

Discussion Paper

Deutsche Bundesbank
No 04/2012

Stress testing German banks against a global cost-of-capital shock

Klaus Duellmann

Thomas Kick

Editorial Board: Klaus Düllmann
Frank Heid
Heinz Herrmann

Deutsche Bundesbank, Wilhelm-Epstein-Straße 14, 60431 Frankfurt am Main,
Postfach 10 06 02, 60006 Frankfurt am Main

Tel +49 69 9566-0

Telex within Germany 41227, telex from abroad 414431

Please address all orders in writing to: Deutsche Bundesbank,
Press and Public Relations Division, at the above address or via fax +49 69 9566-3077

Internet <http://www.bundesbank.de>

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ISBN 978-3-86558-796-1 (Printversion)

ISBN 978-3-86558-797-8 (Internetversion)

Abstract

This paper introduces a stress test of the corporate credit portfolios of 24 large German banks by a two-stage approach: First, a macro-econometric model is used to forecast the impact of a substantial increase of the user cost of business capital for firms worldwide on three particularly export-oriented industry sectors in Germany. Second, the impact of this economic multi-sector stress on banks' credit portfolios is captured by a state-of-the-art CreditMetrics-type portfolio model with sector-dependant unobservable risk factors as drivers of the systematic risk. The German credit register provides us with access to highly granular risk information on loan volumes and banks' internal estimates of default probabilities which is key for an accurate assessment of the impact of the stress scenario. We find that the increase of the capital charge for the unexpected loss needs to be considered together with the increase in banks' expected losses in order to assess the change of banks' capital ratios. We also confirm that highly granular information on the level of borrower-specific probabilities of default has a significant impact on the outcome of the stress test.

Key words: Asset correlation, portfolio credit risk, macroeconomic stress tests

JEL: G21, G33, C13, C15

Non-technical summary

This paper introduces a stress test of the corporate credit portfolios of 24 large German banks by a two-stage approach: A macro-econometric model is used in the first step to forecast the impact of a substantial increase of the user cost of business capital for firms worldwide on three particularly export-oriented industry sectors in Germany. By a model-based stress scenario we ensure a consistent quantification of the stress impact in these sectors. The impact of this economic multi-sector stress on banks' credit portfolios is then captured in the second step by a credit risk portfolio model.

The stress test was carried out in a top-down fashion in November 2008 at the peak of the recent financial crisis. The hypothesis of a severe increase of the user cost of business capital which was the basis of the stress scenario did not occur. Furthermore, the banks in the sample have substantially strengthened their capital basis since then. Therefore the results are for the purpose of illustration. They should not be construed as relevant for the much improved current state of the financial sector, even if a similar stress scenario did occur in the future.

The main contribution of this paper instead should be seen in the *implementation* of an innovative stress test design that links results from advanced macro-econometric models for the stress scenario with a state-of-the-art credit risk portfolio model to gauge the impact on banks' capital ratios. Our stress test design could provide an example for the assessment of the stability of banks on a stand-alone basis. Since the 24 banks considered have a share of 56% of total assets of the German banking system our stress testing tool could also contribute to an assessment of the stability of the banking sector as a whole.

The main findings from our two-stage stress testing approach are as follows:

- Measuring the impact of the stress scenario on banks' capital ratios requires the consideration of the expected loss of the credit portfolio together with higher capital charges for the unexpected loss of the credit portfolio.
- Using highly granular portfolio data is crucial for measuring the impact of the stress scenario. This granularity can typically only be achieved either by a direct request to banks for their portfolio data or if one has access to a supervisory credit register. In our paper we demonstrate empirically that the use of a coarser data set, for example by using sector-specific instead of borrower-specific default probabilities, which is still common in the literature, can significantly distort the results.
- Our analysis confirms previous results in the literature that inter-sector correlations play a key role in measuring stress impact on credit portfolio losses.
- As the 24 banks considered have a share of 56% of total assets of the German banking system our stress testing tool also allows assessment from a financial stability perspective.

Nichttechnische Zusammenfassung

In dieser Analyse werden die Unternehmenskreditportfolien der 24 größten deutschen Bankinstitute einem Stresstest unterzogen. Die Studie basiert auf einem zweistufigen Ansatz: Einem makroökonomischen Modell zur Prognose der Auswirkung eines weltweiten drastischen Anstiegs der Kapitalkosten (Eigen- und Fremdkapital) für Unternehmen auf die drei hauptsächlich exportorientierten Wirtschaftssektoren in Deutschland. Mittels des modellbasierten Stress-Szenarios wird eine konsistente Quantifizierung der Stresswirkung in diesen Sektoren sichergestellt. In einem zweiten Schritt kommt ein Kreditrisiko-Portfoliomodell zur Anwendung, um hierdurch die Multi-Sektor-Stresswirkung auf die Kreditportfolien der Institute zu bestimmen.

Der in diesem Papier beschriebene “Top-down”-Stresstest wurde im November 2008 durchgeführt, d.h. auf dem Höhepunkt der jüngsten Finanzkrise. Die dem Stresstest zugrunde liegende Hypothese eines drastischen Anstiegs der Kapitalkosten ist jedoch nicht eingetreten. Darüber hinaus haben die untersuchten Institute zwischenzeitlich ihre Kapitalbasis in erheblichem Umfang gestärkt. Die Ergebnisse der vorliegenden Studie sind damit lediglich zur Illustration des Stresstests bestimmt, d.h. selbst wenn in Zukunft ein vergleichbares Stress-Szenario eintreten sollte, können die hier dargestellten Ergebnisse nicht als relevant für den aktuellen Zustand des Finanzsystems angesehen werden.

Der Hauptbeitrag dieses Papiers ist damit in der *Implementierung* eines innovativen Stresstest-Designs zu sehen, welches die Ergebnisse eines hochentwickelten makroökonomischen Modells zur Simulation von Stress-Szenarien mit einem “state-of-the-art” Kreditrisiko-Portfoliomodell kombiniert. Zielgröße des Tests ist dabei die Wirkung des Stress-Szenarios auf die Kapitalquoten der Banken. Das Stresstest-Design kann zur Untersuchung der Stabilität einzelner Institute herangezogen werden. Da die 24 Banken in unserer Stichprobe einen Anteil von rund 56 % der Bilanzsumme des deutschen Bankensystems aufweisen, ermöglicht der Stresstesting-Ansatz auch Rückschlüsse auf die gesamte Finanzstabilität.

Die Haupteergebnisse aus dem zweistufigen Stresstesting-Ansatz sind wie folgt:

- Die adäquate Messung der Wirkung eines Stress-Szenarios auf die Kapitalquoten von Banken erfordert die Berücksichtigung der erwarteten Kreditportfolioverluste bei gleichzeitigem Einbezug erhöhter Kapitalanforderungen für die unerwarteten Verluste des Portfolios.
- Die Verfügbarkeit von hochgranularen Portfoliodaten stellt eine zentrale Voraussetzung für die Bestimmung der Auswirkungen von Stress-Szenarien dar. Eine solche Granularität kann üblicherweise nur mittels direkter Datenanfrage bei Banken oder durch die Nutzung eines bankaufsichtlichen Kreditregisters erzielt werden. Im vorliegenden Papier wird empirisch gezeigt, dass die Verwendung eines größeren Datensatzes, wie bspw. bei der (in der Literatur weit verbreiteten) Nutzung von Sektor-spezifischen statt Kreditnehmer-individuellen Aus-

fallwahrscheinlichkeiten, zu einer erheblichen Verzerrung der Stresstest-Ergebnisse beitragen kann.

- Unsere Analysen bestätigen Erkenntnisse aus der einschlägigen Literatur, dass Intersektor-Korrelationen eine zentrale Rolle bei der adäquaten Messung der Stresswirkung auf Kreditportfolioverluste spielen.
- Da die betrachteten 24 Institute einen Anteil von 56 % der Bilanzsumme des deutschen Bankensystems aufweisen, erlauben die Ergebnisse des Stresstests Rückschlüsse auf die Finanzstabilität.

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1. Introduction

This paper introduces a stress test of the corporate credit portfolios of 24 large German banks. The stress test was carried out in a top-down fashion in November 2008 at the peak of the recent financial crisis. In the analysis a scenario for 2009 is assumed in which the investment premium (i.e., the user cost of business capital) for all firms worldwide is heavily raised by 500 basis points. This means an immediate and substantial increase of firms' capital (equity capital and borrowed capital) expenses. Except for investigating an innovative stress scenario the main contributions of this paper to the extensive literature on stress testing are the following:

- (1) It puts forward a methodology how a global economic stress scenario built on a macroeconomic model can be linked to a multi-factor portfolio model of credit risk. The stress test design with its two main components, the macro econometric forecast model and the portfolio model, is visualized in Figure 9 in the Appendix.
- (2) The results reflect not only the impact of a higher default rate under stress but the whole impact on the regulatory capital ratio including also higher capital charges for the unexpected loss due to higher default probabilities under stress.
- (3) Our analysis is set apart by the level of detail of risk information on the banks' credit portfolios. In addition to borrower-specific information on loan volumes we have banks' internal estimates of their default probabilities and also recovery rate estimates on a portfolio basis.

