Crash Testing German Banks*

Klaus Duellmann and Martin Erdelmeier
Deutsche Bundesbank

In this paper we stress-test credit portfolios of twenty-eight German banks based on a Merton-type multifactor credit-risk model. The stress scenario is an economic downturn in the automobile sector. Although the percentage of loans 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 percent for the total portfolio. This result confirms the need to account for hidden sectoral concentration risk because the increase in expected loss is driven mainly by correlation effects with related industry sectors. Therefore, credit-risk dependencies between sectors have to be adequately captured even if the trigger event is confined to a single sector. Finally, we calculate the impact on banks' own-funds ratios, which decrease on average from 12 percent to 11.4 percent due to the stress event, which indicates that banks overall remain well capitalized. These main results are robust against various robustness checks, namely those concerning the granularity of the credit portfolio, the level of intersector asset correlations, and a cross-sectional variation of intrasector asset correlations.

JEL Codes: G21, G33, C13, C15.

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1. Introduction

Credit risk in loan portfolios, which is closely linked to changes in the economic environment, is widely perceived as the most relevant risk faced by banks. In an increasingly volatile financial environment, stress tests have recently become more important as an instrument to gauge the impact of specific adverse developments in the economy. It is, therefore, no surprise that regulators in the Basel II framework emphasize their use—in particular, in connection with credit concentrations.[1] Credit concentrations become important in extreme events ("tail risk"), and portfolio models which capture sectoral as well as name concentrations are an obvious tool to assess this type of risk.

In this paper, we stress-test credit portfolios of large German banks based on a one-period default-mode version of a standard Merton-type portfolio model in the spirit of Gupton, Finger, and Bhatia (1997) and Finger (1999). The stress scenario refers to a single sector, the automobile sector. It is based on a downturn prediction of 10 percent for the German automobile production index, suggested by historical data. The stress scenario reflects an exceptional but plausible event because it summarizes a continuum of stress events which, together, occur under baseline conditions with a probability of 33 percent and include the downturn forecast as the expected value under stress conditions. Rather than focusing on a particular stress forecast, however, this paper focuses on the main drivers of the stress impact on banks' credit portfolios—including, for instance, the role of borrower-dependent compared with pooled probabilities of default or the influence of sectoral and name concentrations.

The stress-test methodology is based on recent work by Bonti et al. (2006). Our approach differs from their work and other work on stress tests of credit risk by the following five characteristics:

(i) 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, intersector dependencies need to be accounted for, which is achieved by using a multifactor portfolio risk model.

[1] See Basel Committee on Banking Supervision (2005).

(ii) 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 taken into account. In our setup, we consider instead a stress scenario comprising a range of stress events such that the probability of the stress scenario is quite significant.

(iii) Our approach can also be used to identify hidden sectoral credit concentrations, as it allows us to identify risk concentrations under stress conditions across highly correlated sectors. Previous studies have found that sectoral concentration and, to a lesser extent, also name concentration have a material impact on the portfolio risk.[2]

(iv) The use of the German credit register allows us to apply our stress-test methodology consistently to a sample of twenty-eight banks, taking into account their credit portfolios to the extent that loans are included in the credit register. 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 level.

(v) Traditionally, the focus of stress tests is on the expected loss (EL) conditional on the stress event and its increase relative to baseline conditions. We also consider the impact on economic capital (EC), defined as the difference between a 99.9 percent value-at-risk (VaR) and the (unconditional or baseline) EL.[3] As a robustness check, we also calculate the *expected shortfall* (ES) or tail conditional expectation. Since these risk measures refer only to the potential loss of the credit portfolios, they do not convey immediate information about the impact of the stress scenario on a bank's solvency. For this purpose, we calculate and compare in addition banks' own-funds ratios before and after stress.

[2]See, for example, Heitfield, Burton, and Chomsisengphet (2006) or Duellmann and Masschelein (2007).

[3]Since we assume that under baseline conditions we have no further information on future realizations of the risk factors, the expected values under baseline conditions are always unconditional.

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. The threshold where the distribution of the risk factor is truncated is set so that the event that the risk factor falls below the threshold has the same probability as the event that the automobile production index falls below a corresponding threshold. This corresponding threshold of the automobile production index is in turn defined so that the expected value of the index, conditional on being below the threshold, equals the forecast of a downturn in the automobile sector. In this way the stress forecast is linked to the threshold of the unobservable risk factor without having to specify a functional relationship between this risk factor and the production index. This stress-test methodology is plausible in the sense that the stress scenario should be believable and have a certain probability of actually occurring. It is also consistent with the existing quantitative framework since we employ the same model which is also used under baseline conditions and we make use of all information contained in the parameter estimates of this model.

The need to take into account the reaction of other risk factors if one or more risk factors are stressed in order to avoid a material underestimation of the stress impact has been recognized in Kupiec (1998). Our stress-test design and the underlying credit-risk model draw heavily on the work by Bonti et al. (2006) but differ in important ways. Firstly, since we have access to the German central credit register, we can apply it to a cross-section of twenty-eight different 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.[4] A related methodology was also applied by Elsinger, Lehar, and Summer (2006), with a stronger focus on financial stability aspects.

[4]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.

Our results can be useful from the perspective of a risk manager, a central bank, or a supervisor. From a risk-management perspective, our results provide an empirical implementation of the stress-testing methodology proposed by Bonti et al. (2006). Although the number of twenty-eight banks in the sample is relatively low compared with the total number of 2,301 German banks in 2006, their aggregated total assets amount to almost 60 percent of the total assets of the German banking system.[5] Therefore, from a financial stability perspective, our results can give valuable information as to the resiliency of a major part of the German banking system against an external shock to the automobile sector. 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:

- EL increases under stress conditions by 70–80 percent for all banks in the sample. As a consequence, the own-funds ratio decreases on average from 12 percent to 11.4 percent. Therefore, the German banks in the overall sample could sustain losses from a stress event in the automobile sector, at least up to the extent captured by our stress test.
- EC increases under stress by 8–20 percent and somewhat more sharply if ES is applied as a risk measure (12 percent to 22 percent). In both cases, it is still significantly lower than the increase in EL, always measured relative to the value under baseline conditions. Expressed in percentage points, referring to the nominal loan exposure, the average increase in EL across banks (0.34 percentage points) is, however, lower than the average increase in EC (0.54 percentage points).
- The significant impact on EC and the even stronger impact on EL are mainly driven by the effect of intersector correlations. If only the isolated impact on the automobile sector is considered, EL of the total portfolio increases by less than 2.5 percent. This low number is explained by the relatively small portfolio share of the automobile sector. Therefore, the results underline the need to account carefully for intersector

[5]Furthermore, the total credit exposure of the twenty-eight banks amounts to 75 percent of the total credit exposure of German banks to nonfinancial firms, measured in terms of banks' credit volume captured by the credit register.

dependencies even if a stress scenario in a single sector is analyzed.

