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Many a little makes a mickle: macro portfolio stress test for small and medium-sized German banks

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Non-technical summary

Research Question

Understanding the link between macroeconomic development and banks' ability to absorb losses and to generate income is crucial for macroprudential analysis. Besides conducting stress tests for large banks, there is a need to quantify the impact of different macroeconomic scenarios on the solvency of small and medium-sized German banks, a group often neglected in stress testing, and to detect the main risk drivers influencing the banks' capital ratios.

Contribution

Our macroeconomic stress test is especially designed for small and medium-sized banks employing the standardised approach to credit risk. Thereby, we apply a unique dataset for Germany which allows us to differentiate between savings, cooperative and credit banks on a bank-by-bank level. The stress test combines a multi-factor portfolio model for the simulation of credit risk with an income stress test based on dynamic panel-econometric models, thus particularly taking into account the reliance of small and medium-sized banks on interest income.

Results

Our results show that, with respect to the total capital ratio, savings and especially cooperative banks prove to be very resilient to the macroeconomic stress scenario because of a very solid capital base. Credit banks display greater heterogeneity and more than 6% of the sample's credit banks fall below 8% of total capital in the stress case, mainly due to a smaller cushion of capital. When assessing the relative importance of impairments and other net income components, we identify losses in credit portfolios as the most important driver of banks' risk under stress while the effect of the other income components is comparably small.

Nichttechnische Zusammenfassung

Fragestellung

Das Verständnis des Zusammenhangs zwischen der gesamtwirtschaftlichen Entwicklung und der Fähigkeit von Banken, Verluste zu absorbieren bzw. Gewinne zu erzielen, spielt im Rahmen der makroprudenziellen Analyse eine zentrale Rolle. Da bei der Quantifizierung des Einflusses verschiedener makroökonomischer Szenarien auf die Solvabilität von Banken bisher vor allem Großbanken im Fokus der Analysen standen, besteht die Notwendigkeit für die Konzipierung und Durchführung eines makroökonomischen Stresstests für die oft vernachlässigte Gruppe kleiner und mittelgroßer Banken, um die wichtigsten Risikofaktoren für die Eigenkapitalquoten dieser Institute zu identifizieren.

Beitrag

Der verwendete makroökonomische Stresstest ist speziell für kleine und mittelgroße Banken konzipiert, welche den Kreditrisikostandardansatz verwenden. Dabei wird ein einzigartiger Datensatz für Deutschland verwendet, der es ermöglicht, zwischen Sparkassen, Genossenschaftsbanken und Geschäftsbanken auf Einzelbankebene zu unterscheiden. Bei diesem Stresstest wird ein Mehrfaktoren-Portfoliomodell zur Simulation des Kreditrisikos mit einem Ertragsstresstest auf Basis dynamischer panelökonometrischer Modelle kombiniert. Auf diese Weise wird im Besonderen der Abhängigkeit der kleinen und mittelgroßen Banken vom Zinseinkommen Rechnung getragen.

Ergebnisse

Gemessen an der Gesamtkapitalquote bescheinigen die Ergebnisse des Stresstests den Sparkassen und vor allem den Genossenschaftsbanken eine sehr hohe Widerstandsfähigkeit im Stressszenario. Beide Bankengruppen profitieren von einer sehr soliden Kapitalbasis. In der Gruppe der Kreditbanken, die durch größere Heterogenität gekennzeichnet ist, weisen im Stressszenario über 6 % der Banken eine Gesamtkapitalquote von weniger als 8 % auf, was hauptsächlich der dünneren Ausgangskapitalisierung geschuldet ist. Bei der Betrachtung der relativen Bedeutung der Abschreibungen und der anderen Einkommenskomponenten kann festgestellt werden, dass die Verluste im Kreditportfolio unter Stress den größten Risikofaktor für die untersuchten Banken darstellen, während der Effekt der anderen Einkommenskomponenten vergleichsweise gering ausfällt.

Bundesbank Discussion Paper No 23/2015

Many a Little Makes a Mickle: Macro Portfolio Stress Test for Small and Medium-Sized German Banks*

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Abstract

We develop a macroeconomic portfolio stress test that is specifically geared towards small and medium-sized banks. We combine a credit risk stress test which simulates credit impairments via a CreditMetrics type multi-factor portfolio model with an income stress test in the form of dynamic panel data regressions. Based on a stress scenario that extends experience of the financial crisis by integrating the current low interest rate environment, we analyse the stress impact on banks' capital ratios. Our results show that savings banks and cooperative banks prove to be very resilient to macroeconomic stress, while more than 6% of our sample's credit banks "fail" the stress test, mainly due to their lack of capital. The main stress drivers prove to be credit impairments rather than other net income components.

Keywords: Macro Stress Tests, Macroprudential Supervision, Small and Medium-sized Banks, Income Stress Test, Credit Risk
JEL classification: C13, C15, G21, G33

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1 Motivation

Macroeconomic stress tests have gained considerably in importance in the years since the financial crisis due to their particular suitability for the analysis of banking supervision and financial stability issues (e.g. European Central Bank, 2010). They provide a sound analytical link between general macroeconomic conditions and the quality of banks' credit portfolios and income components (Deutsche Bundesbank, 2010). It is therefore not surprising that moving away from the sole application of sensitivity analyses and conducting fully developed scenario analyses has since been identified as one of the core principles in sound frameworks of bank solvency stress testing (e.g. Jobst, Lian Ong, and Schmieder, 2013). Results from highly integrated stress tests like the EBA stress test (European Banking Authority, 2011), the Bank of England's Risk Assessment Model of Systemic Institutions (RAMSI, e.g. Burrows, Learmonth, and McKeown, 2013), the IMF Financial Sector Assessment Program (FSAP, Jobst et al., 2013), the rich stress testing model of the Bank of Canada (Gauthier and Souissi, 2012; Gauthier, Gravelle, Lui, and Souissi, 2013), and the ECB approach (Henry and Kok, 2013) have highlighted the particular importance of capturing credit impairment flows correctly, while an analysis of the income components of small and medium-sized banks emphasizes the importance of modelling net interest income as well as net fee and commission income thoroughly (Deutsche Bundesbank, 2010).

