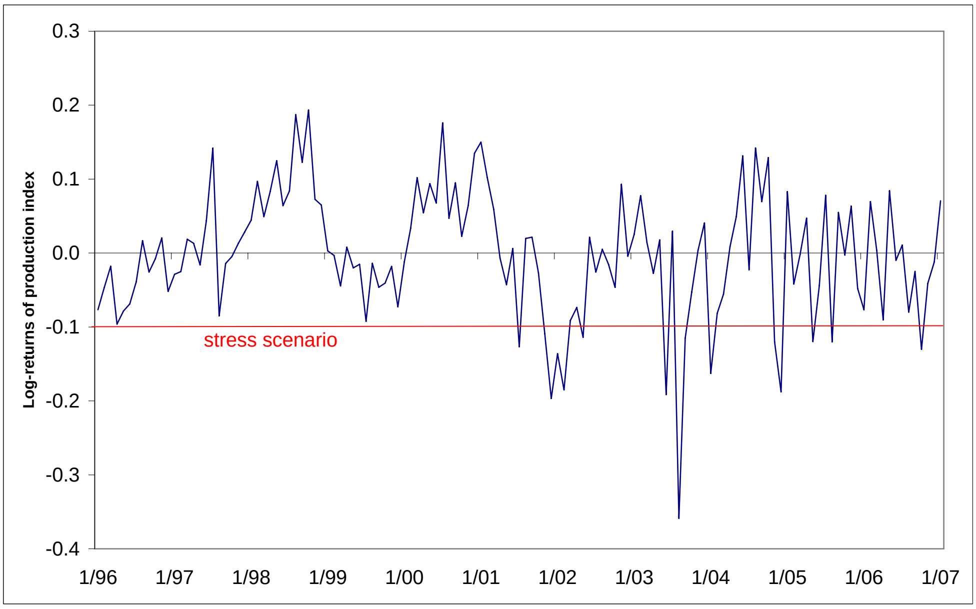
Figure 5 illustrates the distribution of the risk factors before (upper part) and after (lower part) the application of the stress scenario, both for the sector *automobiles and parts* (left side) and *industrial goods and services* (right side). The mean values of the distributions are marked as vertical lines.

[10] See article *The big-car problem* of 22 February 2007, www.economist.com.

[11] See “*Kreditkrise greift auf Autobanken über*” of 21 November 2007, www.handelsblatt.com.

Figure 4. Log-returns of the production index of the automobile sector

This figure shows the yearly log-returns of the production index of the automobile sector from January 1996 to January 2007.



In the left part of Figure 5, the impact of the stress scenario and the restriction of the risk factor in the 33% quantile can be clearly identified. Due to correlation effects, the stress event also affects the remaining sectors which is illustrated for the sector industrial goods in the right part. As a consequence, the empirical distribution of this sector factor and its mean are likewise shifted towards the negative domain.

4. Results for the Stress Scenario

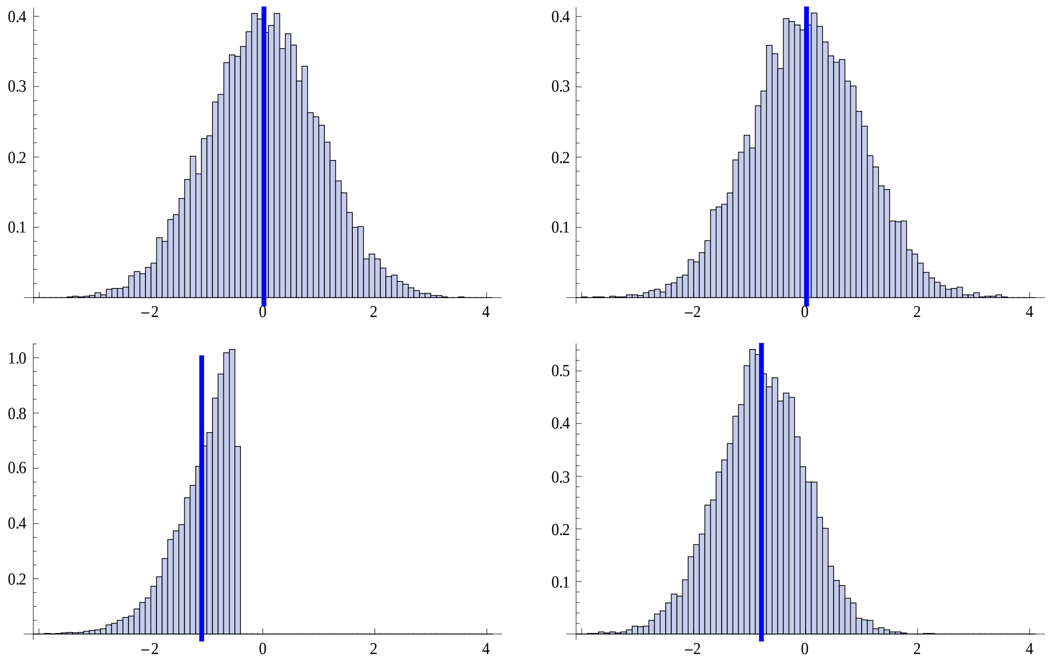
The results for EL and EC are based only on loans to non-financial companies and shown in Figure 6. The changes in EL, EC and ES due to the stress event are sorted in ascending order according to the relative increase in EL. To improve comparability, all results are indicated as percentage points referring to the total loan exposure of the banks' respective credit portfolios. Based on the chosen stress scenario, the results indicate a considerable and relatively similar increase in EL in a range between 70% and 80%.[12]

It has to be considered that for all banks the share of loans granted to the sector *auto-*

[12]Compared to the other institutions, the increase in EL of one particular bank amounting only to approximately 60% is considerably lower. The reason is the business model of this bank which has the consequence that loans are granted to sectors with relatively low correlations with the automobile sector.