- The level of EC is substantially higher (on average about 16 percent) 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 indicative 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. Further robustness checks, however, are needed if PDs are heterogenous at the borrower level.
- Our results are robust against replacing a constant intrasector asset correlation by sector-dependent correlation estimates. More specifically, the average increase in EL, EC, and ES under stress is approximately only 3 percent lower than in the case of a constant intrasector asset correlation.
- A robustness check with larger intersector 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, the use of constant versus sector-dependent intrasector asset correlations, and the level of intersector 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 by the Deutsche Bundesbank. The reference date is September 2006. The credit register contains bank loans exceeding €1.5 million; i.e., smaller loans are not considered. Credit information is available only at the borrower level, not at the 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-risk mitigation techniques in the form of guarantees and plain-vanilla credit default swaps are taken into account in the exposure amount.

The sample of twenty-eight banks comprises all German banks that have at least 1,000 borrowers/borrower units included in the credit register. This limit was imposed in order to ensure that the loan information in the credit register is sufficiently representative of the bank's actual credit portfolio.

The analysis requires every borrower and borrower unit 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, this information is not available in the database. The industrial sector covering the largest percentage of the borrower unit's total loan amount is used instead. This assignment is reasonable since, on average for all borrower units, the share of the largest industrial sector amounts to 89 percent.

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

[6]A borrower unit comprises, for example, companies that are formally independent but that are considerably influenced or controlled by one of these companies.

[7]See table 4 in the appendix.

standard for trading and investment decisions. It distinguishes four hierarchical sector levels that comprise ten sectors at the top level and 104 subsectors at the base level. For this study, we use the second aggregation level, which comprises eighteen sectors. For the analyses, the ICB classification has two main advantages: Firstly, stock indices are readily available which can be directly mapped to the ICB classification. Secondly, the industrial sectors used in the credit register of the Bundesbank can also be easily matched to the ICB classification.

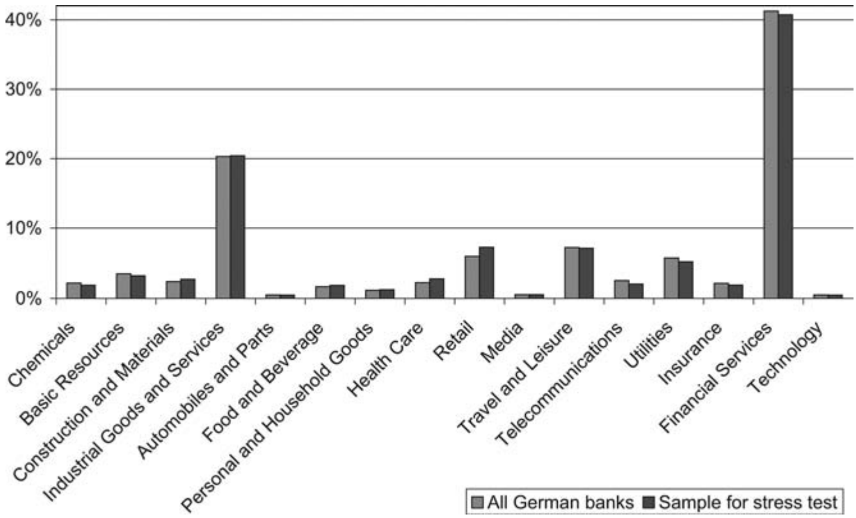
The banking sector is excluded from the study owing to its specific characteristics—for example, the monitoring by banking supervisors and the particularities of the interbank market, which constitutes a major section of interbank exposures. Furthermore, since no German company is listed in the *oil and gas* sector, the analyses are limited to sixteen sectors instead of eighteen.

The intersector correlations are estimated from weekly log-returns of stock indices over a time frame of two years just before the reference date. In order to differentiate between industry sectors, Dow Jones Eurostoxx sub-indices are used, which can be matched to the sixteen ICB sectors. The correlation matrix was estimated from index returns during 2005 and 2006 and is shown in table 5 in the appendix.

Figure 1 shows the distribution of the aggregated credit claims among the sectors, both for the twenty-eight selected banks and for all domestic banks. The twenty-eight chosen banks cover approximately 75 percent of the volume of claims granted to nonfinancial companies included in the credit register. This explains why 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* (approximately 40 percent) and *industrial goods and services* (approximately 20 percent). Since banks in their function as borrowers are excluded from our analyses and since insurance firms are assigned to a separate sector, a considerable percentage of loans to the *financial services* sector is given to other financials—in particular, to capital investment companies.

The share of the *automobiles and parts* sector appears relatively small. Yet it has to be considered that, owing to the sector correlation matrix, the stress event also affects other industries with

Figure 1. Sectoral Distribution of Credit Exposures



Note: This figure shows the relative loan share of individual sectors relative to the total credit volume, both for banks in the sample and all German banks.

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.

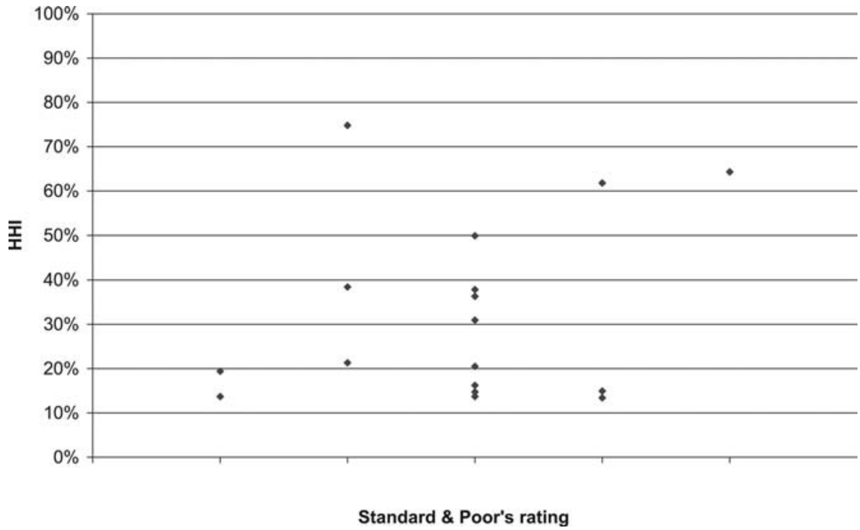
Table 1 provides some more detailed balance-sheet information on the sample of banks. Four banks are large private banks; eight are "other" private banks (i.e., excluding large private banks); thirteen