Furthermore, using borrower-specific risk characteristics and sector-dependent asset correlations as input ensures that our portfolio model fully captures credit risk due to either name concentration or sectoral concentrations which have been identified as key drivers of credit risk.¹

¹ See Duellmann and Masschelein (2007).

Following Bonti et al. (2006), we implement our stress scenario by truncating the distribution of three *core factors* representing the three (primarily) stressed industry sectors. In this way we increase the robustness of the results compared with a point-forecast of the systematic risk factors which is commonly used in stress tests. Instead we consider half-spaces of the three core factors which are defined such that their expected values under normal conditions correspond to the respective stress forecasts provided by the macro-econometric model.

- Although only three sectors (or, more precisely, core factors) are primarily stressed, the stress impact is transmitted to the remaining 13 industry sectors through the inter-sector correlations. As a consequence, the marginal distributions of those *peripheral factors* are shifted to the left which means that our model captures also the secondary stress effects on the remaining sectors.
- Furthermore, the design of the stress scenario allows to calculate the probability of the stress scenario under non-stress conditions which provides a meaningful indicator of the stress severity. This is important since the absence of a probability measure for the stress scenario has been identified as one of their main limitations.²
- To assess the stress impact on the banks' solvency situation, we calculate not only the expected losses conditional on the stress event but also the reduction of the banks' solvency ratios.

Apart from being relevant for credit risk stress tests of single institutions, our results can also be relevant from a financial stability perspective. Since the 24 banks included in the sample have a share of 56% of total assets of the German banking system, our analysis covers the major part of the German banking sector in terms of credit volume.

² See Committee on the Global Financial System (2000).

In the literature, similar stress testing concepts have been employed by Bonti et al. (2006) and Elsinger et al. (2006). Our approach finds further motivation by a theoretical result in Breuer et al. (2009) on selecting an optimal stress scenario. They suggest a measure of plausibility that is not prone to the problem of dimensional dependence of maximum loss and derive a way to consistently deal with situations where some but not all risk factors are stressed. In a partial scenario (i.e., in a scenario in which only the values of some risk factors are directly stressed) its plausibility is maximized if the remaining factors are set to their conditional expected values – which is consistent with our approach. Compared with the work by Duellmann and Erdelmeier (2009) this paper presents four main innovations:

- (1) using a macro-econometric model as the basis of the stress scenario,
- (2) stressing multiple core factors instead of a single core factor,
- (3) using borrower-specific default probabilities instead of sector-specific PDs,
and
- (4) taking also the impact on the capital charge in the denominator of the capital ratio into account.

According to Hanson et al. (2008), the availability of borrower-specific instead of sector-specific default probabilities can be expected to have a major impact on the final results. The most important innovation conceptually however is arguably the use of a macro-econometric model as the basis of the stress scenario.

In order to refine the model from a single-sector sensitivity analysis to a scenario-based macroeconomic stress testing tool, the portfolio model is linked to predictions from the world model NiGEM (National institute Global Econometric Model). In this macroeconomic forecast model different stress scenarios can be simulated and different core factors can be stressed. The stress factors we consider in our analysis are the German investment premium and effective exchange rate (i.e., cost fac-

tors German firms face in this stress situation) as well as German equity prices (to account for the general business climate in Germany). Those three risk factors enter a VAR model as exogenous variables in order to put "stress" on the production indices (endogenous variables in the VAR) of three particularly export-dependent industry sectors in Germany: chemicals, industrial goods, and automotive. Our main findings are as follows:

- Our results confirm that the common use of sector-specific loan volumes and default probabilities, estimated from historical default rates, can distort results and strongly advocate to use borrower-specific risk characteristics.
- Inter-sector correlations play a key role in measuring the stress impact on credit portfolio losses.
- Considering higher capital charges for the unexpected loss of the credit portfolio in addition to the expected loss of the credit portfolio has a significant impact on banks' capital ratios in the stress scenario.

The structure of the paper is as follows. Sections 2 and 3 present the two building blocks of our stress testing framework, the macro-econometric model and the portfolio model. Section 4 covers an illustration and a descriptive analysis of the data base. The stress test results for banks' credit portfolios and the impact on the solvency ratios are presented in Section 5. The respective contributions of default risk, and regulatory capital are analyzed in Section 6. The final Section 7 summarizes and concludes.

2. Macro-econometric Model

In order to refine the model from a pure sensitivity analysis (for example, a 10% decrease of a production index) to a scenario-based macroeconomic stress testing tool the portfolio model is linked to the National institute Global Econometric Model (NiGEM). This macroeconomic simulation and forecast tool is based on more than 3,600 equations and historical data back to 1961. Hence, in this model several stress scenarios can be simulated and specific stress factors can be extracted and used for stressing the portfolio model.³

In our analysis an adverse scenario for 2009 is assumed in which the investment premium (i.e., the user cost of business capital) for all firms worldwide is heavily raised by 500 basis points which means a relative increase of this variable by more than 300%. Hence, this increase in the investment premium will immediately and substantially affect firms' cost structures and capital (equity capital and borrowed capital) expenses. Additionally, within NiGEM other variables are affected by the initial "global cost-of-capital shock", which can also be extracted and used for stressing the portfolio model. In order to account for the general business climate in Germany we consider in our stress tests also the effective exchange rate for Germany as an additional cost factor German firms face in this stress situation and German equity prices as additional factors.

Those three risk factors enter a VAR model as exogenous variables in order to put "stress" on the production indices (endogenous variables in the VAR) of the three industry sectors in Germany which are stressed directly: *chemicals*, *industrial goods*, and *automotive*. These sectors together constitute the most export-dependent part of the German economy. With a share of 38% of the total corporate

³ For combining macroeconomic scenario analysis and portfolio model stress tests see also Segoviano and Padilla (2006).

loan volume of the banks in the sample they also build a major part of banks' lending business. In order to "stress" the production indices we estimate the following VAR model:⁴

$$\begin{aligned}
 Y_t &= A(L)Y_{t-1} + BX_{t-i} + \mu_t. \\
 Y_t' &= [PI_CHE_t \quad PI_IND_t \quad PI_AUTO_t], \\
 X_{t-i}' &= [INVEST_PREM_t \quad EFF_EX_RATE_{t-2} \quad EQUITY_{t-4}],
 \end{aligned}
 \tag{1}$$

The endogenous variables of the model consist of seasonally adjusted production indices for the *chemicals* (PI_CHE), *industrial goods* (PI_IND)⁵, and *automotive* sector (PI_AUTO), which enter the VAR with a lag-structure of one to three quarters.

The second group, X_{t-i} , consists of the German investment premium (INVEST_PREM), the German effective exchange rate (EFF_EX_RATE), as well as the German equity prices (EQUITY). These variables, for which we assume that they are exogenous to the rest of the VAR model, are included to "stress" the production indices. Therefore, these variables with lags of up to four quarters influence the other variables of the VAR model, but there is no feedback to these variables.⁶

The VAR model is estimated in growth rates, except the investment premium, which is in levels. The sample period is from 1992q1 to 2008q1. Likelihood ratio tests are applied to determine the VAR model's lag-order to be three. The eigenvalue stability condition is satisfied; all eigenvalues lie inside the unit circle. More-

⁴ For the estimation of VAR models see Mojon and Peersman (2001); De Graeve et al. (2008); etc.

⁵ The production index for *industrial goods* is not available according to the sector definition in the portfolio model. Therefore, this index is proxied by three major sub-indices: *metal production and processing*, *electrical engineering*, and *machine building*. Weighting of the sub-indices is done by each sub-sector's gross value added.

⁶ The maximum correlation amongst the exogenous variables in the VAR model is almost 13%.

over, according to the Augmented Dickey-Fuller unit-root test all (endogenous and exogenous) variables in the model are stationary on the 0.2%-level.

Table 1
Regression statistics for the VAR model

This Table presents regression statistics for the VAR model. Notice that all coefficients of the exogenous variables show plausible signs and that almost all of them turned out to be significant.