There is a growing literature on credit risk stress testing (e.g. Sorge and Virolainen, 2006; Foglia, 2009; Vazquez, Tabak, and Souto, 2012). Such papers apply either portfolio models (e.g. Pesaran, Schuermann, Treutler, and Weiner, 2006; Duellmann and Erdelmeier, 2009; Duellmann and Kick, 2014; Henry and Kok, 2013) or econometric approaches based on macro variables (e.g. Sorge and Virolainen, 2006; De Graeve, Kick, and Koetter, 2008; Buncic and Melecky, 2013; Jokivuolle and Virén, 2013). Credit risk stress tests have mainly focused on assessing the resilience of large systemically important Internal Ratings-Based Approach (IRB) banks, while smaller banks that employ the standardised approach to credit risk measurement are rarely in the focus of stress tests (exceptions are for example Deutsche Bundesbank, 2010; Jobst et al., 2013). This omission becomes particularly worrisome in economies with a less centralized banking sector and a large number of local banks, as is the case, for instance, in Germany and Austria. The International Monetary Fund (2011a) claims that stress tests should also cover small and medium-sized banks in order to obtain a more complete coverage of the banking sector. While small and medium sized banks are not systemically important on their own, their risks are concentrated in a network with respect to each banking group, which has become an increasingly relevant topic in banking supervision. Moreover, gaining a thorough understanding of the stress resistance of smaller banks is of particular importance due to their significant role in providing a functioning credit flow to the real economy, mainly for small and medium-sized enterprises (SMEs). A stress test specifically geared towards small and medium-sized banks therefore seems necessary.

A variety of studies highlights the need to investigate the link between macroeconomic development and profitability (e.g. Albertazzi and Gambacorta, 2009; Burrows et al., 2013; Coffinet and Lin, 2013). Particularly for small and medium-sized banks, interest income is a fundamental income source and therefore a major determinant of small banks' stress resilience (e.g. Deutsche Bundesbank, 2013). Most studies focus on earnings at the aggregate level or the net interest margin, but only a few studies use their results to conduct profound scenario analyses and forego investigations of individual subcomponents, such as net interest income, fee income, and operating expenses. While some studies examine banks' earnings as an aggregate (e.g. Quagliariello, 2004; Athanasoglou, Brissimis, and Delis, 2008; Coffinet and Lin, 2013), others deliver insights into the differences between individual subcomponents (e.g. Lehmann and Manz, 2006; Albertazzi and Gambacorta, 2009; Coffinet, Lin, and Martin, 2009), such as interest income, fee income, and trading income. Only the link between macroeconomic factors and profitability is investigated by, for instance, Andersen, Berg, and Jansen (2008); Albertazzi and Gambacorta (2009), while others conduct scenario analyses (e.g. Lehmann and Manz, 2006; Coffinet et al., 2009). Coffinet and Lin (2013) identify GDP growth, interest rate maturity spread, and stock market volatility as the three main macroeconomic drivers of profitability in the French banking sector. In their stress analysis they show that French banks' profitability is resilient even to severe macroeconomic shocks. In a more detailed breakdown, Coffinet et al. (2009) indicate that income components, such as interest margins, fee income and trading income, are determined by specific macroeconomic variables. While GDP growth impacts significantly on fees and commissions, interest margins are more driven by interest rate spreads. Albertazzi and Gambacorta (2009) additionally include operating expenses and loan loss provisions as subcomponents, along with interest income and non-interest income. They provide the insight that not only individual subcomponents react differently to macroeconomic developments, but also that country-specific features influence earnings' sensitivity to macroeconomic changes.

We complement the existing stress testing literature in developing a macroeconomic stress testing framework which especially takes into account the particular needs for stress testing small and medium-sized banks and thereby analyse the differences in the resilience of the several banking groups. More precisely, we combine a multi-factor portfolio model for stressing the banks' credit portfolios with an income stress test. Deutsche Bundesbank (2010) and International Monetary Fund (2011b) have already analysed income components for small German banks using linear panel regressions. In our paper we apply a multi-sectoral credit portfolio model for small and medium-sized banks in line with Duellmann and Erdelmeier (2009) and Duellmann and Kick (2014). The use of a detailed data set from the Deutsche Bundesbank's German Borrowers Statistics, which captures the bank's credit portfolios across business sectors, allows us to consider sectoral portfolio concentrations and correlations among business sectors.[1] Furthermore, we refine the income stress test model by using dynamic panel models suggested by Blundell and Bond (1998) and Arellano and Bover (1995). As Borio, Drehmann, and Tsatsaronis (2014) propose, we develop a sharp stress scenario which is comparable to the economic environment during the financial crisis, and this is complemented by interest rate assumptions that account for the risks of the current low interest rate environment. In contrast to Duellmann and Erdelmeier (2009) and Duellmann and Kick (2014), all business sectors are stressed simultaneously. Our analysis is relevant from a supervisory perspective in that it provides a detailed framework for analysing the resilience of small

[1] Among others, Duellmann and Kick (2014) and Efthyvoulou (2012) show the importance of considering the stress impact on sector level.

and medium-sized banks to macroeconomic shocks and, in particular, for working out the differences between credit banks, savings banks, and cooperative banks. This approach can easily be transferred to assess the resilience of other banking systems.

Our results show that cooperative and savings banks prove to be robust to our macroeconomic stress scenario. The main reason for this is their solid capital base, in addition to comparatively low credit impairments for cooperative banks. Credit banks' resistance is more heterogeneous. A significant portion of 6% falls below the minimum total capital requirements of 8%. The stress impact on credit impairments is most pronounced for savings banks, followed by credit and cooperative banks. The impairment distribution shows that the largest portion is mainly located in the sectors private households, industrial goods and services followed by SME retail. The low impact on capital ratios for cooperative banks can be explained by their larger exposure and lower probabilities of default (PDs) in the relatively safe private household sector compared to the other two banking groups. The main stress drivers for all banking groups are impairments with a proportion of the entire stress effect varying between 79% (cooperative banks and credit banks) and 83% (savings banks) compared to the other net income components.