Table 1. Average Balance-Sheet Ratios

Banking Sector	Number of Banks	Average Balance-Sheet Total (€ million)	Average Market Capitalization (€ million)
Large Private Banks	4	764,603	30,883
Other Private Banks	8	108,639	4,304
Savings Banks	13	217,650	—
Cooperative Banks	3	154,864	—

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

Figure 2. Rating of Standard & Poor's and Herfindahl-Hirschman Index



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

belong to the savings bank sector, which also comprises the *Landesbanken*; and the remaining three are cooperative banks.

In order to measure if sectoral concentrations have an impact on a bank's credit quality, we employ the Herfindahl-Hirschman Index (*HHI*). If such a relation existed, it would underline the importance of sectoral concentrations for the credit quality. If not, no conclusion is possible because it may simply be due to limitations of heuristic risk measures or because the bank accounts for sectoral risks otherwise—for example, through holding an additional capital buffer. Figure 2 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 also captures the borrowers' credit risk:

$$HHI = \sum_i w_i^2 \text{ and } HHI^* = \sum_i \frac{PD_i}{\overline{PD}} w_i^2, \qquad (1)$$

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 portfolio share of the i-th sector defined as the ratio of the loan amount in the i-th sector to the total loan amount of the portfolio. Comparisons between, firstly, the capital ratio and both HHI indices and, secondly, PDs and HHI indices do not suggest any strong interrelation either. Although the exact reason for the weak relation between the concentration indices and the banks' risk ratings (or other risk indicators) is left for further research, a model-based assessment of sectoral concentration risks, which is carried out in this paper, offers at least a viable and theoretically superior alternative.

3. Stress Scenarios and Methodology

3.1 Credit-Risk Model

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

[8] A generalization of the model framework toward a mark-to-market valuation which considers migration risk in addition to default risk would be possible, but is not implemented in the current approach owing to data constraints.

on the ratings or PDs of individual borrowers, the PDs are estimated from historical default rates on a sector basis. Table 4 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 percent, which is the value set by supervisors for senior unsecured corporate exposures in the foundation internal ratings-based approach of Basel II. The indicator function $1_{\{\ldots\}}$ 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 threshold c_i. Since Y_i has a standard normal distribution by construction (see below), the default threshold $c_i = \Phi^{-1}(PD_i)$ 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 up to the end of the risk horizon. It has two 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 (sector factor) $X_{s(.)}$ and the second component is the borrower-dependent (or idiosyncratic) risk factor ϵ_i. Both components are mutually and 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 $s : \{1, \ldots, N\} \rightarrow \{1, \ldots, S\}$ denote a mapping of the borrower to a sector. The sector factors $X_{s(.)}$ are normally distributed. The estimate of their correlation matrix Ω is given by table 5 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 risk factors Z_k:

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

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

The coefficient r determines the relative weight of the systematic and nonsystematic 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. The intrasector correlation equals r^2 and is the same for all sectors.[9] For practical purposes, we take the average asset correlation $\overline{\rho}$ of small and medium-sized German companies,[10] an empirical value of 0.09, and the mean value $\overline{\omega} = 0.648$ of the correlation matrix given by table 5 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 simulations. 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). EL, EC, and ES are used as risk measures for the credit portfolio before and after stress. Both EC and ES refer to the 99.9 percent quantile of the loss distribution. Following common industry practice, both risk measures are defined after subtraction of (unconditional) EL.

3.2 Design of the Stress Scenario

The key idea of our stress-testing methodology is based on Bonti et al. (2006). The stress scenario is defined by constraints on the systematic risk factors of those sectors that we want to stress. Constraining the sample space of these factors offers several advantages. The probability of stress conditions before stress is automatically known, which gives an indication about the severity of the scenario. Furthermore, the original model parameters are kept with the consequence that all the information used for their estimation is still

[9]The assumption of constant intrasector correlations across sectors is relaxed in section 5.

[10]See Hahnenstein (2004).

harnessed. Contrary to stressing correlations directly, the problem of keeping the stressed correlation matrix positive semidefinite is avoided.

In the baseline scenario—i.e., before the stress event occurs—a standard normal distribution is assumed for all sector factors. In the stress scenario, only realizations of the sector factor that are below a scenario-specific threshold are considered. 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 in which the expectation value of an observable macroeconomic variable closely related to the risk factor of the stressed industry sector is used as input. In order to determine the threshold value of the unobservable 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, the truncated distribution of the risk factor considered in the stress test reflects realistic stress conditions observed in the past.

As we are dealing with a special/predetermined sector, we need to consider the available information on sector-specific expected developments and trends. We thus take into account forecasts that, owing to stricter environmental regulations, the demand for cars could increasingly shift toward less expensive, more fuel-efficient models over the coming years. The German automobile industry, which is traditionally mostly present in the segment of powerful vehicles in the upper price range, would be particularly affected by such developments, which could trigger a drop in German automobile production. Yet how strongly it will be affected depends on its ability to adapt to these emerging trends.

A sudden decline in automobile production, however, can also have other explanations. Market disturbances such as the subprime crisis starting in summer 2007 could also negatively affect the automobile industry. A declining demand for vehicles due to stricter credit conditions could cause the situation of an already fragile U.S. car market to deteriorate. Since automobile exports have made an increasingly important contribution to the economic success of

German automobile producers in recent years, this could also have material repercussions for the German automobile 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 twenty-eight banks. Our trigger event refers to an expected decline in automobile production by 10 percent, which is motivated by historical data. The detrended log-returns of the underlying automobile production index between 1996 and 2007 are illustrated in figure 3. 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 a 10 percent decline of the index value, subsequently assumed as a reference point for the stress scenario. Since various more pronounced drops in the index value occurred during the observation period (e.g., in fall 2003), a decrease of 10 percent is regarded as an exceptional, but not an extreme, scenario.