Figure 5. Frequency Distribution of the Systematic Risk Factors

This figure shows simulated frequency distributions of the systematic risk factors before stress (upper part) and after stress (lower part) of the sectors *automobiles and parts* (left) and *industrial goods and services* (right).

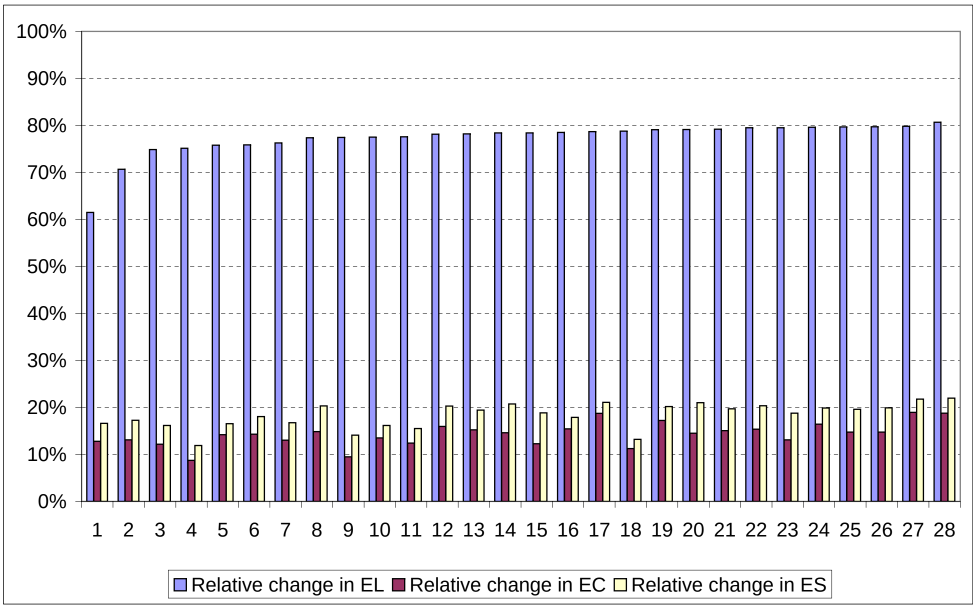


mobiles and parts does not exceed 2% and thus is only a minor part of the entire credit portfolio. Therefore, compared to the entire bank portfolio, the effect of the stress event on loans to the automobile sector is rather limited. For this reason, Figure 7 only shows a slight positive relation between the portfolio share of the automobile sector and the EL increase of the entire credit portfolio.

In order to explain the relatively large increase in EL across all banks, it is important to consider the correlations between the sectors. Owing to these correlations, the stress is transferred from the automobile sector to other sectors which can have a considerably bigger share of the credit portfolio. The sector *industrial goods and services*, for example, which has a comparatively high correlation with the automobile sector comprises a portfolio share between 3.4% and 33.5% among all chosen banks. Since the declining credit quality of the automobile sector affects this sector due to a high correlation, the overall increase in EL is more pronounced than if the automobile sector were considered in isolation. Thus, the increase in EL cannot primarily be attributed to loans granted to the automobile sector, but rather to the impact of the stress event on the remaining sectors due to correlation effects. This explains the strong increase in EL among all banks in spite of their differing but relatively low share of loans in the automobile sector.

Figure 6. Impact of Stress Scenario on Expected Loss and Economic Capital

This figure shows the relative change of expected loss (EL), economic capital (EC) and expected shortfall (ES) in the stress scenario for all 28 banks in the sample. The numbers are in percent.

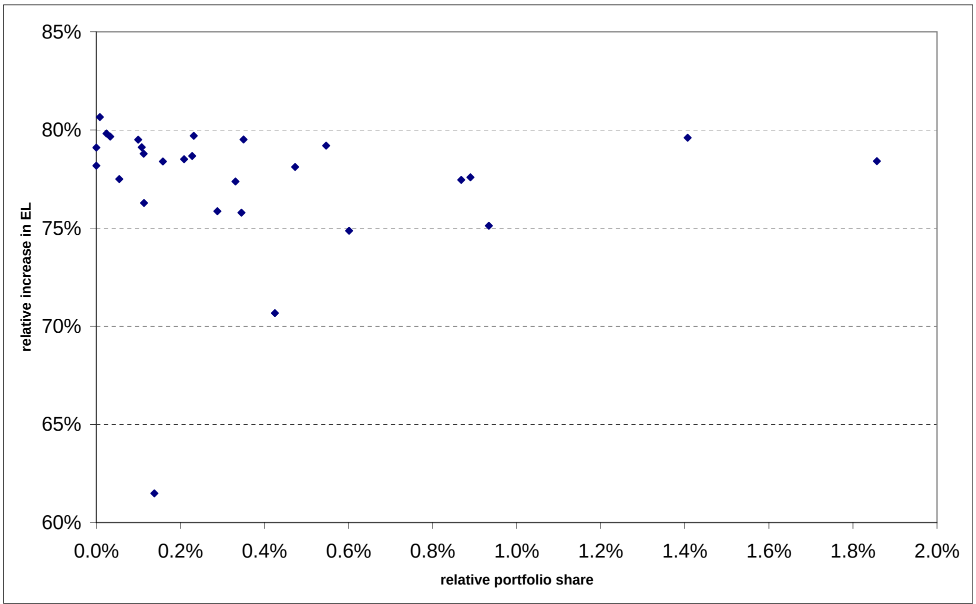


In order to quantify explicitly the importance of inter-sector correlations for the loss distribution under stress, we measure in an auxiliary calculation the difference in the EL increase between two cases: first the case in which only the impact on the automobile sector is included and second the case in which the impact on other sectors driven by the inter-sector correlations is also considered. In detail, for the first case we generate defaults based on systematic factor returns under "normal" conditions while only in the automobile sector they are based on systematic factor returns computed under stress. As a result, in the first case the resulting loss distribution captures only higher losses in the automobile sector due to the stress event whereas the losses in the other sectors are still based on "normal" conditions. For the second case that captures also the stress propagation through inter-sector correlations, we use the previous results.