This paper is structured as follows: we explain the data structure and our descriptive analysis in Section 2. Section 3 presents the theoretical underpinning of our credit risk and income stress methodology. The general macro scenario design is described in Section 4. The stress impact on the total capital ratios and the underlying driving factors are discussed in Section 5. Finally, Section 6 concludes.

2 Data

The credit risk model and the income stress test model of our stress test require several databases provided mainly by the Deutsche Bundesbank. The reference date of our stress test is the end of 2012. We include only banks that apply the standardised approach to credit risk. This approach ensures that while nearly all small and medium-sized German banks fall into this category, we exclude the larger private banks, Landesbanken, and central institutions of the cooperative sector that fall outside the scope of our analysis. Furthermore, we leave subsidiary banks out of the analysis as it is impossible to measure their resilience appropriately in our stress testing framework. Overall, this leaves our sample with $1,578$ small and medium-sized banks that can be subdivided into 63 credit banks, 421 savings banks, and $1,094$ cooperative banks.

The main source of our data set is the borrowers statistics provided by the Deutsche Bundesbank. Since end-2002, loan exposures (both corporate and mortgage loans) to the domestic real economy and the respective changes in the valuation of these loans have been reported by all German banks to the Deutsche Bundesbank on a quarterly basis. As all write-offs are similarly reported as valuation changes, this database contains both write-offs and write-ups. These elements are sufficient to obtain PDs and credit exposures to feed into the credit portfolio model. While borrower-specific information is not available, the borrowers statistics allow us to derive credit exposures as well as PDs for each business sector and credit institution. When applying this data set, a few modifications are necessary. Instead of simply using end-of-2012 data for write-downs and write-ups, we make use of 10-year annual averages from 2003 to 2012. We are able to capture a through-the-cycle perspective for our PD estimates. Thus, we approximate the PD for each credit portfolio sector i and each bank via its default flow per credit exposure.

$$\mathbf{PD}_i = \frac{CWD_i - CWU_i}{CE_i} \approx \frac{DefaultFlow_i}{CE_i} \quad \forall i = 1, \dots, N, \tag{1}$$

where CWD_i and CWU_i stand for credit write-downs and credit write-ups of sub-sector i and CE_i for the corresponding credit exposure.

Turning to the topic of finding data for the modelling of inter-business sector correlations, we are faced with the issue that no reliable equity index data are available for the sector classification scheme used in the borrowers statistics. As the classification scheme used follows the main sector division in the Statistical Classification of Economic Activities in the European Community (NACE), we mapped the banks' credit exposure in the NACE main sectors to the sectors of the Industry Classification Benchmark (ICB), which was developed by Financial Times Stock Exchange with Dow Jones. The advantage of this approach is that Dow Jones Eurostoxx sector indices can be directly matched to the second ICB sector level, which is comprised of 18 sectors. From the Eurostoxx sector indices we can then compute inter-sectoral correlations via annual log returns. We exclude the banking sector from these 18 sectors as this sector cannot be appropriately treated in our framework.[2] The correlations were estimated from weekly Eurostoxx Net Index Returns from August 2007 until May 2010. As the considered time period covers the financial turmoil and the financial crisis, the estimations of the correlations can be considered as very conservative. On average, the correlations are high, comprising values from 0.20 up to 0.96 with an arithmetic mean of 0.68 (Table 6).[3]

In order to make this approach feasible for the applied portfolio model, we also apply a mapping between our GDP sector data and our ICB sectors. An appropriate assignment to the ICB sectors is easily possible. Where multiple macroeconomic sectors belong to a single ICB sector, an equal weighting scheme is applied. As no appropriate GDP sector and DJ Eurostoxx subindex exist for the sector private household, we created an artificial private household sector by weighting the other corporate sectors with the sectoral distribution of the social security liable workforce. The basic idea behind this approach is that, in the event that the corporate sector in which the borrower is working becomes depressed, the likelihood of losing one's job and failing to repay one's loan increases as well.

Data for risk-weighted assets (RWA) as well as total capital for each credit institution in our stress test stem from the prudential information system (Bankaufsichtliches Informationssystem, BAKIS), which is a database ran by the Deutsche Bundesbank and the German Federal Financial Supervisory Authority (BaFin). An overview of several im-

[2] Duellmann and Kick (2014) mention three arguments: Firstly, using the banking sector as a risk driver conflicts with the overall goal of a stress test to measure the banks' risk, and a recursion problem is created. Secondly, loans to banks differ significantly from loans to non-banks due to collateral and maturity changes. Thirdly, as banks are highly regulated entities it is difficult to model the impact of a stress scenario appropriately.

[3] Becker and Schmidt (2013) and So, Wong, and Asai (2013) show the importance of correlations and their estimations on portfolio risk.

portant aggregated balance sheet figures concerning the three considered banking groups is provided in Table 1. Cooperative and savings banks are well capitalized with respect to the total capital ratio, whereas the median total capital ratio of the credit banks is considerably lower.

Table 1: Balance Sheet Figures

This table shows summary statistics for the banks considered in the study. We include exclusively banks that apply the standardised approach to credit risk. Capital ratios are calculated as total regulatory capital ratios, including Tier 1 to Tier 3 Capital in the enumerator and the capital charges for credit, market and operational risk in the denominator.

Banking Sector	Number of Banks	Total Assets (EUR m)	Book Claims (EUR m)	Median Tot. Cap. Ratio (in %)
Credit Banks	63	228,556	156,446	13.39
Savings Banks	421	1,102,919	694,344	16.08
Cooperative Banks	1,094	742,322	435,345	16.78

Furthermore, BAKIS provides information on individual German banks' income components, which we use to estimate the income stress test model. This allows us to apply bank-specific observations from 1995 to 2012 on an annual basis. A moderate outlier treatment is applied, in which we truncate the relevant variables at the 99.9^{th} and the 0.1^{th} percentile. In the period under consideration many mergers took place in Germany. In order to account for them, we separate each merged bank from the two pre-merger banks, thus maintaining three independent observations. We use the three-month Euribor and the 10-year German government bond yields, as well as national GDP growth rates, which come from the Federal Statistical Office (Statistisches Bundesamt) in order to calculate the macroeconomic impact on banks' earnings. The stress scenario of the credit risk stress test is described in detail in Section 4. It is constructed on the basis of GDP industry sector indices that were provided by the Statistical Federal Office.