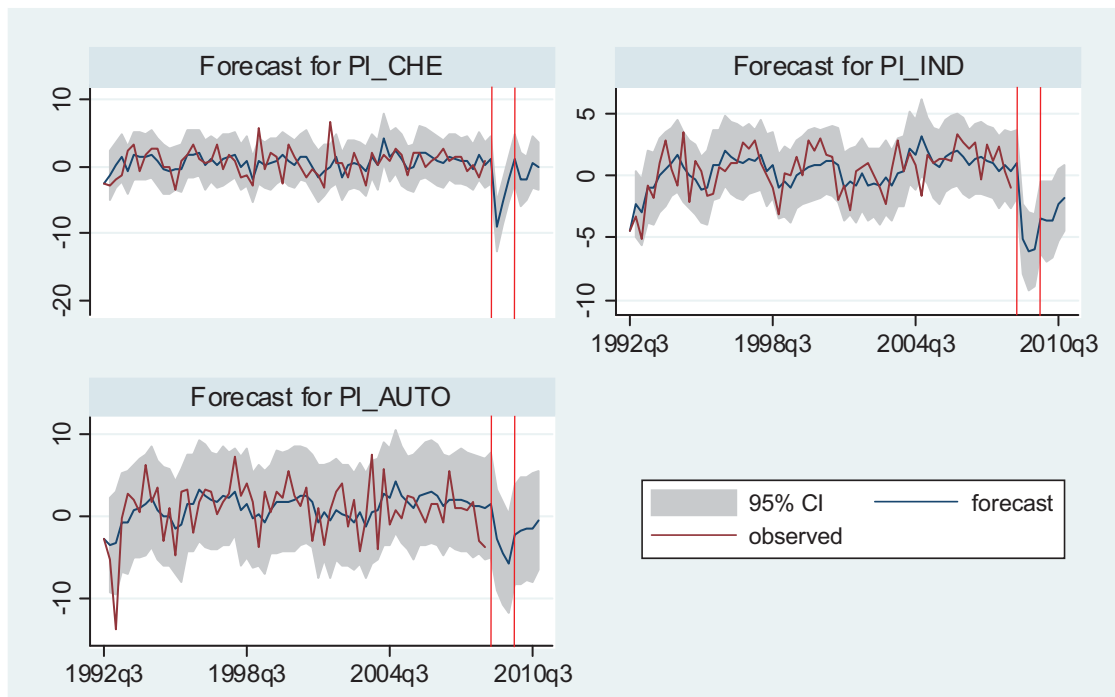
	(1)	(2)	(3)
COEFFICIENT	PI_CHE	PI_IND	PI_AUTO
L.PI_CHE	-0.2411** (0.1089)	0.1541 (0.0988)	0.0376 (0.2037)
L2.PI_CHE	-0.1153 (0.1134)	0.1918* (0.1029)	0.1230 (0.2122)
L3.PI_CHE	-0.0678 (0.1067)	-0.0135 (0.0967)	-0.0158 (0.1995)
L.PI_IND	-0.0718 (0.1471)	0.1068 (0.1334)	0.5582** (0.2751)
L2.PI_IND	-0.0751 (0.1493)	0.1306 (0.1354)	0.1598 (0.2792)
L3.PI_IND	-0.4069*** (0.1440)	-0.1141 (0.1306)	-0.3052 (0.2693)
L.PI_AUTO	0.1549** (0.0705)	-0.0548 (0.0639)	-0.2147 (0.1318)
L2.PI_AUTO	0.0827 (0.0769)	-0.0189 (0.0697)	0.0194 (0.1438)
L3.PI_AUTO	-0.1421** (0.0700)	-0.0469 (0.0634)	-0.0523 (0.1308)
EQUITY_14	0.0880*** (0.0267)	0.0431* (0.0242)	0.0540 (0.0500)
EFF_EX_RATE_12	-0.3193*** (0.1105)	-0.3301*** (0.1002)	-0.5315** (0.2066)
INVEST_PREM_10	-1.2243*** (0.3544)	-0.7659** (0.3214)	-0.5174 (0.6627)
Constant	3.0911*** (0.6366)	1.7552*** (0.5773)	2.1526* (1.1904)
Observations	65	65	65
R-squared	0.4419	0.4768	0.3146

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Regression statistics are shown in Table 1. With the theoretically and empirically chosen lag-structure of up to four lags all of the coefficients of the exogenous variables show plausible signs and almost all of them are significant for each of the three industry sectors to be stressed. At this point sufficient significance is of importance as the exogenous variables “transport” scenario-specific stress from the simulation model and, hence, establish the link between NiGEM and the VAR model.

Figure 1. **Industry sector indices**

This figure presents predictions (and observed values) of production indices for the three industry sectors in Germany: *chemicals* (PI_CHE), *industrial goods* (PI_IND), and *automotive* (PI_AUTO). The predicted values for 2009, which are conditional on the “global cost-of-capital shock” scenario, are highlighted in the graph.



In Figure 1 we report predictions of production indices for the three industry sectors in Germany together with observed values and 95% confidence bands. The

good forecasting power of the model is indicated by only a few observations which lie outside the confidence bands as well as the (for this type of model) relatively high R-squared shown in Table 1. Within 2009 for each sector a substantial decline in the production index is predicted by the VAR model, where the “shock” is distributed differently over quarters in every industry sector. While the *chemicals* sector reacts with a high negative growth rate in the first quarter of 2009 and turns to a positive growth rate in the fourth quarter, the other sectors show the highest negative production index growth rates in the middle of 2009. With an average quarterly growth rate of -5.15% the industrial goods sector, which is by far the largest directly stressed sector in the portfolio model, is mostly affected by the “global cost-of-capital shock” scenario.⁷

In addition to the graph, predicted changes in the production indices for the “global cost-of-capital shock” scenario are listed in Table 2 and compared with the baseline scenario.⁸

Table 2

Predicted changes in production indices

This Table shows the predicted stressed values for 2009 in the “global cost-of-capital shock” scenario compared to a baseline scenario. Each number reflects the quarterly change of the respective production index in percent.

Year / quarter	Sector chemicals		Sector industrial goods		Sector automotive	
	Baseline	Global cost-of-capital shock	Baseline	Global cost-of-capital shock	Baseline	Global cost-of-capital shock
2009 Q1	-0.56	-9.13	0.27	-5.09	0.72	-2.90
2009 Q2	1.38	-5.30	0.93	-6.12	1.60	-4.56
2009 Q3	0.21	-1.89	0.45	-6.03	0.95	-5.83
2009 Q4	1.43	1.12	1.15	-3.37	1.80	-2.37

⁷ With a share of 35% of the total corporate loan volume of the banks in the sample the *industrial goods* sector is the second largest sector, after *financial services*, in the portfolio model.

⁸ The baseline scenario reflects the changes in the production indices under “normal (expected) circumstances”.

3. Portfolio Model

In order to measure the impact of the stress scenario on banks' credit portfolios, we employ a Merton-type linear multi-factor model that is similar to the models which are commonly used in best-practice financial firms. In the following we describe first the credit risk model, afterwards its link to the macro-econometric stress forecasts and finally how the impact on banks' solvency can be measured by stress-induced changes of their capital ratios.

3.1. The Credit Risk Portfolio Model

For the assessment of credit risk we apply an asset value model that belongs to the class of *conditionally independent factor models* (see Schönbucher (2001)) where the credit risk of a single borrower is modeled by a stylized asset value process. The asset return Y_n of the n -th out of N borrowers in the portfolio is driven by two risk factors: a systematic risk factor X_s , that is sector dependent, and a firm-specific (idiosyncratic) risk factor U_n . Let $s : \{1, \dots, N\} \rightarrow \{1, \dots, S\}$ denote a mapping of the borrower to a sector. The asset return Y_n is defined as:

$$Y_n = r \cdot X_{s(n)} + \sqrt{1 - r^2} \cdot U_n.$$

The systematic and the firm-specific risk factor are both independent and standard normally distributed. The systematic risk factors of the 16 business sectors are jointly standard normally distributed with correlation matrix Ω .

Since Y_n is standard normally distributed by construction, the default barrier γ_n can be inferred from the probability of default p_n ,

$$\gamma_n = \Phi^{-1}(p_n),$$

where $\Phi()^{-1}$ denotes the inverse of the cumulative standard normal distribution function.

The portfolio comprises loans to N borrowers which have each a share of w_n of the total portfolio volume. LGD_n denotes the expected *Loss Given Default*. It is treated as a deterministic variable and set uniformly to 45% which is the value used in the foundation IRB approach of Basel II for senior unsecured loans.