The relative increase in EL in the first case is depicted in Figure 8 depending on the portfolio share of the automobile sector. The level of the EL increase which is for all banks below 2.5% is low compared with the increase of 70-80% if the inter-sector correlation effects are also considered. It is, however, well explained by the relatively low exposure share of the automobile sector which is for all banks below 2% of their total portfolio exposure. Furthermore, the scattergram reveals a positive, broadly linear relation between the increase in EL and the portfolio share of the automobile sector. Such a relation is not observable in Figure 7 since the overall change in EL is mainly driven by correlations with larger sectors.

Figure 7. Portfolio Share of Automobile Sector and Expected Loss

This figure shows the relative portfolio share of the sector *automobiles and parts* per bank compared to the relative increase in the expected loss of the total portfolio conditional on the stress scenario.



Another striking observation in Figures 6 and 7 are the relatively small differences in the EL increase between banks when disregarding one outlier bank with a lower increase of around 60%. This is all the more surprising given that the portfolio distribution among sectors varies from bank to bank such that different correlations take effect. One possible explanation is the similar portfolio share of a limited number of sectors for all banks in the sample, in particular the sectors *industrial goods and services* and *financial services*.[13] Since both sectors cover 60% of the entire credit portfolio on average, the increase in EL is mainly driven by their correlation with the automobile sector. Since the portfolio shares of both sectors are relatively similar across banks, the EL also rises in a similar range.

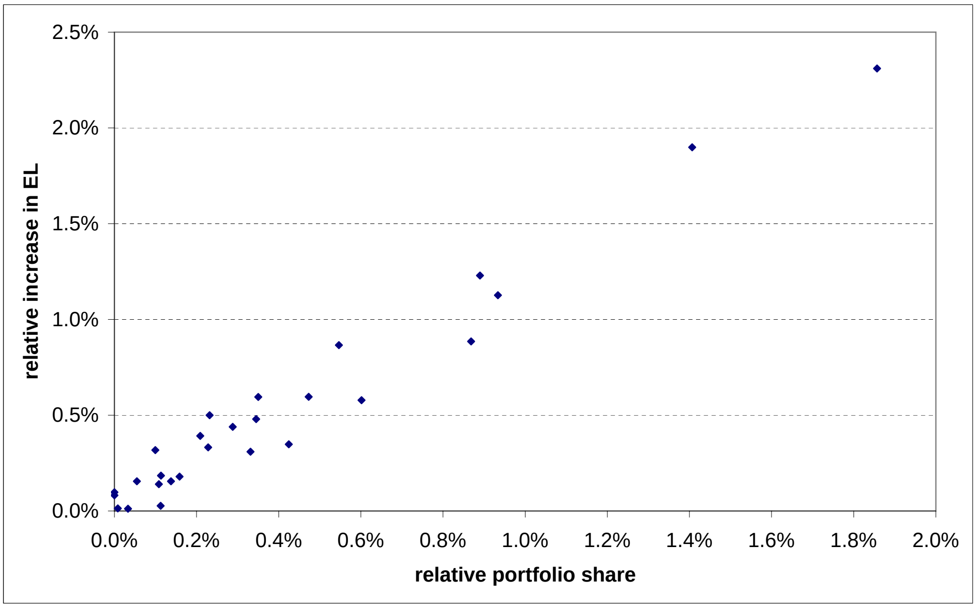
Compared to the overall increase in EL, the increase in EC is considerably lower according to Figure 6. It amounts from 8.7% to 18.8% compared to 70-80% for EL. An increase in EC can be interpreted in economic terms as higher capital requirements. An increase in EL is a first-order effect as it immediately affects net income and can trigger a bank failure if capital is exhausted and a bank becomes overindebted.[14] An increase in EC, however, is a second-order effect as it concerns the solvency under a high percentile which is in turn conditional on the stress scenario. For this reason, EL is considered as the primary concern of bank's risk management and serves as the key risk measure in the subsequent impact analysis on regulatory own funds ratios.

[13]See also Figure 2.

[14]According to the German insolvency code, overindebtedness automatically causes insolvency.

Figure 8. Portfolio Share of Automobile Sector and Expected Loss Without Considering Inter-Sector Correlations

This figure shows the relative portfolio share of sector *automobiles and parts* per bank compared to the share of the relative increase in the expected loss only in this sector conditional on the stress scenario.



The results for ES in Figure 6 differ from those for EC in that the measured relative increase in risk is slightly higher. This is to be expected since ES refers to a point further in the tail of the loss distribution than EC.

From a risk management perspective, it is not only important how the level of risk changes under stress conditions. Rather it is important to consider also the impact on the bank's solvency. In the following, the regulatory own funds ratios of the chosen banks are used in order to approximate the impact of the stress event on banks' minimum required capital. The regulatory requirements for own funds after stress are approximated as follows:

$$OFR^{stress} = \frac{regulatory\ own\ funds - \Delta EL_{\%}^{stress} \cdot credit\, exposure^{corporates}}{risk\, weighted\, assets\ incl.\ market\, risk}$$

$\Delta EL_{\%}^{stress}$ denotes the relative change in EL due to the stress event.