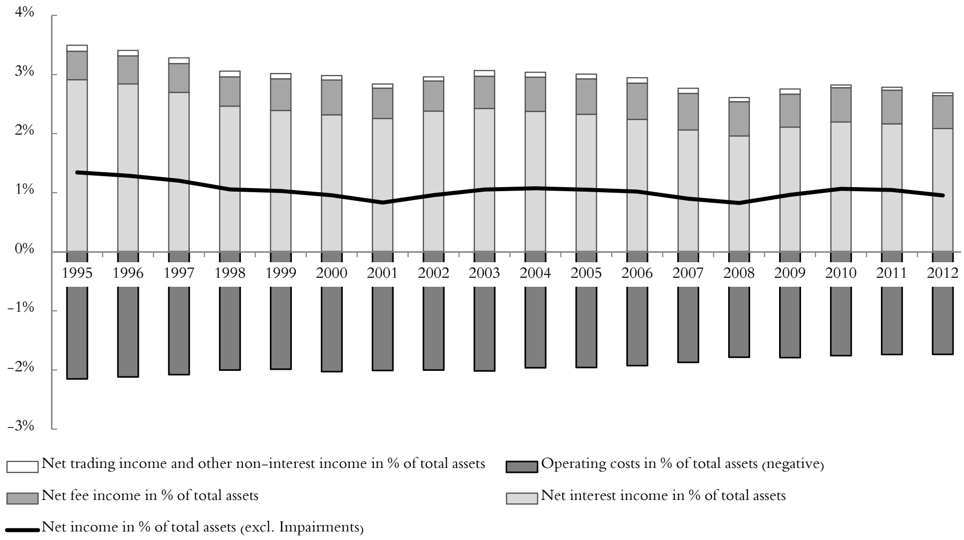
Regarding our income stress test, we analyse the most important income components of net operating results. Figure 1 shows the aggregate volume of the individual income components relative to total assets as well as operating costs to total assets. Interest income is still the most important income stream for most German banks, although its relative importance has declined over the years in favour of net fee income. The median ratio of net fee income to net interest income of the banks increased by 10 percentage points (pp) between 1995 and 2012. Figure 1 shows that, in relation to total assets, not only have earnings declined slightly, administrative expenses, too, show a declining trend. Net trading income as well as other non-interest income play only a minor role for small and medium-sized German banks.

3 Model

Figure 2 gives an overview of our stress test framework. It consists of three main

Figure 1: Income Components

This figure shows the development of income components relative to total assets as well as operating costs to total assets for savings banks, cooperative banks, and small commercial banks considered in the stress test exercise.



components. The basis component is the macroeconomic stress scenario reflecting the experience of the recent financial crisis. The macro shock defined in the stress scenario is transfered into both the credit risk portfolio model as well as the income stress test model. In the credit risk portfolio model, a stress test of the banks' credit portfolios is conducted. In the income stress test model the main income components are stressed with respect to the chosen stress scenario. Summing up these two effects leads to the total stress effect on each bank, which is expressed as reduction of the capital ratios.

In order to measure the influence that the macroeconomic stress scenario has on the solvency of small and medium-sized banks, we analyse its impact on the total capital ratios over a one-year horizon. This ratio is compared to the expected development of the regulatory ratios under a baseline scenario of forecasted economic growth for 2013 (Deutsche Bundesbank, 2012a).

While the simulated impairments as well as the calculated earnings will affect the available capital in $t+1$, the risk-weighted assets remain unstressed in our analysis as the considered banks only apply the standardised approach to credit risk. This is because the borrowers of the banks in our sample are mostly unrated SMEs, so that increases of their PDs will not have an impact on their risk weights. To express this formally, the analysed total capital ratio under baseline and stress conditions for $t+1$ is defined as

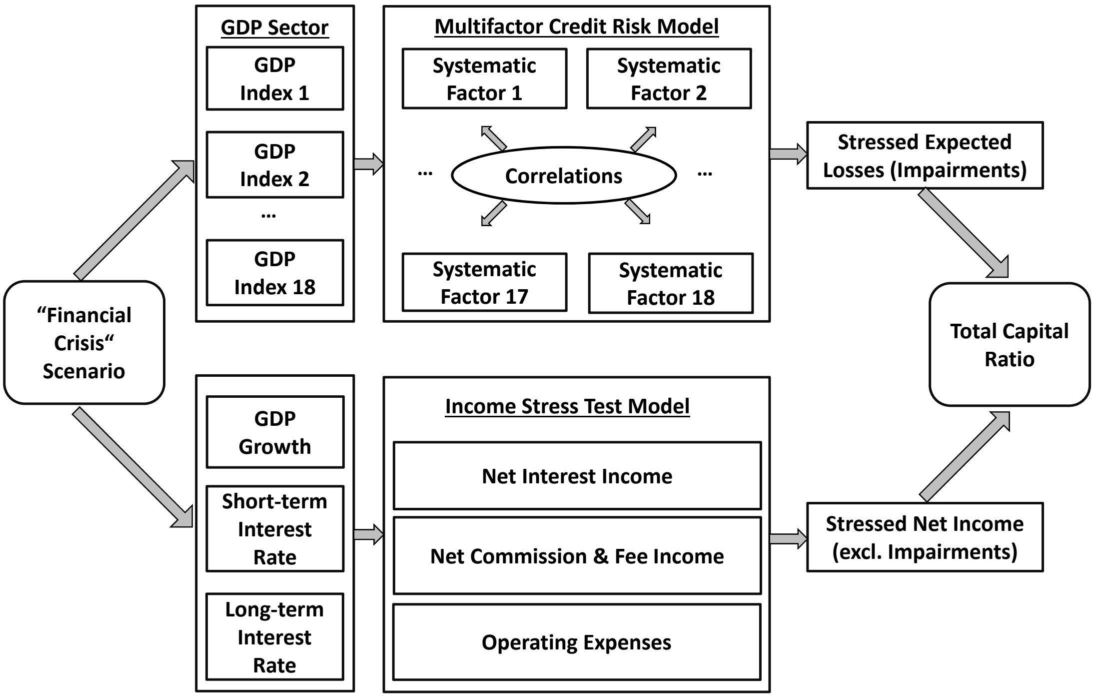
$$\mathbf{TotCR}^{j}_{t+1} = \frac{(\mathbf{T1C}_t + \mathbf{T2C}_t + \mathbf{T3C}_t) + \left[\mathbf{NIeI}^{j}_{t+1} - \mathbf{I}^{j}_{t+1}\right]}{12.5 \cdot (\mathbf{K}_{CR,t} + \mathbf{K}_{MkR,t} + \mathbf{K}_{OpR,t})}, \tag{2}$$