Figure 3. Log-Returns of the Production Index of the Automobile Sector

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

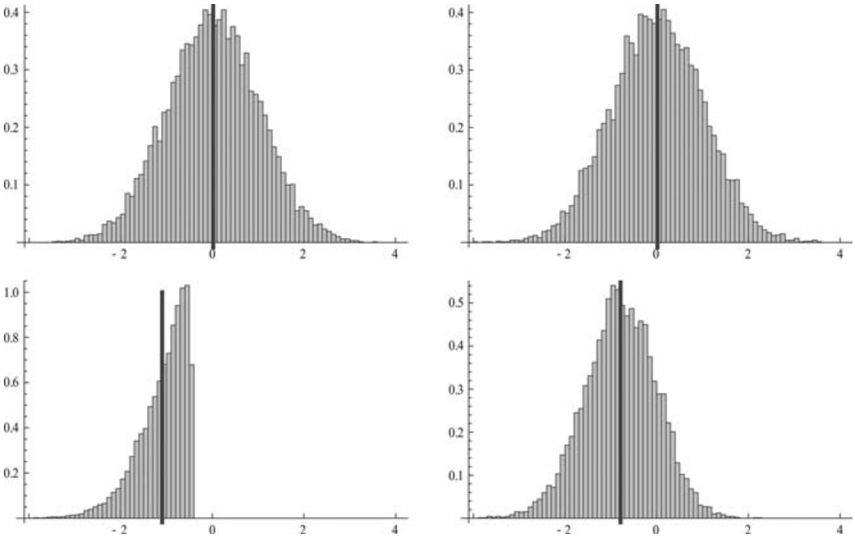
In order to consider the stress scenario within the portfolio model, the expected decrease in the index value induced by the stress event needs to be mapped to the systematic and unobservable risk factor of the automobile sector. For this purpose, the empirical distribution of the historical yearly log-returns of the index is restricted by an upper threshold in such a way that the log-returns of the truncated distribution average the expected index decline of 10 percent under stress conditions. Given a conditional expected index return of -10 percent, the upper threshold of the log-returns implies a probability of 33 percent that returns are below the threshold. The probability of 33 percent is transferred to the risk model, i.e., to the unobservable systematic risk factor of the *automobiles and parts* sector. Because of a standard normal distribution of the sector factor (before stress), the scenario threshold amounts to -0.44.

In principle, it is well possible that the production index and the sector factor are not highly correlated—for example, in the case of a nonlinear dependence. Our approach takes this into account by distinguishing between both of them and linking them such that the probabilities of the scenarios are the same under stress conditions.

The impact of the stress event is also captured for the remaining sectors, which is a crucial advantage of employing the underlying multifactor risk model. Since the sector factors are correlated with one another, the stress event is transferred to other sectors and affects the distributions of the remaining sector factors. Figure 4 illustrates the distribution of the risk factors before (upper part) and after (lower part) the application of the stress scenario, both for the *automobiles and parts* (left side) and *industrial goods and services* (right side) sectors. The mean values of the distributions are marked as vertical lines.

In the left-hand part of figure 4, the impact of the stress scenario and the restriction of the risk factor in the 33 percent quantile can be clearly identified. Owing to correlation effects, the stress event also affects the remaining sectors, which is illustrated in the right-hand part for the *industrial goods and services* sector. As a consequence, the conditional distribution of this sector factor and its mean are likewise shifted toward the negative domain. Due to the above average correlation with the *automobiles and parts* sector (see table 5 in the appendix), this shift is also above average.

Figure 4. Frequency Distribution of the Systematic Risk Factors



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

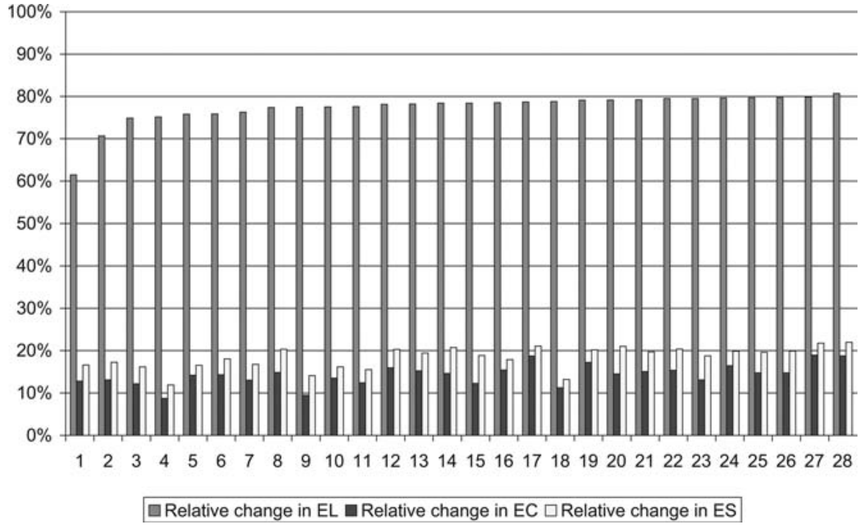
4. Results for the Stress Scenario

In this section we present the results of the stress test—first, in terms of EL of the credit portfolios of the banks in the sample and, second, in terms of the impact on the banks' own-funds ratios.

The results for EL, EC, and ES are based only on loans to nonfinancial companies and are shown in figure 5. The changes in EL, EC, and ES due to the stress event are sorted in ascending order according to the relative increase in EL. Based on the chosen stress scenario, the results indicate a considerable and relatively similar increase in EL in a range generally between 70 percent and 80 percent.[11] A higher relative increase in EL than in EC is only observable

[11] Compared with the other institutions, the increase in EL of one particular bank amounting only to approximately 60 percent is considerably lower. The reason for this 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. Impact of Stress Scenario on Expected Loss, Economic Capital, and Expected Shortfall