Under these assumptions, the *default loss* L_N^{def} in period t (i.e., the portfolio loss due to default events) is defined by

$$L_N^{def} = \sum_{n=1}^N w_n \cdot LGD_n \cdot 1_{\{Y_n \leq \gamma_n\}}.$$

The distribution of portfolio losses is obtained from Monte Carlo simulations, which require a Cholesky decomposition of the correlation matrix Ω of systematic risk factors X_1, \dots, X_S .

The unconditional expected loss $EL^{baseline}$ refers to the loss under normal (i.e., non-stressed) conditions and is given by

$$EL^{baseline} \equiv \mathbb{E}(L_N) = \sum_{n=1}^N w_n \cdot LGD_n \cdot p_n.$$

The expected loss conditional on the stress scenario $\mathbb{E}(L)^*$ is given by

$$EL^{stress} \equiv \mathbb{E}(L_N^*) = \sum_{n=1}^N w_n \cdot LGD_n \cdot p_n^*$$

where p_n^* denotes the PD of the n -th borrower conditional on the stress scenario.

Therefore, the impact of the stress scenario on the expected loss is given by

$$\Delta EL = EL^{stress} - EL^{baseline} = \sum_{n=1}^N w_n \cdot LGD_n \cdot (p_n^* - p_n).$$

In order to gauge the impact on the capital ratio we distinguish between the increase of the expected loss and the post-shock increase of the UL for credit risk. The latter effect influences the denominator of the capital ratio as it increases the risk weighted assets through higher PDs.

3.2. *Linking the Stress Forecast to the Portfolio Model*

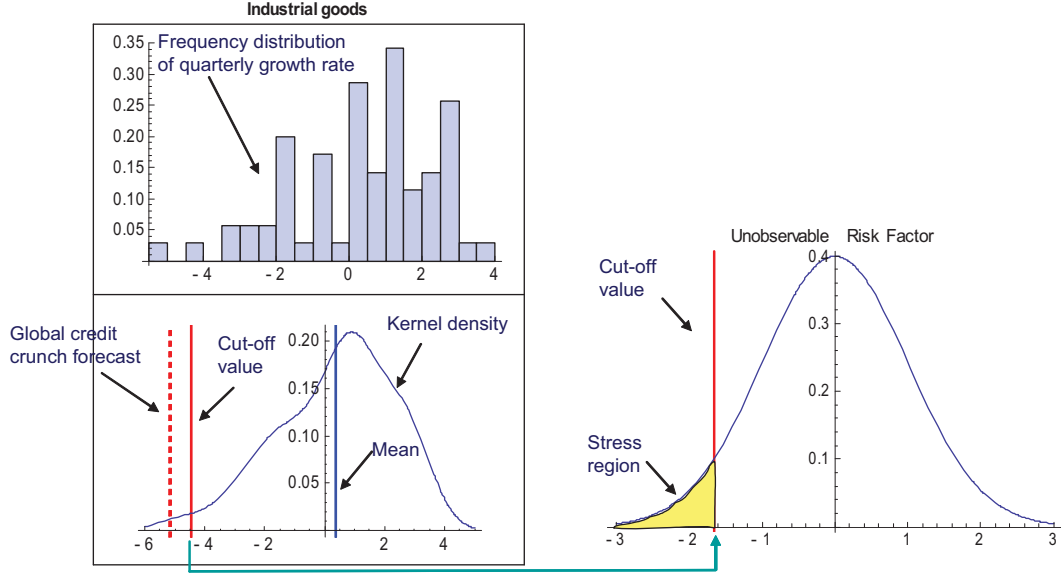
An important challenge in any macroeconomic stress test is the mapping from forecasts of observable macroeconomic variables to the corresponding variables of the credit risk portfolio model. This link is described below in detail. We are aware that it is by no means a unique solution and offers room for exploring alternatives.

The stress impact on the portfolio loss is captured by restricting the distribution of the primarily stressed sectors, collected in the index set J^* . In order to link the credit risk model and the macro-econometric model, the forecasts of the three primarily stressed sectors need to be mapped to the corresponding three unobservable risk factors of the portfolio model. Since the relationship between the observable risk factors of the macro-econometric model and the unobservable risk factors of the portfolio model need not be linear, we implement this mapping by the more robust requirement that the probabilities of occurrence should correspond (under non-stress conditions) in both cases.

The mapping of the macroeconomic variables is demonstrated in Figure 2 taking the sector *industrial goods* as example. At first, a (Gaussian) kernel density estima-

Figure 2. Stress Scenario Mapping in Sector *Industrial Goods*

This Figure shows the mapping of the stress scenario from the observable macro factor for Sector *industrial goods* to the corresponding unobservable risk factor in the portfolio model.



tion is carried out to obtain a continuous distribution of 70 quarterly observations of the macro variable from the second quarter 1991 to the third quarter 2008. Next, we determine the cut-off value c_j ($j \in J^*$) which has the property that the expected value of the macro variable Ξ_j , conditional on being below the cut-off point is exactly the stress forecast $\hat{\xi}_j^*$:

$$\mathbb{E} [\Xi_j | \Xi_j \leq c_j] = \hat{\xi}_j^* \forall j \in J^*.$$

From the kernel density distribution we can now determine the probability $q(c_j) = \mathbb{P}(\Xi_j \leq c_j)$. The probability $q(c_j)$ enables us to determine immediately the corresponding cut-off point $\Phi^{-1}[q(c_j)]$ of the corresponding unobservable risk factor X_j since the distribution of this factor is standard normal by construction.

For the sector *industrial goods*, for example, the stress forecast $\hat{\xi}_j^* = -5.16$ implies a cut-off point $c_j = -4.4$ which is not exceeded (unconditionally) by a probability of 4.9% (see Figure 2). This relatively low probability of the stress scenario indicates that it is quite severe. Since the corresponding unobservable risk factor of the sector is standard normally distributed, its corresponding cut-off point is -1.7 .

3.3. Impact on Regulatory Capital Ratios

The key indicators to measure the impact of the stress event on the banks' solvency are the capital ratios conditional on the stress scenario. The Tier 1 capital ratio $T1CR$ of a bank that has adopted an *Internal Ratings Based (IRB)* approach is defined in the Basel II framework (see Basel Committee on Banking Supervision (2006)) by

$$T1CR = \frac{T1C - \frac{1}{2} \max\{EL - TEP, 0\}}{12.5 (K_{CrR} + K_{MkR} + K_{OpR})}$$

$T1C$: *Tier 1 Capital* consisting of core capital net of deductions (for example, for certain investments in subsidiaries and securitization-related positions)

EL : Expected loss of the credit portfolio

TEP : *Total Eligible Provisions* to offset expected losses from credit risk

K_{CrR} : *Regulatory capital charge* for unexpected losses from credit risk in the banking book

K_{MkR} : *Regulatory capital charge* for market risk in the trading book

K_{OpR} : *Regulatory capital charge* for operational risk.

The bank can offset its EL with total eligible provisions to the extent that these provisions have not yet been used to offset the baseline EL.

In the baseline case, the capital ratio is based on the “unstressed” values of expected loss and regulatory capital. The capital ratio $T1CR^{stress}$ conditional on

the stress scenario reflects the default losses and the increase of regulatory capital. This capital ratio is affected by an increase of expected losses and by the increase of regulatory capital charges due to the higher PDs conditional on the stress scenario. The first component affects the numerator of the capital ratio and the second one the denominator. The capital ratio $T1CR^{stress}$ conditional on the stress scenario is defined as

$$T1CR^{stress} = \frac{T1C - \frac{1}{2} \max\{EL^{stress} - TEP, 0\}}{12.5 (K_{CrR}^{stress} + K_{MkR} + K_{OpR})}.$$

Banks are required to re-estimate LGD if a default occurs. We assume that the result is the same as before default.⁹

The regulatory capital K_{CrR} is given by the asymptotic single risk factor model used in the internal ratings based approach in Basel II. It is defined as

$$K_{CrR}(p_1, \dots, p_N) = \sum_{n=1}^N w_n LGD_n \left[\Phi \left(\frac{\Phi^{-1}(p_n) + \sqrt{\rho(p_n)} \Phi^{-1}(0.999)}{\sqrt{1 - \rho(p_n)}} \right) - p_n \right] \frac{1 + b(p_n) \cdot (T - 2.5)}{1 - 1.5 b(p_n)}$$

with

$$\rho(p_n) = 0.24 - 0.12 \left(1 - e^{-50 p_n} \right)$$

and

$$b(p_n) = (0.11852 - 0.05478 \ln(p_n))^2.$$

The maturity T is set to 2.5 years which is its value in the foundation IRB approach.

The regulatory capital conditional on the stress event is computed by replacing p_1, \dots, p_n by the default probabilities obtained from the MC simulation.