where

$j \in \{stress, baseline\}$

Figure 2: Stress Test Design

This figure illustrates the two channels of our stress test approach. The channel in the upper part works via the multifactor credit risk model. This model estimates the impact of the "financial crisis" scenario on the impairments of the considered banks. In the lower part the income stress test model is illustrated. The income stress test model measures the stress impact on the income components of the banks.



$\mathbf{TotCR}_{t+1}^{j}$ stands for the total capital ratio in $t+1$ under stress or baseline conditions

$\mathbf{T1C}_t, ..., \mathbf{T3C}_t$ are the values for Tier 1,..., Tier 3 Capital at t

$\mathbf{K}_{CR,t}$,$\mathbf{K}_{MkR,t}$ and $\mathbf{K}_{OpR,t}$ are the current reported regulatory capital charges for credit, market, and operational risk at t

$\mathbf{I}_{t+1}^{j}$ is the forecasted impairment charge for $t+1$ in the stress or baseline case

$\mathbf{NIeI}_{t+1}^{j}$ is the forecasted net income (excluding impairments) for $t+1$ in the stress or baseline case

The stress impact on the capital ratios exclusively lies in the additional term in the numerator $\mathbf{NIeI}_{t+1}^{j} - \mathbf{I}_{t+1}^{j}$. These two variables carry the stress effect to the sample banks.

3.1 Stress Test Models for Income

Our income stress test models allow us to predict the development of the income components under various macroeconomic scenarios. We only estimate the most important components of net operating income, i.e. net interest income, net fee income and operating expenses. We abstain from analysing net trading income. Since macroeconomic variables are not suitable to predict the development of the trading income sufficiently, panel estimations do not provide reliable forecasts (Deutsche Bundesbank, 2013). For other non-interest income we use three-year averages rather than estimating their development, since this income source is only a small part of overall income and its components are heterogeneous.[4]

We estimate the following satellite models in order to forecast future income streams[5]

$$Y_{i,t} = \alpha + u_i + \beta_1 Y_{i,t-1} + \sum_{j=1}^{N} \beta_j \cdot X_{j,t} + \sum_{j=1}^{N} \lambda_j \cdot \omega_{j,i,t} + \epsilon_{i,t} \tag{3}$$

$Y_{i,t}$ represents the income variable as a percentage share of total assets for bank i in period t. We introduce a lagged dependent term, since income streams are expected to be persistent over time. u_i is a time-invariant unobservable bank-specific effect. ω captures bank-specific variables and vector X represents macroeconomic variables. We select the most relevant macroeconomic indicators for each equation. In the equation for the net interest margin we introduce the three-month money market rate (Euribor) and long-term government bond rates (10 years) as macroeconomic variables in order to analyze the impact of changes in the yield curve on net interest income. For the estimation of net fee income we select real GDP growth as a macroeconomic variable, since a positive economic environment is generally positively connected to fee income. These dynamic panel models are estimated by the two-step generalized method of moments (GMM) system estimator developed by Blundell and Bond (1998) and Arellano and Bover (1995), with the Windmeijer (2005) standard error correction. Consistent estimation requires that instruments are valid (i.e. endogeneity of instruments can be rejected) and rejection of serial autocorrelation of order two in the residuals. The Arellano-Bond test shows that the absence of second-order autocorrelation cannot be rejected. Joint validity of instruments is tested using the Hansen test of overidentification restrictions. The rejection of the null hypothesis would indicate that instruments are not valid.[6] As too many instruments could cause biased results, we collapse instruments as suggested by Roodman (2009a,b) and applied in various studies (e.g. Chiorazzo and Milani, 2011; Stolz and Wedow, 2011). Furthermore, we reduce instruments by restricting lags (e.g. Packer and Zhu, 2012). To be precise, we only use lags of order 2 to 4 (2 to 3) for the level equation and lags of order 3 to 5 for the equation in differences.[7]

The regression results from the models described above are illustrated in Table 2. The results for the net interest income show evidence of maturity transformation, since the long-term interest rate has a positive sign and the short-term interest rate has a negative sign. In the main, the covariates also show the expected sign. Credit risk is measured by

[4]As we control for mergers in our econometric model, the time horizon for some banks is shorter than three years. In this case we use the two-year average respectively the preceding value.

[5]Stress Tests based on regression analysis are subject to the assumption that all banks in the sample are affected in a systematic way by macroeconomic shocks.

[6]We prefer Hansen's statistic to the Sargan statistic since it remains robust when standard errors are assumed to be non-spherical.