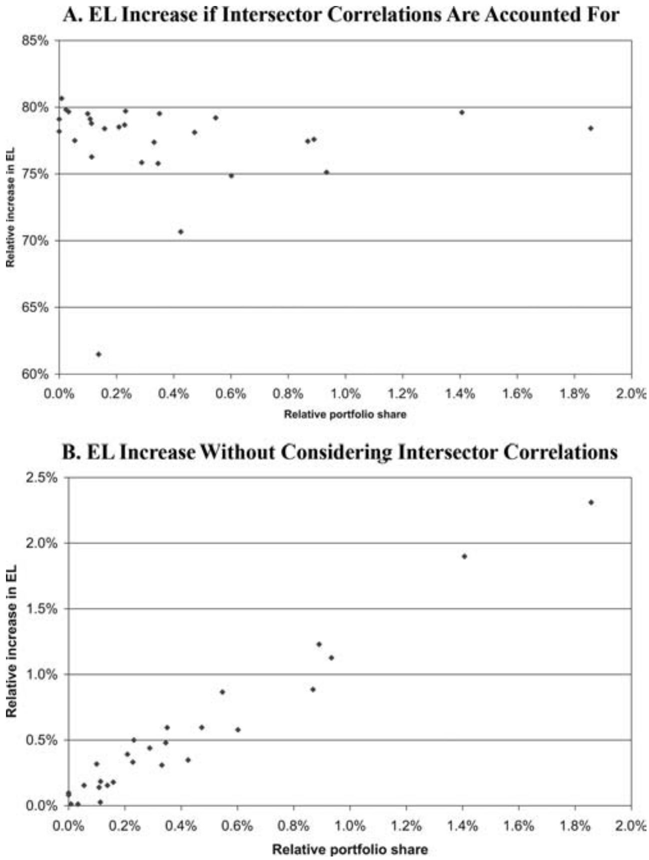
Notes: This figure shows the relative change of expected loss (EL), economic capital (EC), and expected shortfall (ES) in the stress scenario for all twenty-eight banks in the sample. The figures are shown as percentages.

if measured relative to the baseline values of EL and EC. Expressed in percentage points (referring to the nominal loan exposure), the average increase in EL across banks (0.34 percentage points) is, however, lower than the average increase in EC (0.54 percentage points).

Note that, for all banks, the share of loans granted to the *automobiles and parts* sector is below 2 percent and thus is only a very minor share of the entire credit portfolio. Therefore, compared with the overall bank portfolio, the overall effect of the stress event on loans to the automobile sector is rather limited. This is confirmed by panel A of figure 6, which plots the relative increase in EL against the relative portfolio share of the automobile sector for the twenty-eight banks in the sample. As expected, only a weakly positive relation between the portfolio share of the automobile sector and the EL increase is observable.

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

Figure 6. Portfolio Share of Automobile Sector and Expected Loss



Notes: This figure shows the relative portfolio share of the *automobiles and parts* sector per bank compared with the relative increase in the expected loss of the total portfolio conditional on the stress scenario. Intersector correlations are accounted for in the first diagram but not in the second diagram.

automobile sector to other sectors that can have a considerably bigger share of the credit portfolio. The *industrial goods and services* sector, for example, with a relatively high correlation with the automobile sector, has a portfolio share between 3.4 percent and 33.5 percent 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 be attributed primarily to loans granted to the automobile sector, but rather to the impact of the stress event on the remaining sectors due to correlation effects. Note that the impact of correlations should not be interpreted in the sense of economic causality such that the model would explain a stress impact in those sectors in reaction to a stress event in the automobile sector. What is captured instead is an impact in a statistical sense such that “bad” draws of the automobile risk factor are more often accompanied by “bad” rather than “good” draws of the other risk factors. The correlation with other sector factors can explain in this sense the strong increase in EL among all banks despite the relatively low percentage of loans in the automobile sector.

In order to quantify explicitly the importance of intersector 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 intersector correlations is also considered. In detail, for the first case we estimate losses under baseline conditions for all sectors except the automobile sector. For loans in the automobile sector, we consider instead losses conditional on stress conditions. For the second case, which also captures the stress propagation through intersector correlations, we use the previous results.

The relative increase in EL in the first case is depicted in panel B of figure 6, depending on the portfolio share of the automobile sector. The level of the EL increase, which is below 2.5 percent for all banks, is low compared with the increase of 70–80 percent if the intersector correlation effects are also considered. It is, however, well explained by the very minor exposure share of the automobile sector, which is below 2 percent of their total portfolio exposure for all banks in the sample. 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 panel A of figure 6, in which the overall change in EL is mainly driven by correlations with other sectors rather than by the exposure size in the automobile sector.

Another striking observation in figure 5 is that there are relatively small differences in the EL increase between banks when disregarding one outlier bank with a lower increase of around 60 percent. 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 certain sectors—in particular, *industrial goods and services* and *financial services*, which have not only a relatively high correlation with the automobile sector but also a large share of the banks' credit portfolios (see also figure 1). Since both sectors cover 60 percent 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.

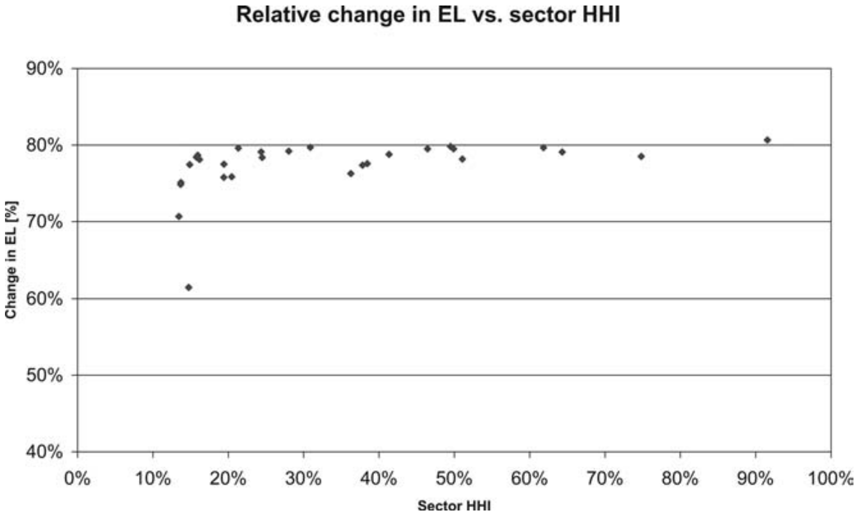
According to figure 5, the increase in EC measured relative to its value under baseline conditions is lower than the overall increase in EL (8.7–18.8 percent for EC compared with 70–80 percent for EL). An increase in EL is a first-order effect, as it immediately affects net income and can trigger a bank failure if capital is exhausted and a bank becomes overindebted.[12] An increase in EC, instead, means that a larger capital buffer is needed at the end of one year for potential future losses. This is still important, as it could affect the capital ratio, which is an important indicator of a bank's risk-absorbing capacity. Compared with an increase in actual losses, however, it is only a second-order effect, as it concerns the solvency under a high percentile, which is, in turn, conditional on the stress scenario. Therefore, 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.