⁹ Furthermore, we do not consider a capital charge for any remaining systematic risk in the LGD of defaulted exposures which would have to be added to UL capital (see Basel Committee on Banking Supervision (2006), para. 471.)

4. Descriptive Analysis

The portfolio model requires input data on the portfolio composition of the banks, the risk characteristics of the borrowers and the correlation structure. The reference date of the analysis is end of September 2008.

Information on banks' portfolios and on their borrowers is based on the German credit register. This central credit register is maintained by the Deutsche Bundesbank and comprises borrowers with a total credit volume of at least 1.5m €. For every borrower we have information on the total credit volume, its default probability and the NACE code of the industry sector which it belongs to.

The aggregate loan volume of every borrower in the credit register accounts for important credit risk mitigation techniques, namely guarantees, sureties, and plain vanilla credit default swaps. Loans granted within a borrower unit are not considered. Foreign borrowers are included but private and sovereign borrowers are excluded from the analysis.

A unique feature of the German credit register is its aggregation of single-entity borrowers to so called "borrower units" which capture default dependence through business ties or legal linkages.¹⁰ This is an important prerequisite in order to capture the granularity or the name concentration of a credit portfolio which can have a significant impact on its risk.¹¹

The default probabilities of the borrowers are based on the internal rating system of the lender. These rating systems have been validated by the German supervisors

¹⁰ The use of borrower units requires a rule to cope with two special cases: Firstly, the case of different default probabilities assigned to different borrower entities and, secondly, the case of different sector assignments. In the first case, the default probability of the borrower unit is calculated as a credit-volume weighted average. In the second case, the sector of the borrower with the largest loan volume is assigned.

¹¹ See, for example, Duellmann and Masschelein (2007) or Heitfield et al. (2006).

under pillar 2 of the Basel II framework. Since the rules of the *Internal Ratings Based Approach* (IRB approach) are based on a bucket-based rating system, the default probabilities of two borrowers are different only if they belong to different rating categories. Combining information on loan size and default probability, precludes, however, an aggregation on the level of rating buckets. Therefore, we still refer to default probabilities as borrower-specific.¹²

The industry sector scheme used in the credit register does not easily allow to estimate inter-sector correlations from stock index returns. For this purpose, the NACE codes are mapped into a coarser classification scheme that is linked to stock indices and allows to estimate correlations from historical index returns. We employ the *Industry Classification Benchmark* (ICB), invented by the Financial Times Stock Exchange and by Dow Jones. This sector scheme comprises 18 sectors on the aggregation level that is used in this paper.

Since no German company is listed in the *oil and gas* sector, we exclude it. Furthermore, we exclude the banking sector for three reasons: Firstly, the purpose of the stress tests is to measure credit risks of banks, so using the banking sector as a risk driver induces a recursion problem. Secondly, loans to banks are quite special in that they are often highly collateralized and in times of need the maturity of new engagements is adapted to changed risk perceptions. Thirdly, banks are highly regulated entities which makes it difficult to forecast the impact of a stress scenario. Since these characteristics cannot be meaningfully captured in our stress testing framework, we prefer to exclude this sector, even if it is in terms of volume clearly important. With these specifications, the number of industry sectors decreases to 16.

The ICB scheme enables us to estimate the inter-sector correlations from weekly

¹² In cases, where no default probability is available, for example, because the lender evokes “partial use”, we take the average default probability of all borrowers of the bank which belong to the same industry sector.

log-returns over two years of Dow Jones Eurostoxx sub-indices. Table 5 in the Appendix presents the correlation estimates. Correlations between the three core sectors are relatively high. The correlation between *chemicals* and *industrial goods*, for example, is higher than between *chemicals* and any other sector.

The coefficient of the systematic (sector-dependent) risk is calibrated such that the asset correlations are on average commensurate with empirical findings in order to avoid a potential overestimation of correlations due to the use of equity index correlations. Since the asset correlation of any pair of borrowers i and j is given by

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

the parameter r can be determined if the asset correlation and the correlation between the two sector factors are known. The intra-sector correlation equals r^2 and is the same for all sectors.¹³ For practical purposes, we take the average asset correlation $\bar{\rho}$ of small and medium-sized German companies¹⁴, an empirical value of 0.09, and the mean value $\bar{\omega} = 0.608$ of the correlation matrix given by Table 5 in the Appendix. With these values, r is calculated by $\sqrt{\bar{\rho}/\bar{\omega}}$.

The sample of banks is restricted by two preconditions: Firstly, the bank must have adopted an IRB approach in 2008 since only those banks are required to report their default probabilities.¹⁵ Secondly, the credit portfolio must be sufficiently large that the part included in the credit register is sufficiently representative to draw inference on the whole portfolio. More precisely, we require for this purpose that only banks with loans outstanding to at least 800 borrowers are included in the

¹³ The assumption of constant intra-sector correlations can be relaxed but results have been quite robust against this simplifying assumption (see Duellmann and Erdelmeier (2009)).

¹⁴ See Hahnenstein (2004).

¹⁵ The analysis includes two banks which do not have an approved IRB approach but which report their PDs nonetheless.

sample.

Only 24 banks meet both requirements. They comprise 5 large and internationally active private banks, 7 other private banks, 9 public sector banks (including 8 *Landesbanken*), and 3 banks from the cooperative sector. Further information on their balance sheet total, their market capitalization is presented in Table 3. The sector *large private banks* which comprises institutions that are internationally active and have at least 3 bn € Tier 1 capital also has the major share of the sample in terms of average total assets (56%).

Table 3
Accounting information on banks in the sample

This Table presents information on the sectoral breakdown of the sample of 24 German banks, their average total assets and their average equity capital (both in million €).

Banking sector	Number of banks	Average total assets	Average equity capital
Large private banks	5	438.9	13.3
Other private banks	7	75.3	2.1
Public sector	9	178.6	1.6
Cooperative sector	3	113.4	4.9

A crucial assumption which needs to be addressed for the calculation of capital ratios is the hybrid character of PDs in internal rating systems, i.e., the mix of point-in-time and through-the-cycle components. This fact is covered by the formula

$$PD^{Stress} = \frac{1}{2}PD^{IRB} + \frac{1}{2}PD_{PIT}^{Stress}.$$

Therefore, for the calculation of capital ratios the following additional assumptions are made:

- The increase in PDs cannot be compensated by increasing margin income.

- Differences in credit definitions and recognition of risk mitigation techniques in the credit register and in the minimum regulatory capital requirements have only minor impact.
- Both stress scenario and asset correlations are estimated from German/European data but applied to the total portfolio that also includes exposures to industrial services borrowers.

Figure 3 presents the sectoral decomposition of the aggregate credit portfolios of all banks in the sample. The two dominant sectors in terms of volume are the *industrial goods and services* sector and the *financial services* sector. The three primarily stressed sectors taken together amount to roughly 40% of banks' total corporate loan exposure.

Figure 3. Sectoral distribution of aggregate loan volume

This figure presents the empirical distribution of the aggregate loan volume of 24 large German banks according to the ICB sector scheme. Reference date is September 2008.