[7]Lag length is chosen to satisfy diagnostic tests for autocorrelation of order two and endogeneity of instruments tested by Hansen's test.

the ratio of loan loss provisions (llp) to customer credits (e.g. Liebeg and Schwaiger, 2006). Higher borrower default risk is expected to be accompanied by higher interest rates that a bank charges from creditors and, therefore, by higher net interest margin. The equity ratio is calculated as equity capital to risk-weighted assets (RWA). Equity ratio is a common variable in order to account for management's risk aversion (Ho and Saunders, 1981). We use RWA in the denominator rather than total assets, since increasing the accounting-based equity ratio could also be a sign of more risk in the credit portfolio rather than higher risk aversion. Here, a higher equity ratio indicates less risk, which could probably facilitate access to deposits and borrowed funds at lower costs. The ratio of customer loans to total assets is introduced to give information about the composition of a bank's asset portfolio. Interest rate earnings should be higher, the more a bank is involved in lending activities. Funding gap measures a bank's refinancing requirement that is not captured by deposits, and is calculated as the difference between customer credits and customer liabilities as a percentage of total assets. The higher the funding gap, the higher the interest expenses per total assets.

As a second income source, we analyse net fee income. Fees and commissions are basically positively influenced by real GDP growth, but the coefficient seems to be quite small. The answer to this lies in the years 2010 and 2011. After a strong cyclical downturn in 2009, Germany's economy recovered with high growth rates in 2010 and 2011. However, fees and commissions recovered only slightly or remained static. This effect may be due to bank customers' restraint in purchasing and their risk aversion caused by the financial crisis. Additionally, the difficult market environment caused falling stock market prices (Deutsche Bundesbank, 2012b). To control for this kind of structural break, we interact a dummy variable, which takes the value 1 for the years 2010 and 2011, with real GDP growth. This interaction term has a negative sign, as the relationship between GDP growth and fee income should be weaker or even negative in 2010 and 2011. As bank-specific variables we introduce loan loss provisions to total customer loans and the equity to RWA ratio. Loan loss provisions to total customer loans is introduced to account for a possible relationship between credit risk and fee-generating activities. As proposed by Lepetit, Nys, Rous, and Tarazi (2008), Nys (2008), and Cosci, Meliciani, and Sabato (2009), granting loans could be used to establish long-term customer relationships which might be helpful in selling further fee-generating products afterwards. It could be beneficial for the bank to take higher credit risk into account if the bank anticipates higher income through fees and commissions in return.

Operating expenses are negatively connected with GDP growth. In a positive macroeconomic environment, resources could be exploited more efficiently. Furthermore, fewer resources are needed in order to check and monitor credits since default events become more unlikely. Equity to RWA is positively connected with operating expenses since more precaution, for example in the credit origination process, is normally accompanied by higher costs. The negative sign of the logarithmic total assets could be a result of scale economies.

Table 2: Regressions Results: Net Interest Income, Fee Income, and Operating Expenses (to Total Assets)

This table shows the two-step GMM estimations with Windmeijer error correction for net interest income, net fee income, and operating expenses each as a percentage of total assets. Instruments are collapsed and limited. Abbreviations/variable definitions: llp = loan loss provisions; rwa = risk-weighted assets; interaction = interaction between real GDP growth and a year dummy, which takes value 1 for the years 2010 and 2011 and 0 otherwise; funding gap = difference between customer credits and liabilities as a percentage of total assets; ln(TA) = total assets in logarithm. Instruments are collapsed.

Variable	Net interest income as % of total assets	Net fee income as % of total assets	Net fee income as % of total assets	Operating expenses as % of total assets
Lagged dependent term	0.4948*** (0.0196)	0.7441*** (0.1832)	0.7670*** (0.1690)	0.8686*** (0.0325)
Return on ten-year government bonds	0.1178*** (0.0035)	- -	- -	- -
Three-month interest rate	−0.0989*** (0.0020)	- -	- -	- -
Real GDP growth	- -	0.0071*** (0.0013)	0.0119*** (0.0038)	−0.0094*** (0.0012)
Llp to customer loans	0.0925*** (0.0153)	0.0460** (0.0181)	0.0411** (0.0170)	- -
Equity to RWA	0.0050*** (0.0016)	0.0278* (0.0151)	0.0275* (0.0158)	0.0145*** (0.0047)
Customer loans to total loans	0.0163*** (0.0011)	- -	- -	- -
Funding gap	−0.0882*** (0.0009)	- -	- -	- -
ln(TA)	- -	- -	- -	−0.0294*** (0.0064)
Interaction	- -	- -	−0.0198** (0.0100)	- -
Constant	−0.1351** (0.0613)	−0.1474** (0.0635)	−0.1550** (0.0723)	0.7309*** (0.1729)
No of instruments	12	10	11	10
Lags of instruments for lagged dependent variable				
difference equation	3-5	3-5	3-5	3-5
level equation	2-3	2-4	2-4	2-4
Hansen-test χ^2	5.90	8.41	8.36	8.02
Hansen-test p-value	0.207	0.135	0.138	0.155
AR(1) test p-value	0.000	0.084	0.073	0.000
AR(2) test p-value	0.375	0.468	0.446	0.209

Robust standard errors in parentheses; ***, **, * denote significance at a 1 per cent, 5 per cent or 10 per cent level.

3.2 Credit Risk Portfolio Model

To capture the influence of our stress scenario on the credit portfolio of small and medium-sized banks we apply a multi-factor Merton-type model that comes under the category of conditionally independent factor models. This modelling approach is motivated by their popularity in financial institutions for credit risk management. In the first step we describe the portfolio model, illustrate how we can capture the correlation structure for the systematic factors, and finally we outline how our macroeconomic stress scenario is linked to the portfolio model.