All banks in the sample belong to one of three German banking sectors, namely private banks, public banks and cooperative banks. Because of substantial differences in their business models we split the sector of private banks into "large (private) banks" and "(other) private banks". A bank is considered "large" in this case if its regulatory capital exceeds 3bn euros. The category of public sector banks comprises savings banks and *Landesbanken* which are owned by the German federal states (*Bundesländer*) and other public sector entities.[15]

For each of these four categories of banks, Table 1 indicates the average own funds ratio before and after the stress event. Owing to the stress scenario, the mean own funds ratio decreases by 0.43 percentage points from 12.04% to 11.61%. It has to be considered that the corporate portfolio only covers a part of the entire credit portfolio of a bank. Furthermore, the data available from the credit register of the Bundesbank only capture loans of a certain magnitude and therefore do not take into account exposures e.g. to small companies.[16] For these reasons, the impact on the own funds ratio is dampened, i.e. the estimated change in the ratio has to be regarded as a minimum level of the decrease to be expected.

Table 1

Regulatory Own Funds Ratios

This table shows regulatory own funds ratios before and after considering the impact of the stress event on the credit portfolio. The results are aggregated for four different categories of banks. The last column shows the own funds ratios which are calculated by using "stressed" correlations for the automobile sector (for further details see Section 5.2).

Banking sector	**Number of banks**	**Average of own funds ratio**		
		before stress [%]	**after stress [%] with correlations**	
			normal	**elevated**
Large banks	4	11.95%	11.75%	11.70%
Private banks[17]	8	10.59%	9.91%	9.81%
Public banks	13	12.42%	12.02%	11.95%
Cooperative banks	3	14.37%	14.20%	14.17%
Mean value		**12.04%**	**11.61%**	**11.54%**
Median		**11.35%**	**11.15%**	**11.10%**

Figure 13 in the Appendix illustrates the percentage change in EL of all banks in the sample against the HHI, calculated on a sector basis. The diagram suggests a slightly positive relation between both measures, yet it also points out the limits of relatively simple yardsticks for concentration risk such as the HHI. Hence only model-based analyses are able to provide robust results on the effects of the stress event.

[15] Results for individual banks are not reported here due to their confidential nature.

[16] See Section 2 for further details.

[17] Excluding large banks.

5. Sensitivity Analysis

5.1. Impact of Name Concentration

The stress test results for EL, EC and ES presented in the previous section can be considered conservative in the sense that the granularity or name concentration of the portfolio is overestimated because the credit register does not contain credit exposures below the reporting limit. Therefore, diversification benefits from smaller exposures in the portfolio are not captured. Although data constraints prevent us from measuring this effect directly, it is possible to estimate an upper bound by assuming that the portfolio is infinitely fine-grained in every business sector. Under this assumption, applying the law of large numbers conditionally on the factors shows that the limiting loss is given by the expected loss conditional on the (orthogonal) systematic risk factors $Z_1, ..., Z_S$[18]

$$L^{\infty} \equiv \mathbb{E}\left[L|Z_1, ..., Z_S\right] = \sum_{k=1}^{S} \bar{w}_k \, LGD \, \Phi\left(\frac{\Phi^{-1}(p_k) - r \sum_{j=1}^{S} \alpha_{k,j} \, Z_j}{\sqrt{1-r^2}}\right) \tag{6}$$

with sectoral exposure weights $\bar{w}_k = \sum_{\{i:\, s(i)=k\}} w_i$. The simplified "asymptotic" model represented by the loss distribution from (6) is computationally much more tractable. Although it still requires Monte Carlo-simulation, random numbers only need to be generated for the systematic risk factors but no longer for the idiosyncratic risk component.

For clarity, we refer in the following to the original bank portfolios as "finite" portfolios, and the portfolios with the same risk characteristics except infinite granularity in every business sector are referred to as "infinitely granular" portfolios. Table 2 compares summary statistics of EL, EC and ES, both for the finite portfolio analysed in the previous section and for the infinitely granular portfolio under a "normal" and a stress scenario. All statistics refer to the sample of 28 banks. The statistics for the finite portfolios summarize the results depicted in Figure 6.

We discuss first the results for the EL measure. The EL statistics under "normal" conditions are necessarily the same for both portfolios because in the case of homogenous and independent PDs and LGDs the expected value does not depend on the exposure distribution inside a business sector. Under stress, the mentioned EL statistics likewise increase by almost the same amount both in case of finite and infinite granularity. This result, which is to be expected for EL as risk measure, suggests that the asymptotic approximation of the loss distribution as given by (6) properly reproduces the EL impact of the stress scenario in the finite portfolios. This result is plausible for the following reason. Name concentration becomes important in the extreme adverse tail of the loss distribution. In our stress test we consider, however, a half space of the stressed systematic factor such that many factor realizations of this and other sectors are predominantly still relatively close to the center and distant from the extreme tail.

Contrary to the EL measure, for which we find quite similar results for the infinitely granular portfolio and the finite portfolio, the increase in the risk measure EC is significantly

[18] See Gordy (2003).

Table 2
Summary Statistics of Risk for Real and Infinitely Granular Portfolios

This table shows summary statistics of expected loss, economic capital and expected shortfall for a sample of 28 banks. We differentiate, firstly, between banks' real portfolios and infinitely granular portfolios with otherwise the same risk characteristics and, secondly, between a normal and a stress scenario. All results are given in percent.