The results for ES in figure 5 differ from those for EC in that the measured relative increase in risk is slightly higher. This is to be expected since—given the same confidence level—ES refers to a point further in the tail of the loss distribution than EC.

Figure 7 plots 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

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

Figure 7. EL Impact of Stress Scenario Against Sector-Based HHI



Notes: This figure shows the impact of the stress scenario on the expected loss (EL) against the sectoral concentration of the twenty-eight 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.

also points out the limits of relatively simple yardsticks for concentration risk such as the *HHI* or *HHI**. Hence, only model-based analyses are able to provide robust results on the impact of the stress event.

From a risk-management perspective, it is not only important how the level of risk changes under stress conditions. It is also important to consider the impact on the banks' solvency. Below, the regulatory own-funds ratios (OFR) 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:

$$OFR^{stress} = \frac{regulatory\ own\ funds - \Delta EL_{\%}^{stress} \cdot credit\ exposure^{corporates}}{risk\text{-}weighted\ assets\ incl.\ market\ risk}. \quad (6)$$

$\Delta EL_{\%}^{stress}$ denotes the change in EL due to the stress event. It is measured in percentage points, i.e., relative to the nominal credit amount. Although a proxy of the credit exposure to corporate borrowers could be extracted from the credit register, we use a different data source from banks' regular reports for the following reason. The credit register only contains loans above the reporting limit of €1.5 million, with the consequence that a comparison across banks could be biased.[13] Therefore, the stress effects would be underestimated for banks focusing on clients with single credit exposures below this reporting limit. As a consequence, $credit\,exposure^{corporates}$ is taken from regular reports by banks (*Bilanzstatistik*) encompassing the total credit exposure to nonbanks. Although these aggregate numbers do not account for off-balance-sheet exposures, as do exposure numbers in the credit register, we believe that the greater coverage justifies their use. The impact of off-balance-sheet exposures is still reflected in $\Delta EL_{\%}^{stress}$, which is based on credit-register data. In other words, our approach intends to combine more risk-relevant information from the credit register with data from a different source which better reflect banks' total credit exposures. It is conservative because $\Delta EL_{\%}^{stress}$ is based on the granularity level of the credit register. This granularity level is lower than for the total credit portfolio because the loans below the reporting limit will increase the portfolio's granularity.

Conditional on the stress scenario, the mean own-funds ratio decreases by 0.62 percentage points from 12.04 percent to 11.42 percent, which indicates that banks in the sample overall remain well capitalized.

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

[13]See section 2 for further details.

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 of potential diversification effects 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 $Z_1, \ldots, Z_S$,[14]

$$L^{\infty} \equiv \mathbb{E}[L|Z_1, \ldots, Z_S] = \sum_{k=1}^{S} \bar{w}_k \, LGD \, \Phi\left(\frac{\Phi^{-1}(p_k) - r \sum_{j=1}^{S} \alpha_{k,j} \, Z_j}{\sqrt{1-r^2}}\right), \tag{7}$$

with sectoral exposure weights $\bar{w}_k = \sum_{\{i:\, s(i)=k\}} w_i$. The simplified "asymptotic" model represented by the loss distribution from (7) is computationally much more tractable. Although it still requires Monte Carlo simulation, random numbers now only need to be generated for the systematic risk factors but no longer for the idiosyncratic risk components.

Regarding terminology, we refer below 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 analyzed in the previous section and for the infinitely granular portfolio under a baseline and a stress scenario. All statistics refer to the sample of twenty-eight banks. The statistics for the finite portfolios summarize the results depicted in figure 5.

We first discuss the results for the risk measure EL. The EL statistics under baseline 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 in the case of both finite and infinite granularities. This result suggests that the asymptotic approximation of the loss distribution as given by (7) properly reproduces the EL impact of the stress scenario in

[14] See Gordy (2003).

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

Portfolio Granularity Scenario	Finite		Infinite	
	Baseline	**Stress**	**Baseline**	**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

Notes: This table shows summary statistics of expected loss, economic capital, and expected shortfall for a sample of twenty-eight 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 as percentages.

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 of the distribution.

Contrary to the risk measure EL, for which we find quite similar results for the infinitely granular portfolio and the finite portfolio, the level of EC is significantly lower in the infinitely granular case, for both the baseline and the stress scenarios. The difference is 16 percent for the mean and 10–40 percent, depending on the statistic. This increase in EC due to name concentration is moderately stronger than observed in previous studies by Heitfield, Burton, and Chomsisengphet (2006) and Duellmann and Masschelein (2007). 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 percent, depending on the statistic.

Summarizing these results, portfolio granularity has a significant impact on the *level* of EC, but it does not seem to affect in the same way its *relative* increase from 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.

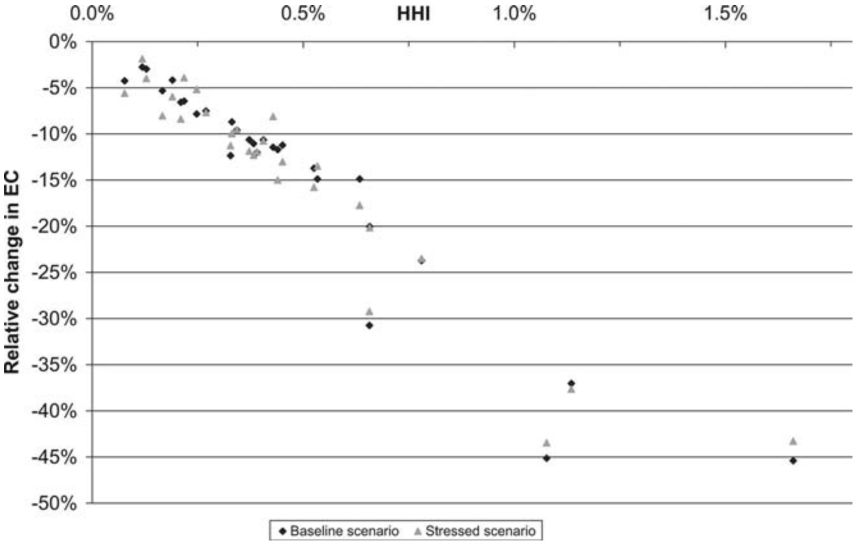
Figure 8 illustrates the impact of portfolio granularity measured by the decrease in EC if the bank's portfolio is replaced by a portfolio of infinite granularity but otherwise the same risk characteristics. The results are shown for the baseline and the stressed scenario. In both cases, the relation between EC and HHI appears to be broadly linear.[15] Furthermore, the magnitude of the impact on EC is almost identical in both cases.