3.2.1 Set-up

In our analysis of the banks' credit risk we apply a one-period asset value model, where the time period between t and $t+1$ corresponds to a one-year horizon. For this we use a model from the class of conditionally independent factor models as outlined in Schönbucher (2001).
In the applied pure-default-mode model (e.g. Glassermann and Li, 2005; Grundke, 2009; Memmel, Guenduez, and Raupach, 2015), we explicitly capture the asset return development of credit portfolios of our sample banks over a one-year horizon and differentiate between the two possible states, default and non-default, for each portfolio at $t+1$. The default state is specified to occur if the asset return between t and $t+1$ falls below a certain default threshold.[8]
We assume that the asset return process is determined by two elements: one that corresponds to an economic sector-dependent factor, and one that captures the idiosyncratic risk component of the banks' business sector portfolio. More explicitly, our sample of banks $j = 1 \dots M$ holds credit portfolios $i = 1 \dots N$, where the respective portfolio's annual log asset return Y_i is driven by the process

$$Y_i = r \cdot X_{s(i)} + \sqrt{1-r^2} \cdot U_i \quad i = 1 \dots N, \tag{4}$$

where $X_{s(i)}$ denotes the sector-dependent systematic risk factor, U_i the idiosyncratic risk of bank j's portfolio i, and $s(\cdot)$ is a mapping from the portfolios to the S sectors of the economy, i.e. $s : \{1, \dots, N\} \to \{1, \dots, S\}$.
The systematic factor and idiosyncratic risk vectors are modelled as multivariate normally and standard normally distributed random vectors, which are mutually and pairwise independent. In addition, their components are given as univariate standard normal random variables.

A default event occurs if $Y_i \leq \gamma_i$ with γ_i being the portfolio-specific default barrier. Observing that Y_i is standard normally distributed due to Equation (4) and our distributional assumptions for $X_{s(i)}$ and U_i, we are able to derive γ_i for a given probability of default p_i via

$$\gamma_i = \Phi^{-1}(p_i) \qquad \forall i = 1 \dots N. \tag{5}$$

[8] As this study considers banks applying the standardised approach to credit risk it is appropriate to use this model framework in order to analyze the stress impact on the banks' regulatory capital. Changes of the borrowers' rating do not influence the regulatory capital ratios except for the default case.

In Equation (4), r determines the relative importance of the systematic compared to the idiosyncratic risk. Furthermore, by exploiting the independence of the idiosyncratic factors, we see that r^2 gives us the intra-sector correlation for all of the S economic sectors. In the same way, the asset correlation $\rho_{i,j}$ between two different sectors $s(i)$,$s(j)$, $s(i) \neq s(j)$ is described by

$$\rho_{i,j} = \rho(Y_i, Y_j) = r^2 \omega_{s(i),s(j)} \tag{6}$$

with $\omega_{s(i),s(j)}$ being the correlation of the systematic factors corresponding to the two sectors. In order to derive r, we use the simplifying assumption that the correlation of systematic factors $\omega_{s(i),s(j)}$ and the portfolios' asset correlations $\rho_{i,j}$ are equal to their means, which in combination with Equation (6) gives us $r = \sqrt{\bar{\rho}/\bar{\omega}}$.[9]

3.2.2 Connecting the Stress Scenario to the Portfolio Model

Having illustrated the set-up of the portfolio model, we now show how we can incorporate our stress scenario and measure its stress impact by applying the modelling approach of Bonti, Kalkbrener, Lotz, and Stahl (2006). Our stress impact is captured by restricting the distribution function of each sector-dependent systematic factor $X_{s(i)}$. While the baseline unstressed variable follows a normal distribution, our stressed distribution follows a right truncated normal with sector-specific cutoff value k_s, $s = 1, \ldots, S$. In order to obtain these cutoff values and to link the latent unobservable variables of the sector-dependent systematic factors X_s to the historical stress scenarios from the observable GDP sector growth rates,[10] we follow a three-step approach.

In the first step we set the expectations of the random variables Z_s, the GDP sector growth rates, equal to the historical stress realization of the applied GDP sectors, conditional on being below a sector-specific cutoff value c_s. We can then solve these equations for those corresponding cutoff values.

In the next step we make the assumption that the unconditional probability of Z_s being below cutoff value c_s corresponds to the standard normally distributed probability of the systematic factor X_s falling below k_s. The advantage of creating a link between X_s and Z_s via their probability measures compared to more classical approaches involving correlation is that we circumvent the potential problem of a non-linear dependence structure between these variables.

Finally, using the distributional assumptions of X_s, we obtain their cutoff values k_s, which can then be used for the simulation of the stressed systematic factors. More precisely, we first apply a Gaussian kernel density estimation (Gkde) on the annualized GDP sector growth rates in order to approximate the probability density function of Z_s. That is, the

[9]For $\bar{\omega}$, we use the average inter-sector correlation of the Eurostoxx index sectors. For $\bar{\rho}$ we use, for practical reasons, the average empirical asset correlation for small and medium-sized German companies of 9% (Hahnenstein, 2004). This estimation is rather high as new asset correlation estimations for German corporates indicate much lower values. However, for the purpose of our study we apply the conservative estimations.

[10]In our model we assume a comonotonicity between the systematic factors and the GDP sector growth rates which induces an upward bias to the results of the credit portfolio stress test. In the context of a macroprudential stress test of banks this assumption is appropriate.

kernel density estimator for the sample of annualized log returns $z_{1,s}, \ldots z_{n,s}$ is given by

$$f_{n,s}(z) = \frac{1}{n \cdot h} \sum_{j=1}^{n} \frac{1}{\sqrt{2\pi}} \exp\left(-0.5 \cdot \frac{\left(z - z_{j,s}\right)^2}{h^2}\right), \tag{7}$$

where n stands for the sample size and h for the bandwidth. To obtain a value for the bandwidth we employ the "Silverman Rule-of-Thumb" (Silverman, 1986), that is

$$h = \sigma \cdot n^{-1/5}, \tag{8}$$

where we use the sample standard deviation of GDP sector i growth rates as an estimator for σ. Basing our kernel density estimation entirely on the historical sample available to us between 1991 and 2012 would not lead to optimal results due to the limited sample size. We therefore increase the quality of our estimation by employing a bootstrap mechanism (e.g. Efron, 1979), where we sample from quarterly GDP sector growth rates, annualize them in a subsequent step and finally use this created data set as input for our Gkde. Using this to restate the conditional expectation as

$$\mathbf{E}\left(Z_s \| Z_s \leq c_s\right) = \int_{-\infty}^{c_s} z_s \cdot \frac{f_{n,s}(z)}{F_{n,s}(c_s)} \mathbf{dz}, \tag{9}$$