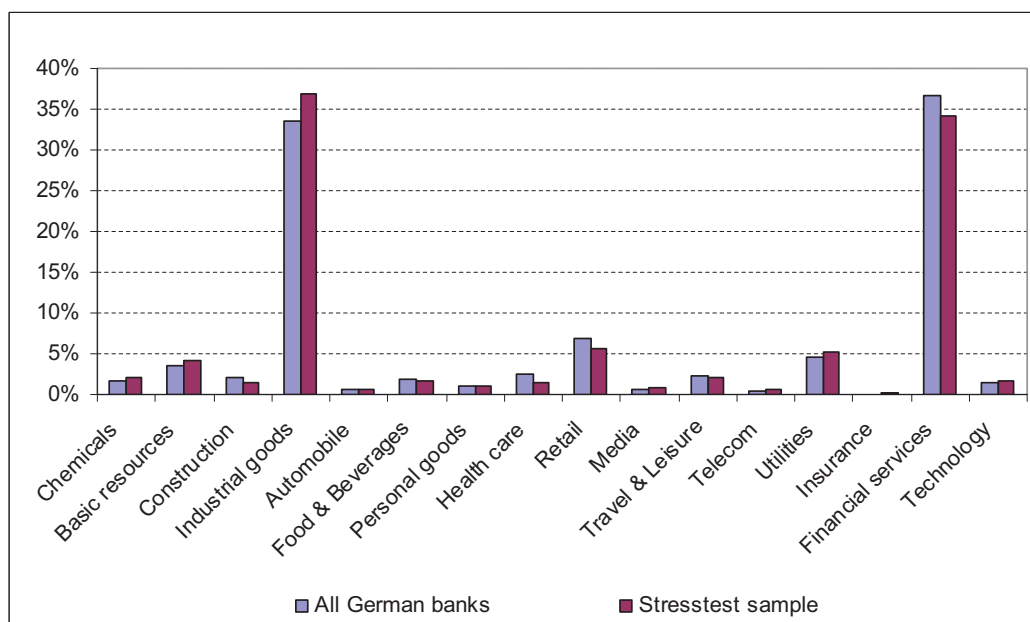
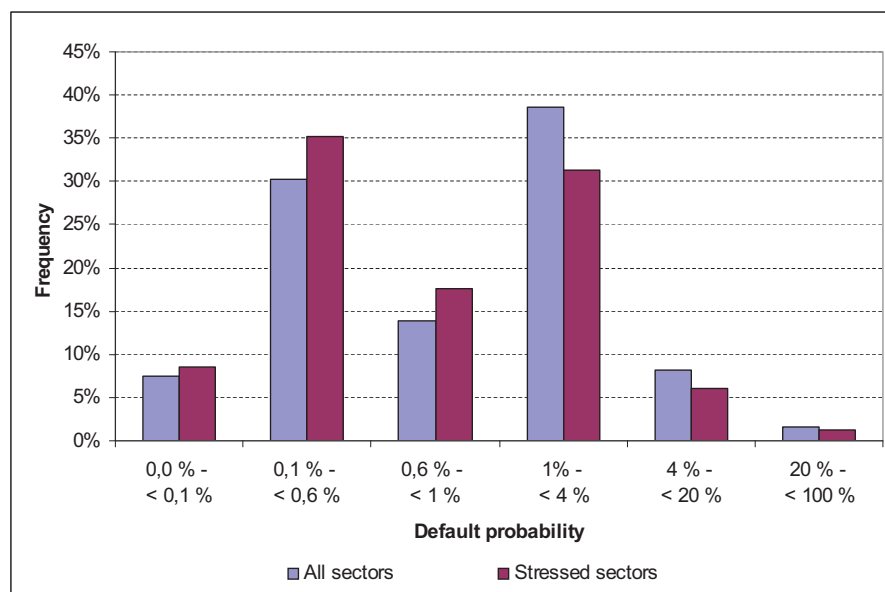


Figure 4 gives the distribution of default probabilities across rating categories,

both for all borrowers in the sample and for the sub-sample of the three primarily stressed sectors. As both distributions are of similar shape we can assume that the stress test results are not distorted by systematic PD-differences between primarily and indirectly (i.e., via correlations) stressed industry sectors.

Figure 4. **Distribution of borrowers across rating categories**

This figure presents the distribution of the aggregate loan volume of 24 large German banks across rating categories, both for all 16 sectors and only for the three directly stressed sectors chemicals, industrial goods, and automotive. Reference date is September 2008.



5. Empirical Results for Portfolio Losses

5.1. Impact on Expected Losses

In order to measure the impact of the stress event on the credit portfolio we compute the expected losses conditional on the stressed core factors. Table 4 shows descriptive statistics of the increase in expected losses of the 24 banks in the sample. The expected losses (*EL*) are always given as percentage of the aggregate nominal value of loans in the bank's credit portfolio. The stress impact (baseline to adverse

scenario) affects individual banks quite differently; the impact reaches from 1.2 percentage points in the minimum while the maximum stress effect amounts to 10.7 percentage points.

Table 4

Descriptive statistics on expected losses in the “global cost-of-capital shock” scenario

This Table shows descriptive statistics of expected losses (*EL*) of 24 large German banks for the baseline situation and conditional on the stress scenario. The numbers are measured as percentage of the aggregate nominal value of loans in the bank’s credit portfolio.

Scenario:	Baseline	Stress	
Statistic	Expected Loss (EL)	EL	Increase of EL in percentage points
Minimum	0.3%	1.5%	1.2
25% quantile	0.5%	2.1%	1.6
Median	0.7%	3.0%	2.3
Mean	1.0%	3.5%	2.5
75% quantile	1.1%	3.7%	2.6
Maximum	5.7%	16.4%	10.7

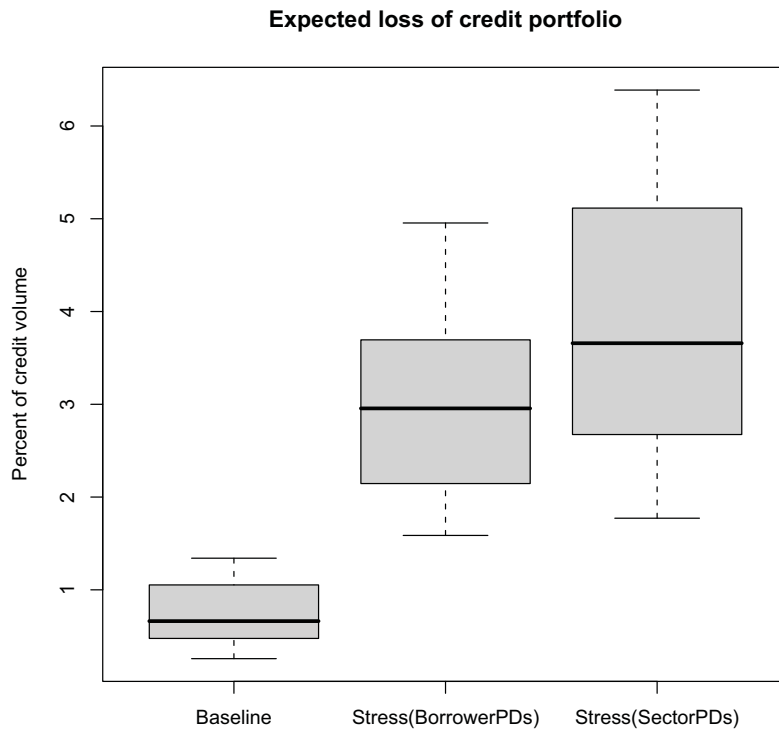
Figure 5 shows the distribution of EL both under normal and under stressed conditions. Under stressed conditions we further differentiate between the case of borrower-specific PDs and the case of sectoral PDs. Sectoral PDs are computed as the average PD of all borrowers in the same sector which are pooled over all banks in the sample. Since the EL calculated from these PDs can significantly differ from the EL based on borrower-dependent PDs, we calibrate the sectoral PDs individually for every bank. The scaling factor used for this purpose is the same for all borrowers of the bank and is defined to equate the EL with borrower-dependent and the EL with sector-dependent PDs.

Although a new stress test with sector dependent PDs uses much coarser information, it still captures more information than typical stress tests based on sectoral

PDs. Firstly, the borrower-dependent loan volume is still used as input. Secondly, since the EL based on borrower-dependent PDs is typically not available, the calibration step is not possible. Both aspects tend to increase the impact of different portfolio characteristics. Therefore, we expect that differences across banks will be more pronounced than in the typical case in which both aspects are not considered.

Figure 5. **Expected losses under normal and stressed conditions**

This figure describes the distribution of expected losses (EL) both under normal and under stressed conditions. The upper and lower limits of the grey box are the 75% and the 25% quantile. The middle horizontal line is the median. The two “whiskers” are defined by the minimum of 1.5 times the length of the inter-quartile range and the distance to the furthest outlier.



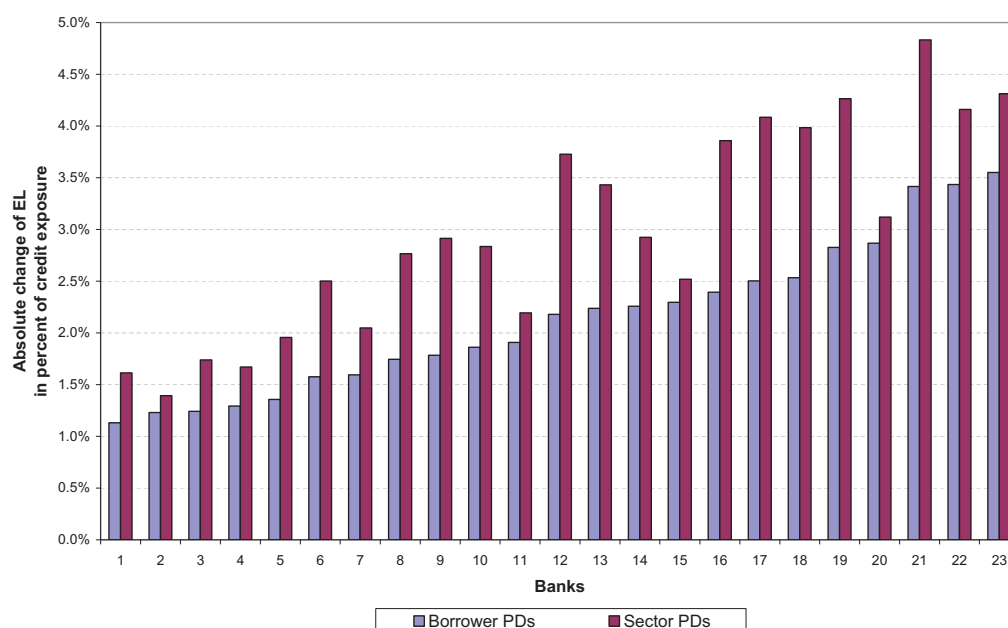
In order to put the size of the stress effect under perspective, Figure 5 is based on the level of EL as percentage of the banks’ credit volume. The median value increases from 0.7% under baseline conditions to 3.0% which implies a credit loss of 2.3% of the credit volume. If sectoral PDs are used, the increase in EL is even stronger. The median EL is 3.7% which implies an increase by 3 percentage points.