A diagram similar to figure 8 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 percent 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.

Finally turning toward the risk measure ES, the numbers in table 2 show a similar, albeit somewhat stronger increase under stress conditions than was 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.

[15] 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 Lütkebohmert 2007 for an example of such a granularity adjustment.)

Figure 8. Impact of Portfolio Granularity on Economic Capital



Notes: This figure shows the HHI calculated on exposure level against the percentage change in EC for portfolios of twenty-eight 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 baseline and stress conditions.

In summary, we find that the level of EC—contrary to EL—is rather different in the portfolios with finite and infinite granularities. The relative increase in EC due to the stress event, however, 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 Sector-Dependent vs. Constant Intrasector Asset Correlations

From an economic perspective, it is plausible to assume that the average level of intrasector asset correlations between firms differs between sectors. It will, for example, be higher in more cyclical industry sectors. This would suggest replacing the constant factor loading r of the systematic risk factor in (3) with a sector-dependent value.

The previous assumption of intrasector asset correlations being constant across sectors is not only common practice. It is also motivated by empirical obstacles in estimating differences in asset correlations of borrowers belonging to the same sector. The arguably most natural way to estimate asset correlations inside a sector is to use stock returns of listed companies and determine the R^2 in an index model using the portfolio of companies in the respective sector as the index portfolio. The work by Hahnenstein (2004) demonstrates how the composition of the index portfolios can substantially bias the results because the R^2 is then driven by the firm's weight in the index portfolio rather than by the "true" asset correlations. This sample bias becomes even more important if the percentage of listed firms in a specific sector is relatively small and the listed companies are less representative of the whole sector.[16]

Even if the *level* of R^2 could be biased, the cross-sectoral differences between the average R^2 values, each computed for all firms in the same sector, may still be indicative of *relative* differences in asset correlations across sectors. Therefore, we calibrate the sector-dependent R^2 values such that their average value over all sectors is the same as the (constant) asset correlation level used in section 4. In other words, we use R^2 only for information on relative differences between the intrasector asset correlations of different sectors. The correlation level is—averaged over sectors—still the same as before. For this purpose, $\hat{R}_j$, the square root of the R^2 value for sector j, is scaled by the ratio of the original factor weight $\bar{r}$ in section 4 and the average of the square root of the $\hat{R}_j$ values over all sectors. The sector-dependent factor weights r_j are then defined as follows:

$$r_j = \frac{\bar{r}}{\frac{1}{S}\sum_{j=1}^{S} \hat{R}_j} \hat{R}_j. \tag{8}$$

Table 3 summarizes both the original and the normalized factor weights of each sector. Depending on the differing factor weights and the exposure distribution among sectors of a respective bank, the resulting impact of the stress scenario can be either more or less severe compared with the use of a unique factor weight.

[16]For this reason, we also refrain from using an empirically estimated function that relates asset correlations, for example, to firm size, as is common procedure in the original CreditMetrics model.

Table 3. Sector-Dependent Factor Weights before and after Normalization

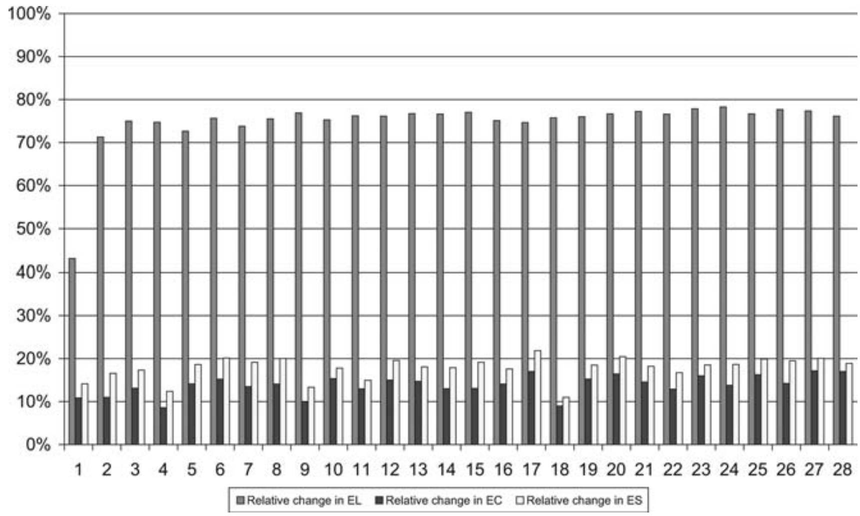
Sector	Factor Weight before Normalization	Factor Weight after Normalization
Chemicals	0.68	0.43
Basic Resources	0.63	0.40
Construction and Materials	0.66	0.42
Industrial Goods and Services	0.59	0.38
Automobiles and Parts	0.66	0.42
Food and Beverage	0.46	0.29
Personal and Household Goods	0.63	0.40
Health Care	0.28	0.18
Retail	0.54	0.34
Media	0.52	0.33
Travel and Leisure	0.59	0.38
Telecommunications	0.59	0.38
Utilities	0.55	0.35
Insurance	0.65	0.42
Financial Services	0.55	0.35
Technology	0.57	0.37

Notes: This table shows both the original and the normalized factor weights calculated for each industry sector. The values are derived from the asset correlations of all companies within a certain sector (R^2-statistic). The normalized values are adapted to the unique factor weight used in the main analysis (see section 3.1).

Figure 9 illustrates the impact on EL, EC, and ES for the twenty-eight banks. For better comparability, all banks are sorted according to the results of the main analysis (see figure 5). Compared with the main results, the EL, EC, and ES increase in a similar magnitude for almost all banks. However, depending on the individual factor weight of each sector and varying exposure distributions among sectors for a respective bank, the mentioned statistics deviate slightly from the main results. Hence, the EL does not exhibit the same monotonic increase as in figure 5.