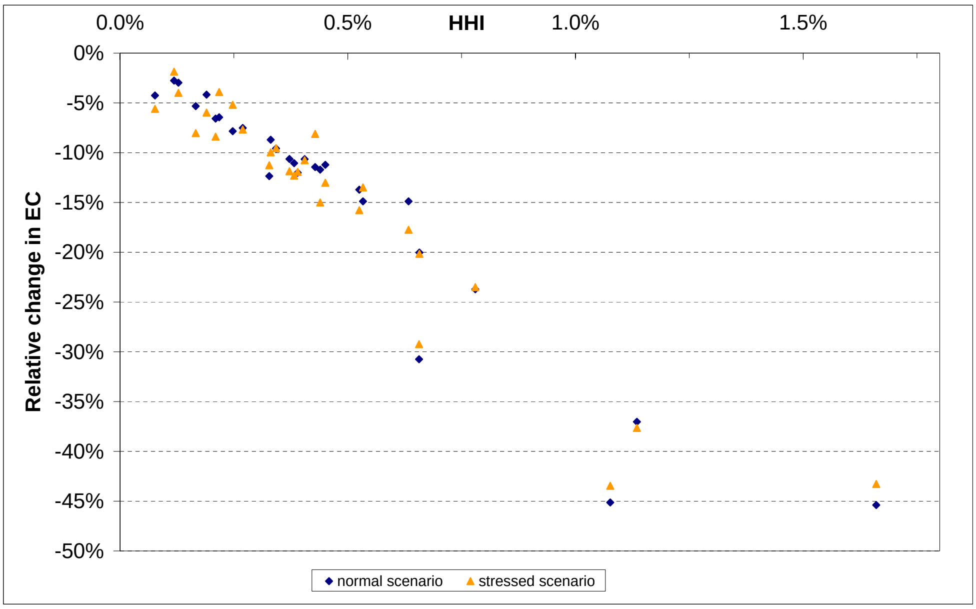
Portfolio granularity	**Finite**		**Infinite**	
Scenario	**Normal**	**Stress**	**Normal**	**Stress**
Expected Loss				
Maximum	0.54	0.92	0.54	0.92
75% quantile	0.45	0.80	0.45	0.80
Mean	0.44	0.77	0.44	0.77
25% quantile	0.40	0.73	0.40	0.72
Minimum	0.38	0.68	0.38	0.68
Economic Capital				
Maximum	5.98	6.65	3.64	4.28
75% quantile	3.97	4.48	3.38	3.87
Mean	3.84	4.38	3.22	3.68
25% quantile	3.43	3.96	3.07	3.44
Minimum	3.05	3.48	2.72	3.07
Expected Shortfall				
Maximum	7.41	8.39	4.94	5.91
75% quantile	5.20	6.16	4.58	5.49
Mean	5.07	5.99	4.39	5.24
25% quantile	4.65	5.52	4.20	4.98
Minimum	4.14	4.82	3.73	4.45

lower in the infinitely granular case. The difference is 10-40%, depending on the statistic, and 16% for the mean. The increase in EC due to name concentration is moderately stronger than observed in previous studies by Düllmann and Masschelein (2007) and Burton et al. (2006). Comparing EC under normal and stress conditions, we find that the increase in EC is similar in both cases, amounting to a range of 9-19% depending on the statistic. According to those results, portfolio granularity has a significant impact on the level of EC. It does not, however, seem to play a major role in its relative increase due to the stress event. This finding confirms that results based on using an infinitely granular portfolio as a proxy can substantially underestimate the *level* of required EC. They seem to provide, however, a good proxy for the *relative stress impact* on EC.

Figure 9 illustrates the impact of portfolio granularity measured by the decrease in EC if the bank's portfolio is replaced by a portfolio of infinite granularity but otherwise the same

Figure 9. Impact of Portfolio Granularity on Economic Capital

This figure shows the HHI calculated on exposure level against the percentage change in EC for portfolios of 28 banks if the portfolio is replaced by a portfolio with infinite granularity in every business sector but otherwise the same risk characteristics. Results are further differentiated between "normal" and stress conditions.



risk characteristics. The results are shown for the "normal" and the stressed scenario. In both cases, the relation between EC and HHI appears to be broadly linear.[19] Furthermore, the magnitude of the impact on EC is almost identical in both cases.

A diagram similar to Figure 9 in which EC is replaced as risk measure by EL does not show a similar dependence on HHI. This is to be expected as exposure concentrations become more important in the tail of the loss distribution. The EL conditional on the 33% quantile of the automobile risk factor, however, is still too close to the center of the distribution to show a similar relation between EC and HHI.

Turning finally towards the risk measure ES, the numbers in Table 2 show a similar, although somewhat stronger increase under stress conditions than observed for EC. A stronger increase is plausible as the ES refers to a point higher in the tail of the loss distribution than the EC.

In summary, we find that although the EL is the same both under normal and stressed conditions, the level of EC is rather different, depending on the portfolio being infinitely

[19] In the case of a single-factor credit risk model and an otherwise homogenous portfolio, a "granularity adjustment" to the EC figure calculated for an infinitely granular portfolio is linear in the HHI (see Gordy and Luetkebohmert (2007) for an example of such a granularity adjustment).

granular or not. However, the relative change in EC due to the stress event is similar for the finite and the infinitely granular portfolio. If EC is replaced by ES, the results are similar except that the increase under stress conditions is more pronounced.