The stress impact is not only stronger in the level if sector-dependent PDs are used, but the results are also much more dispersed across banks as indicated by the larger inter-quartile range and the greater distance between the whiskers.

Figure 6 illustrates the relative increase in the EL under stress both for borrower-specific and for sector PDs. The banks are sorted according to their EL increase for borrower-specific PDs.

Figure 6. **Relative increase in expected losses under normal and stressed conditions**

This Figure illustrates the absolute increase in EL (measured in percent of credit exposure) both in case borrower-specific PDs and in case of sector PDs for all examined banks. For a better comparability, the results are sorted according to the relative increase for borrower-specific PDs. One outlier bank with 98% credit exposure in the financial services sector had to be excluded from the graph.



In the case of borrower-specific PDs, Figure 6 shows a considerable dispersion in the absolute EL increase (measured in percent of credit exposure) which ranges from approximately 1.1% to 3.6%. For sector PDs, the increases in EL range from approximately 1.4% to 4.8% and thus exceed the respective amounts for borrower

PDs, in most cases significantly.

The results illustrated in Figure 6 confirm the substantial information gain in using borrower-specific PDs instead of sector PDs. In the latter case, the observed increase in EL is significantly higher. Therefore, the use of borrower-specific PDs allows a better differentiation between banks concerning the EL impact.

6. Empirical Results for Tier 1 Capital Ratios and Contribution Analysis

In order to evaluate the impact of the stress scenario on the solvency of a bank, the conditional expected losses do not provide sufficient information. A commonly used solvency indicator is the Tier 1 capital ratio which considers also the capital level of the bank that can be used to absorb losses and the regulatory minimum capital requirements.¹⁶ In the following subsections these effects and their contribution to a decline in the Tier 1 capital ratios are analyzed.

6.1. Contribution Analysis

Figure 7 decomposes the effects on Tier 1 capital ratios, i.e., it compares the baseline situation with the effect of increased expected losses as well as the increase in regulatory capital (both conditional on the “global cost-of-capital shock” scenario). The effects are simulated by the portfolio model.

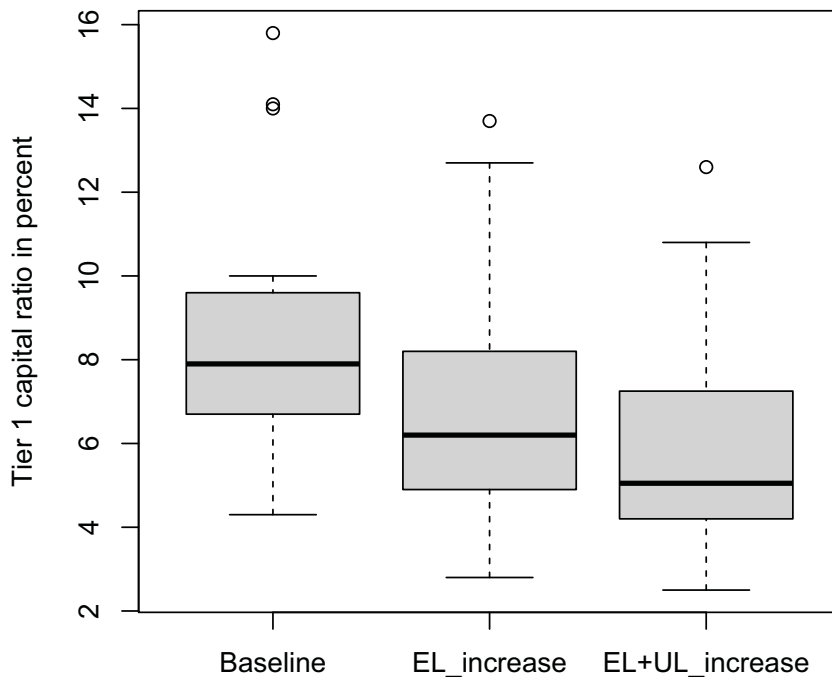
First, the EL conditional on the truncated “core factors” increases¹⁷ which affects the numerator of banks’ Tier 1 capital ratios (see Figure 7, second box plot). This “numerator-effect” causes a decline of the median capital ratio by 1.7 percentage points (i.e., from 7.9% to 6.2%). Second, there is an additional “denominator-

¹⁶ See Section 3.3.

¹⁷ In the portfolio model the Basel II assumption of a LGD of 45% is applied.

Figure 7. **Decomposed impact on capital ratios**

The boxplot compares the decrease in capital ratios in the adverse scenario by the contribution of each component. *Baseline* refers to the situation before stress, *EL_increase* shows the impact of higher expected losses (EL) on the numerator conditional on the stress scenario. In addition, *EL + UL_increase* is the impact on the denominator of the capital ratio from higher PDs in the Basel II risk weight function for the unexpected loss (UL). The upper and lower limits of the grey box are the 75% and the 25% quantile. The middle horizontal line is the median. The two “whiskers” are defined by the minimum of 1.5 times the length of the inter-quartile range and the distance to the furthest outlier.



effect” on the Tier 1 ratios arising from higher PDs in the risk weight function which goes along with a higher level of risk-weighted assets for the unexpected loss (UL). The PD-increase is simulated in the portfolio model conditional on the “global cost-of-capital shock” scenario. The additional effect on the median Tier 1 capital ratio is 1.1 percentage points (i.e., there is a further decline from 6.2% to 5.1% in the median, see Figure 7, third box plot).

Therefore, the overall effect is a decline of the median Tier 1 capital ratio of 2.8 percentage points, of which 60 % (or 1.7 percentage points) is driven by the EL

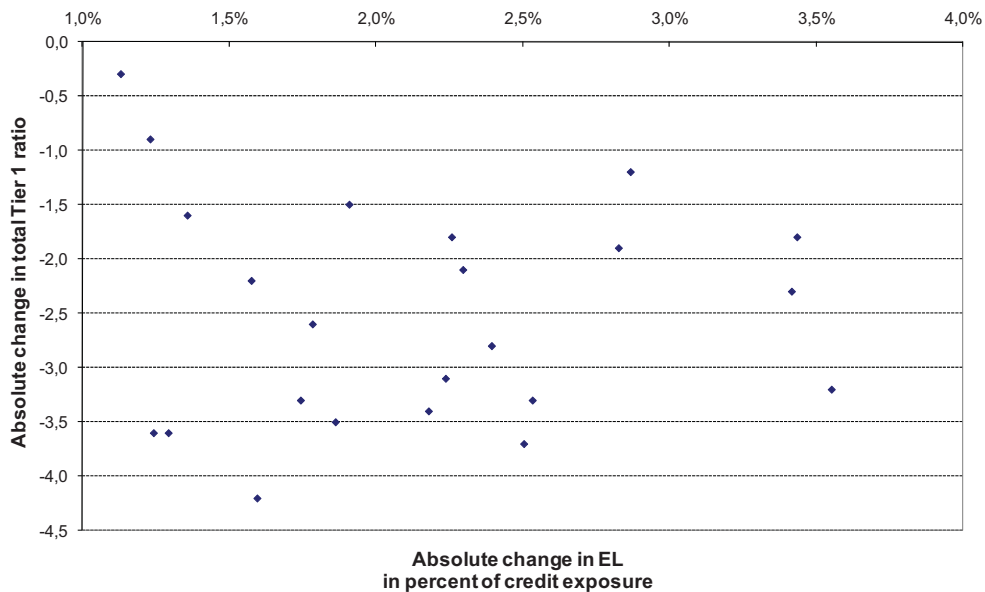
increase and 40 % (or 1.1 percentage points) is due to higher risk weights for the UL. These numbers confirm that it is important to capture also the impact of the stress scenario on UL in order to obtain a complete picture.