As a general tendency, the increase in EL, EC, and ES is marginally lower (approximately 3 percent on average) than in the results based on a uniform factor weight. One possible explanation is that the *financial services* sector, which covers an average portfolio share

Figure 9. Impact of Stress Scenario on Expected Loss, Economic Capital, and Expected Shortfall in Case of Sector-Dependent Factor Weights



Notes: This figure shows the relative change of expected loss (EL), economic capital (EC), and expected shortfall (ES) in the stress scenario for all twenty-eight banks in the sample. The figures are shown as percentages. In contrast to figure 5, the results are based on sector-dependent factor weights calibrated to the uniform weight used in the main analysis.

of around 40 percent and which is highly correlated with the automobile sector, is now assigned a slightly smaller factor weight. As a consequence, the impact from cross-sector correlations is slightly dampened.

In the case of the first bank in figure 9, the EL increase is notably lower than in the results based on a uniform factor weight (around 43 percent compared with 61 percent before). This difference is mainly driven by considerable exposure concentrations within a specific sector which is assigned a below-average factor weight.

5.3 Sensitivity to Higher Intersector 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 last two years of our sample of bank portfolios. It is commonly known that asset correlations are difficult to estimate. Because we use equity returns as the basis of our correlation estimation, one could argue that the co-movement in stock prices is also driven by factors unrelated to credit risk and also that asset correlations appear to be unstable over time.[17] 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 intersector correlation matrix with a correlation matrix estimated for the time period from 1997 to 1998.[18] This period exhibits the highest correlation estimates for the automobile sector over two-year periods between 1995 and 2006.

With this new correlation matrix, we repeat the stress test on the portfolios of the twenty-eight 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 percent across banks, is stronger than in the case of the original correlation matrix (see figure 5). The additional increase does not exceed 16.4 percentage points.

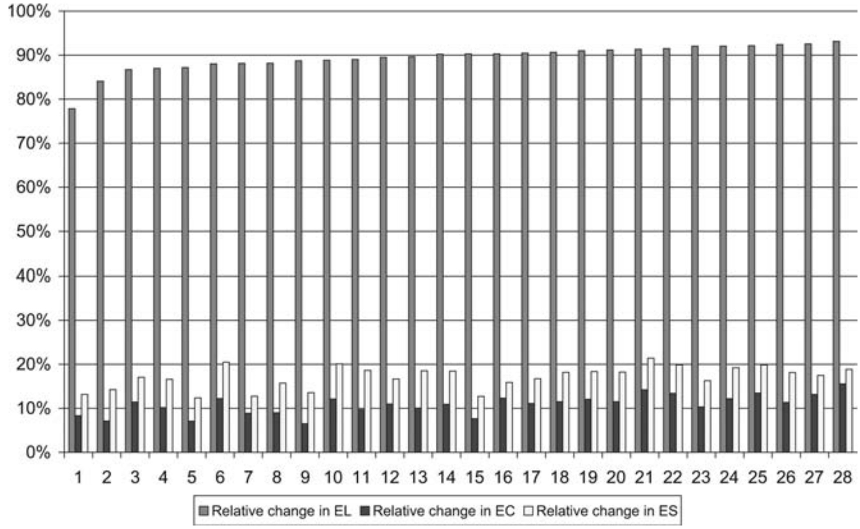
In the case of higher intersector correlations, the relative EC increase is far weaker than the increase in EL and even less than the increase in EC measured in the original stress test in figure 5. Because of the "correlation stress," the loss distribution is shifted to the right-hand side. This shift, however, seems mostly to 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. 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 insofar as the impact on the banks' solvency is concerned.

[17] See, for example, Bollerslev, Engle, and Wooldridge (1988), Ang and Chen (2002), or Duellmann, Scheicher, and Schmieder (2007).

[18] 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



Notes: This figure shows the relative change of expected loss (EL), economic capital (EC), and expected shortfall (ES) in the stress scenario for all twenty-eight banks in the sample. The figures are shown as percentages. In contrast to figure 5, the results are based on sector correlations observed from 1997 to 1998, a period in which the highest correlations are measured.

6. Summary and Outlook

In this paper we stress-test credit portfolios of twenty-eight large German banks based on a Merton-type multifactor default-mode credit-risk model. Rather than focusing on a particular stress forecast, however, the paper focuses on the main drivers of the stress impact on banks' credit portfolios. The ad hoc stress scenario assumes a downturn in the automobile sector. Following Bonti et al. (2006), it 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." Therefore, the typical assumption that the stress is no more severe than its forecast can be avoided.

Our results reveal a strong increase of EL in the corporate credit portfolio across banks which ranges between 70 percent and 80 percent, measured relative to the EL under baseline conditions.

From a bankwide perspective, however, the impact appears to be less serious. The own-funds ratio decreases on average from 12 percent to 11.4 percent. 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 bankwide 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 also determine the impact on EC and ES, which increase under stress by 8–20 percent and 12–22 percent, respectively, again measured relative to baseline conditions. In both cases, this increase is significantly less than for EL. Expressed in percentage points, referring to the nominal loan exposure, the average increase in EL across banks (0.34 percentage points) is, however, lower than the average increase in EC (0.54 percentage points).

The impact on EL, EC, and ES is mainly driven by intersector 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 percent. These findings argue in favor of accounting carefully for intersector dependencies, even for stress scenarios that are related only to a single sector.

The level of EC is, on average, about 16 percent and, therefore, substantially higher for portfolios of real banks than for 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.

Our results are robust against replacing a constant intrasector asset correlation with sector-dependent correlation estimates. A further robustness check with higher intersector 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 in particular on the following two issues, which will both be addressed in a future paper. The current downturn forecast for the automobile industry sector has been obtained from the historical frequency distribution of production index returns for that sector. Using forecasts based on a dynamic macro model of the economy would not only improve the forecasting power but also allow to stress several sectors simultaneously in a consistent way.

In order to consider also name concentration in the credit portfolio, the sector-dependent default probabilities need to be replaced by borrower-dependent PDs conditional on data availability. Recent research confirms that borrower-dependent PDs can have a material impact on portfolio risk.[19] Furthermore, any comparison between different banks can be distorted if the borrower selection and monitoring abilities of the individual institutions are not taken into account.

Appendix

Table 4. Insolvency Rates of Sixteen Business Sectors in 2005 and 2006

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%

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

[19] See, for example, Hanson, Pesaran, and Schuermann (2005) and Duellmann and Masschelein (2007).

Table 5. Correlation Matrix of the Sector Indices

		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 & 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	Indus. 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 & 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 & 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	Pers. & 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

Notes: This table shows intersector correlations of sixteen sector indices following the ICB sector classification. The correlations were estimated from weekly stock index returns in 2005 and 2006.

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