5.2. Sensitivity to Higher Inter-Sector Correlations

The results presented in Section 4 are based on correlation estimates from stock index returns observed between 2005 and 2006. This time span was selected because it comprises the two preceding years of our sample of bank portfolios. It is commonly known that asset correlations are difficult to estimate. As we use equity returns as the basis of our correlation estimation, one could argue that the comovement in stock prices is also driven by factors unrelated to credit risk and also that asset correlations appear to be unstable over time.[20] The correlation estimates depicted in Figures 1, 11 and 12 confirm a substantial variation of correlation estimates over different two-year estimation periods. In order to measure the robustness of our results against errors in the correlation estimates, we carry out a straightforward "correlation stress test". For this purpose we replace the inter-sector correlation matrix by a correlation matrix estimated for the time period from 1997 to 1998.[21] This period exhibits the highest correlation estimates for the automobile sector over two-year periods between 1995 and 2006 which is confirmed by Figure 1.

With this new correlation matrix we repeat the stress test on the portfolios of the 28 banks (see Figure 10). The relative increase in EL is again calculated relative to the unconditional EL which is the same as before. As expected, the relative increase in EL which ranges from 78-93% across banks is stronger as in the case of the original correlation matrix (see Figure 6). The additional increase does not exceed 16.4 percentage points.

In the case of higher inter-sector correlations, the relative EC increase is far less strong than the increase in EL and even less than the increase in EC measured in the original stress test in Figure 6. Because of the "correlation stress", the loss distribution is shifted to the right hand side. This shift, however, seems to mostly affect the losses closer to the center of the distribution rather than in the tail such that EL is more affected than EC.

We finally analyzed the effect of the "stressed" correlations on banks' regulatory own funds ratios. As depicted in the last column of Table 1 in Section 4, the increased correlations have only a secondary impact on this ratio in all four categories of banks. These results suggest that our stress test results are robust against "stressed" correlations in so far as the impact on the banks' solvency is concerned.

6. Summary and Outlook

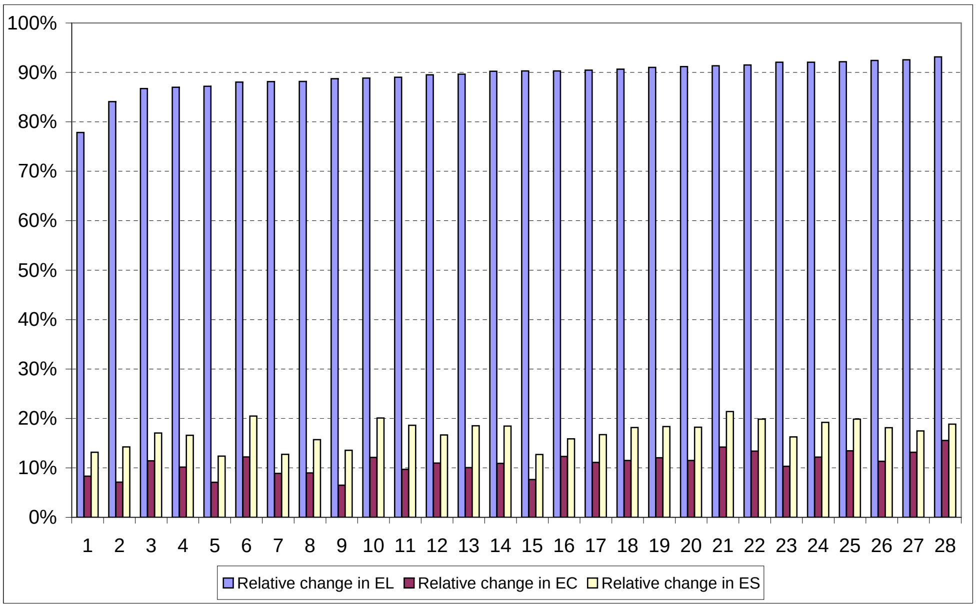
In this paper we stress-test credit portfolios of large German banks based on a Merton-type multi-factor credit risk model. The stress scenario is an economic forecast of a downturn

[20] See, e.g. Bollerslev et al. (1988), Ang and Chen (2002) or Düllmann et al. (2007).

[21] Since the coefficient r of the systematic risk factor depends on the average of the correlation matrix Ω (see Section 3), this coefficient becomes 0.343 for this robustness check.

Figure 10. Impact of Stress Scenario on Expected Loss and Economic Capital in a High-Correlation Scenario

This figure shows the relative change of expected loss (EL), economic capital (EC) and expected shortfall (ES) in the stress scenario for all 28 banks in the sample. The numbers are in percent. Contrary to Figure 6, the results are based on sector correlations observed from 1997 to 1998, a period in which the highest correlations are measured.



in the automobile sector. Following Bonti et al. (2006), this scenario forecast is captured by truncating the distribution of the risk factor assigned to this sector. In this way, a wide range of stress events is considered instead of only a single "point scenario".

Our results reveal a strong increase of EL in the corporate credit portfolio which ranges between 70-80% for the 28 banks in the sample. From a bank-wide perspective, however, the impact appears to be less serious. The own funds ratio decreases on average from 12% to 11.6%. Therefore, the German banks in the sample overall could sustain losses from our stress scenario. Furthermore, this discrepancy in numbers between the single portfolio perspective and the bank wide perspective suggests that it is important to look beyond actual portfolio losses in order to assess the stress impact on a bank. In addition to EL, we determine also the impact on EC and ES which increase under stress by 8%– 20% and 12% – 22% respectively, in both cases significantly less than the EL.

The impact on EC, ES and the even stronger impact on EL is mainly driven by inter-sector correlations propagating the stress impact into other sectors. If only the impact on the automobile sector is considered, EL of the total portfolio, for example, increases by less than 2.5%. These findings argue to account carefully for inter-sector dependencies also for stress scenarios which are related only to a single sector.