6.2. Correlation Analysis: Changes in EL for Defaults vs. Tier 1 Capital Ratios

Finally, Figure 8 plots the change in the Tier 1 capital ratios against changes in EL for defaults due to the stress event, both in percentage points. As the EL is part of the numerator of the capital ratios a negative relationship is not surprising. What we, however, are interested in is the *strength* of this relationship.

Figure 8. **Scatter plot of absolute increase in EL versus absolute decrease in Tier 1 capital ratio**

The Figure compares the increase in the EL as a share of the entire bank portfolio with the calculated decline in the total capital ratio. One outlier bank with 98% credit exposure in the financial services sector had to be excluded from the graph. The figure shows that there is a loose negative relation between both measures.



Although both variables are negatively correlated as expected, the scatter range reveals that this relation is relatively weak. This can only be explained by a different impact of the stress scenario on expected losses from credit defaults and the regu-

latory minimum capital requirements of different banks. This finding confirms that a separate assessment of this impact is not only important in order to capture the total impact of the stress event. Instead, it is also important in order to differentiate between banks in terms of the impact of the stress scenario.

7. Summary and Outlook

In this paper a two-stage approach is used to investigate the impact of a “global cost-of-capital shock” scenario on the credit portfolios of 24 large German banks: A macro-econometric model is applied to forecast the stress impact on three particularly export-oriented industry sectors in Germany, and a state-of-the art Credit Metrics-type portfolio model to capture the impact of this multi-sector stress event on banks’ credit portfolios. Based on the stress forecast from the macro-econometric model we account for default risk in the credit portfolio after one year.

The stress test was carried out in a top-down fashion in November 2008 at the peak of the recent financial crisis. In the analysis a “global cost-of-capital shock” scenario for 2009 is assumed in which the investment premium (i.e., the user cost of business capital) for all firms worldwide is heavily raised by 500 basis points. This means an immediate and substantial increase of firms’ capital (equity capital and borrowed capital) expenses.

The magnitude of the effect from the stress scenario is substantial. If borrower-dependent PDs are used the median level of EL as percentage of the bank’s credit volume increases from 0.7% under baseline conditions to 3.0% which implies a credit loss of 2.3% of the credit volume. On the contrary, if sectoral PDs are used, the increase in EL is even stronger. In this case the median EL is 3.6%, which implies an increase by 2.9 percentage points. Finally, the stress impact is not only

stronger in the level if sector-dependent PDs are used, but the results are also much more dispersed across banks.

We find that the stress effect is also substantial on banks' Tier 1 capital ratios. The EL-effect on the numerator causes a decline of the median capital ratio by 1.7 percentage points. Moreover, there is an additional "denominator-effect" of 1.1 percentage points on the median Tier 1 ratio which arises from a higher level of risk-weighted assets for the unexpected loss. The overall effect of 2.8 percentage points implies a decline in the median capital ratio from 7.9% in the baseline to 5.1% in the stress scenario.

In summary, our main findings are as follows:

- Measuring the impact of the stress scenario on banks' capital ratios requires the consideration of the expected loss of the credit portfolio together with higher capital charges for the unexpected loss of the credit portfolio.
- Using highly granular portfolio information on a borrower level is crucial for measuring the impact of the stress scenario. This granularity can typically only be achieved either by a direct request to banks for their portfolio data or if one has access to a supervisory credit register. In our paper we demonstrate empirically that the use of a coarser data set, for example by using sector-specific instead of borrower-specific default probabilities, which is still common in the literature, can significantly distort the results.
- Our analysis confirms previous results in the literature that inter-sector correlations play a key role in measuring the stress impact on credit portfolio losses.
- As the 24 banks considered have a share of 56% of total assets of the German banking system our stress testing tool also provides valuable information for an assessment of financial stability.

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Figure 9. Overview of the stress test design

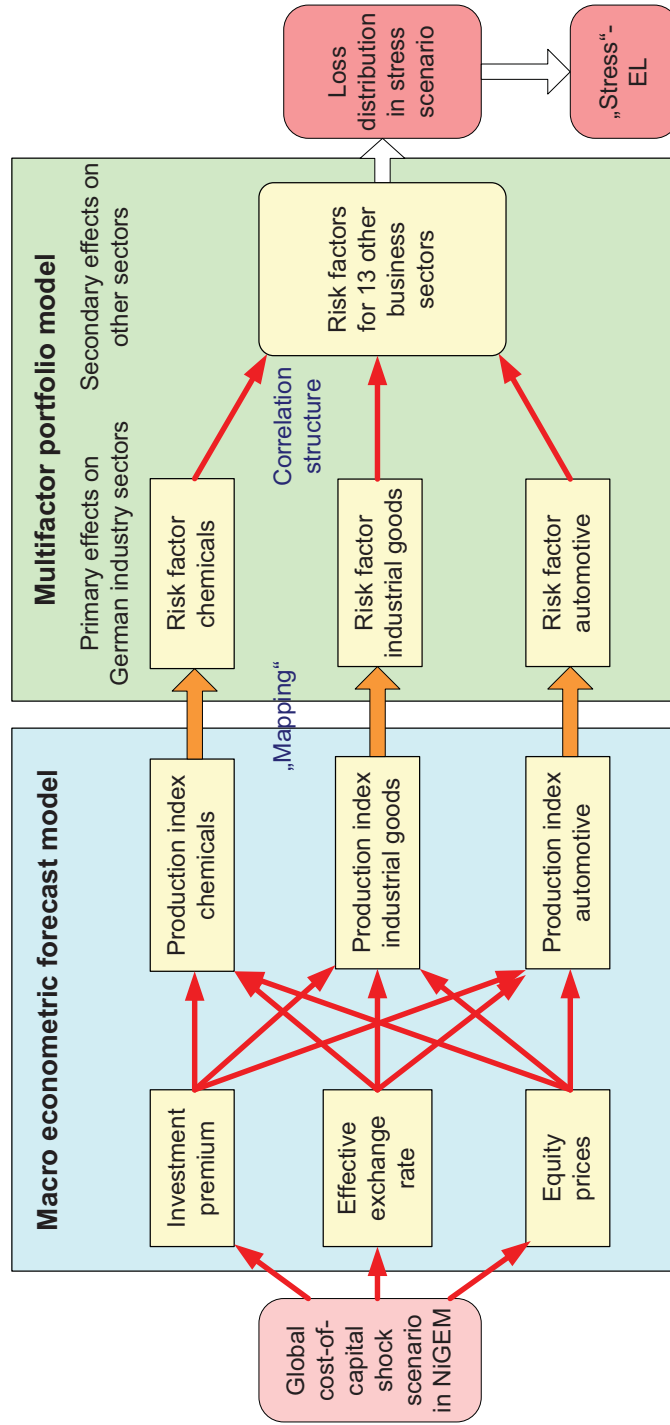


Table 5

Correlation Matrix of the Sector Indices

This table shows inter-sectoral correlations of 16 sector indices following the ICB sector classification. The correlations were estimated from weekly stock index returns from 1 October 2007 until 30 September 2008.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1 Chemicals	1	0.61	0.68	0.78	0.57	0.62	0.66	0.56	0.51	0.72	0.59	0.53	0.74	0.69	0.73	0.55
2 Basic Resources		1	0.57	0.71	0.42	0.32	0.46	0.23	0.43	0.50	0.43	0.26	0.49	0.48	0.61	0.52
3 Construction and Materials			1	0.84	0.80	0.66	0.81	0.52	0.72	0.82	0.80	0.46	0.57	0.75	0.83	0.71
4 Industrial Goods and Services				1	0.72	0.59	0.81	0.47	0.66	0.79	0.73	0.49	0.65	0.70	0.86	0.73
5 Automobiles and Parts					1	0.62	0.74	0.53	0.66	0.70	0.78	0.44	0.39	0.68	0.72	0.64
6 Food and Beverage						1	0.71	0.43	0.70	0.67	0.66	0.44	0.47	0.63	0.63	0.50
7 Personal and Household Goods							1	0.43	0.77	0.79	0.75	0.46	0.52	0.69	0.80	0.75
8 Health Care								1	0.38	0.56	0.49	0.51	0.48	0.55	0.51	0.40
9 Retail									1	0.61	0.72	0.32	0.38	0.63	0.72	0.58
10 Media										1	0.75	0.60	0.57	0.75	0.79	0.72
11 Travel and Leisure											1	0.43	0.439	0.70	0.73	0.65
12 Telecommunications												1	0.57	0.58	0.51	0.54
13 Utilities													1	0.53	0.61	0.46
14 Insurance														1	0.75	0.61
15 Financial Services															1	0.67
16 Technology																1

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