The level of EC is on average about 16% and therefore substantially higher for portfolios of real banks compared with highly fine-grained or *infinitely granular* portfolios with otherwise the same risk characteristics. Since the relative increase in EC and ES under stress conditions is similar in both cases, the computationally more tractable case of an infinitely granular portfolio can provide a reasonable proxy of the *relative* stress impact, at least if PDs are homogenous in every sector as assumed in our study.

A robustness check with higher inter-sector correlations shows a relative increase in EL of up to 16.4 percentage points which is material. The relative increase in EC and ES, however, is slightly lower than in our benchmark case.

Further research is warranted on the following three issues. Our assumption of a homogeneous intra-sector asset correlation is quite common in credit risk modelling but has been questioned by empirical findings, for example by Düllmann et al. (2007), indicating that asset correlations can substantially vary between and inside business sectors.

Furthermore, our results were obtained for a specific sector scheme, in this case the ICB sector classification. It seems reasonable to assess the relative impact of the stress scenario if an alternative sector scheme is used for the same portfolios.

The limitation of sector-dependent default probabilities should be lifted by borrower-dependent PDs. This is not only important in light of recent research[22] that confirms a material impact of borrower-dependent PDs. Instead, any cross-sectional comparison between banks in terms of their risk can be distorted if the individual institution's borrower selection is not accounted for.

[22] See, for example, Düllmann and Masschelein (2007) and Hanson et al. (2005).

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Appendix

Table 3

Insolvency Rates of 16 Business Sectors in 2005 and 2006

This table shows historical insolvency rats from the German Federal Statistical Office for 16 sectors according to the ICB sector classification. The insolvency rates are separately calculated for 2005 and 2006 and averaged in the last column.

Sector	**2005**	**2006**	**Average**
Chemicals	1.4%	0.9%	1.1%
Basic Resources	1.1%	0.8%	1.0%
Construction and Materials	2.4%	1.8%	2.1%
Industrial Goods and Services	1.3%	1.1%	1.2%
Automobiles and Parts	1.4%	0.8%	1.1%
Food and Beverage	0.9%	0.7%	0.8%
Personal and Household Goods	1.0%	0.8%	0.9%
Health Care	1.3%	1.2%	1.2%
Retail	0.9%	0.8%	0.9%
Media	1.5%	1.2%	1.3%
Travel and Leisure	1.1%	1.0%	1.0%
Telecommunications	3.3%	3.0%	3.2%
Utilities	0.1%	0.1%	0.1%
Insurance	0.0%	0.8%	0.4%
Financial Services	0.9%	0.7%	0.8%
Technology	1.0%	0.8%	0.9%

Table 4

Correlation Matrix of the Sector Indices

This table shows inter-sector correlations of 16 sector indices following the ICB sector classification. The correlations were estimated from weekly stock index returns in 2005 and 2006.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Chemicals	1	0.64	0.77	0.80	0.73	0.74	0.82	0.58	0.67	0.70	0.56	0.43	0.70	0.77	0.75	0.59
2	Basic Resources	0.64	1	0.70	0.75	0.54	0.59	0.61	0.35	0.52	0.54	0.45	0.38	0.57	0.65	0.71	0.48
3	Construction and Materials	0.77	0.70	1	0.90	0.70	0.74	0.79	0.46	0.64	0.71	0.70	0.45	0.74	0.78	0.82	0.62
4	Industrial Goods and Services	0.80	0.75	0.90	1	0.73	0.74	0.84	0.49	0.64	0.73	0.71	0.48	0.73	0.83	0.80	0.70
5	Automobiles and Parts	0.73	0.54	0.70	0.73	1	0.65	0.72	0.46	0.62	0.65	0.63	0.50	0.54	0.74	0.66	0.61
6	Food and Beverage	0.74	0.59	0.74	0.74	0.65	1	0.82	0.50	0.68	0.66	0.62	0.43	0.69	0.73	0.73	0.57
7	Personal and Household Goods	0.82	0.61	0.79	0.84	0.72	0.82	1	0.55	0.68	0.72	0.72	0.50	0.70	0.83	0.72	0.68
8	Health Care	0.58	0.35	0.46	0.49	0.46	0.50	0.55	1	0.53	0.45	0.34	0.29	0.40	0.45	0.43	0.40
9	Retail	0.67	0.52	0.64	0.64	0.62	0.68	0.68	0.53	1	0.54	0.52	0.40	0.60	0.67	0.62	0.47
10	Media	0.70	0.54	0.71	0.73	0.65	0.66	0.72	0.45	0.54	1	0.62	0.66	0.58	0.67	0.65	0.68
11	Travel and Leisure	0.56	0.45	0.70	0.71	0.63	0.62	0.72	0.34	0.52	0.62	1	0.59	0.47	0.69	0.57	0.59
12	Telecommunications	0.43	0.38	0.45	0.48	0.50	0.43	0.50	0.29	0.40	0.66	0.59	1	0.39	0.51	0.45	0.51
13	Utilities	0.70	0.57	0.74	0.73	0.54	0.69	0.70	0.40	0.60	0.58	0.47	0.39	1	0.65	0.70	0.49
14	Insurance	0.77	0.65	0.78	0.83	0.74	0.73	0.83	0.45	0.67	0.67	0.69	0.51	0.65	1	0.73	0.71
15	Financial Services	0.75	0.71	0.82	0.80	0.66	0.73	0.72	0.43	0.62	0.65	0.57	0.45	0.70	0.73	1	0.57
16	Technology	0.59	0.48	0.62	0.70	0.61	0.57	0.68	0.40	0.47	0.68	0.59	0.51	0.49	0.71	0.57	1

Table 5

Average Balance-sheet Ratios

This table shows selected balance-sheet ratios of the sample of 28 banks. The balance-sheet ratios are averaged for different banking sectors.

Banking sector	**Number of banks**	**Average balance sheet total (€ million)**	**Average market capitalisation (€ million)**	**Average subscribed capital (€ million)**
Large banks	4	764603.45	30882.93	4038.42
Commercial banks[23]	8	108639.23	4303.80	920.14
Savings banks	13	217650.47	–	4779.70
Cooperative banks	3	154863.72	–	2423.62

Table 6

Ratings by Standard & Poor's rating (end of September 2006

This table shows the long-term ratings by Standard & Poor's to the extent that they are available for the banks in the sample. The ratings refer to end of September 2006.

Rating	**Number of banks**	
	S & P	Fitch
AAA	0	1
AA-	2	1
A+	3	8
A	8	6
A-	3	2
BBB+	1	1

[23]Excluding large banks.

Figure 11. Correlation of Sector Index *Financial Services* and the Remaining Sectors

This figure shows the empirical pairwise correlations between the sector index *financial services* and the sector indices of the 15 remaining sectors of the ICB sector classification.

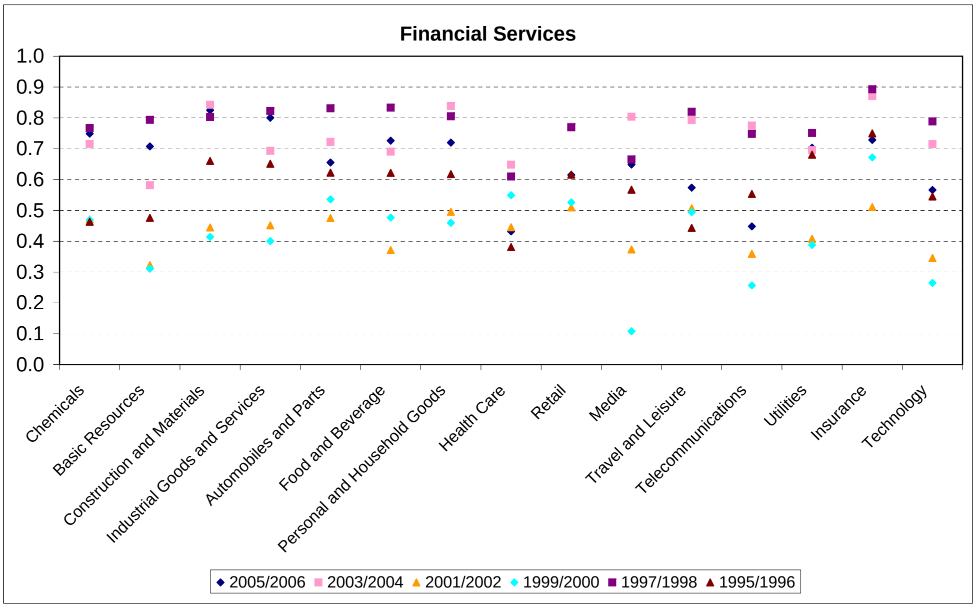

Figure 12. Correlation of Sector Index *Industrial Goods and Services* and the Remaining Sectors

This figure shows the empirical pairwise correlations between the sector index *industrial goods and services* and the sector indices of the 15 remaining sectors of the ICB sector classification.

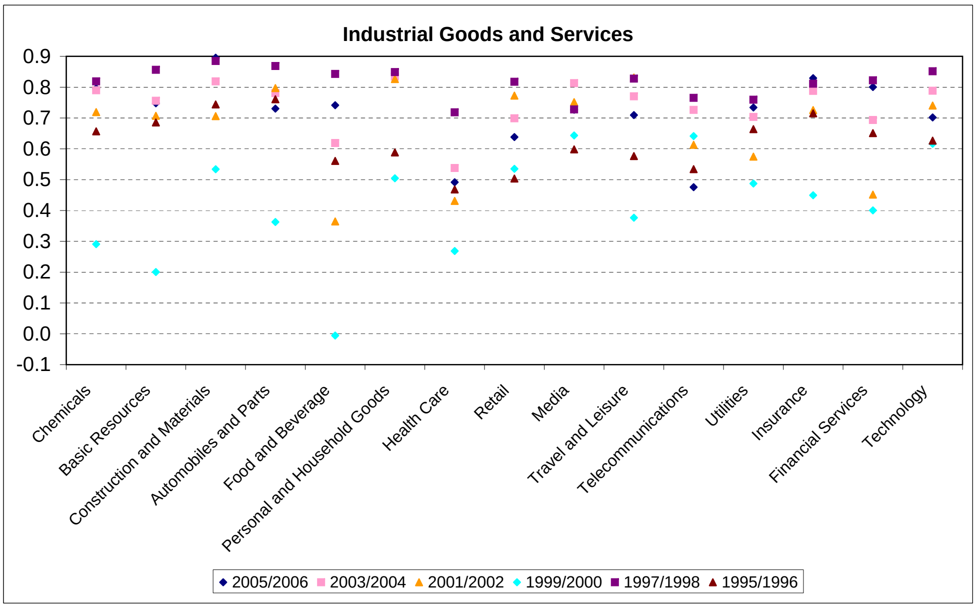

Figure 13. EL Impact of Stress Scenario Against Sector-based HHI

This figure shows the impact of the stress scenario on the expected loss (EL) against the sectoral concentration of the 28 banks in the sample. Sectoral concentration is measured by the Herfindahl-Hirschman-Index (HHI) calculated from the portfolios' sectoral exposures according to the ICB sector classification.