where $F_{n,s}(c_s)$ is the cumulative distribution function of $f_{n,s}$, we can now solve

$$\mathbf{E}\left(Z_s \| Z_s \leq c_s\right) = \xi_s \quad \forall s = 1, \ldots, S \tag{10}$$

for the cutoff value c_s of the GDP sector growth rates given that ξ_s represents the stressed return for business sector s. Finally, relying on our assumption that $\mathbf{P}\left(Z_s \leq c_s\right) = \mathbf{P}\left(X_s \leq k_s\right)$ and the standard normal distribution of our systematic risk factor X_s, we can derive the cutoff values k_s of our systematic risk factors via

$$k_s = \Phi^{-1}\left(\mathbf{P}\left(Z_s \leq c_s\right)\right). \tag{11}$$

3.2.3 Baseline and Stressed Expected Losses

In order to measure the impact of our stress scenario on the credit portfolio, we have to consider expected losses in the baseline and the stress scenario. More precisely, we link the behavior of the stressed GDP sectors to our credit portfolio model by truncating the distributions of the systematic factors, which allows us to simulate, in the first step, stressed PDs, and, in the second step, stressed impairments. We start by simulating a proxy for the expected losses under baseline and stressed conditions. The loss given defaults (LGDs) are fixed at 45% in the baseline case and increase by 5 percentage points under the stress scenario as motivated by Altman (2009):

$$\mathbf{LGD}_{i,h} = \begin{cases} 45\% & \text{if } h = baseline \\ 50\% & \text{if } h = stress \end{cases} \qquad \forall i = 1, \ldots, N, h = \{stress, baseline\},$$

With the help of the estimated PDs in Equation (1), we can use Monte Carlo simulation techniques to derive the distribution of portfolio losses for our small and medium-sized bank sample in the case of the baseline and stress scenario by applying the formula

$$\mathbf{L}_{i,N}^h = \sum_{i=1}^{N} \mathbf{CE}_i \cdot \mathbf{LGD}_i \cdot \mathbf{1}_{\{\mathbf{Y_i^h} \leq \gamma_\mathbf{i}\}} \quad h = \{stress, baseline\}, \tag{12}$$

where $\mathbf{L}_{i,N}^h$ gives us the bank's total credit losses over its N portfolios and $\mathbf{1}_{\{\mathbf{Y_i^h} \leq \gamma_\mathbf{i}\}}$ is an indicator variable that equals 1 in the credit default case of the portfolio and 0 otherwise. Depending on the type of scenario, we can then simulate the portfolio's logged asset returns Y_i^h either with unconstrained (baseline) or truncated (stress) systematic factors X_s^h. Simulation of banks' credit losses in the stress scenario requires us to draw from the truncated multivariate normal vector of systematic risk factors. We apply an approach by Robert (1995), who uses Gibbs Sampling (Geman and Geman, 1984) to reduce the multivariate simulation problem to a sequence of univariate simulations.

Using S portfolio default simulations we can then appeal to the Law of Large Numbers to obtain, for sufficiently large S, a reliable estimator for the baseline and stressed PDs

$$\frac{1}{S} \sum_{j=1}^{S} \mathbf{1}_{\{\mathbf{Y_{i,j}^h} \leq \gamma_\mathbf{i,j}\}} \to p_i^h \quad \forall i = 1, \ldots, N \quad h = \{stress, baseline\}. \tag{13}$$

The expected losses for the bank's entire credit portfolio are computed both under stress and regular conditions as

$$\mathbf{EL}^h = \sum_{i=1}^{N} \mathbf{CE}_i \cdot \mathbf{LGD} \cdot p_i^h \quad h = \{stress, baseline\}. \tag{14}$$

This expected loss will, in turn, serve as our proxy for credit impairments in the baseline and stress case. Then, the impairments I_j in Equation (2) are determined by the expected losses $\mathbf{EL}^h$ for each bank.

4 Macroeconomic Stress Scenario

The goal for our stress scenario design is to create a macroeconomic scenario that captures the experiences of the financial crisis in 2008/2009 and that is augmented by the risks of the current low interest rate environment. More precisely, we explore how an economic downturn comparable in its severity to the recent financial crisis would affect Germany's small and medium-sized banks. In doing so, it is important to take into account that the low interest rate faced at the moment could also constitute a risk factor, especially in combination with the political situation in Europe. A possible scenario affecting interest rate risk could be a further crisis in the interbank market. In this case, even expansionary monetary policy, which would possibly be applied against economic recessions, would not be able to prevent a slight increase in money market rates due to increased risk premia. At the same time, the German government bond market is assumed to serve as a safe haven during the European sovereign debt crisis. Additional capital inflows could lead to a further decline in German government bond yields. This environment especially affects small and medium-sized banks as they rely in particular on maturity transformation.

In leaning on the historical crisis scenario we ensure that the stress scenario exhibits a high degree of severity and it does not depend on the monetary policy stance of the European Central Bank. To ensure a plausible and reasonable scenario, we consider current economic and political developments. As interest rates have fallen dramatically since the beginning of the crisis, the German economy is faced with a new and historically unique interest rate regime. Therefore, we need to determine the stress scenarios for GDP growth and interest rates separately and independently.

In our approach, translating the scenario into macroeconomic variables is straightforward: While a severe economic downturn is represented by a fall in GDP growth, we can capture the risks attached to the interest rate environment by changes in the short- and long-term interest rates. Since our stress test consists of two major blocks, the credit risk portfolio model for the simulation of impairments and the econometric models of income components, we set up key assumptions for GDP and the interest rate environment within our stress scenario which feed into both model classes.

In order to define the stress scenario for the GDP growth, we consistently follow the Deutsche Bundesbank's key events of the financial crisis (Deutsche Bundesbank, 2011) by starting the stress scenario horizon at September 2008, and ending it with the beginning of the gradual withdrawal of the policy measures in December 2009. For this time period we calculate the annualized geometric mean of the sector-specific GDP growth rates. These stress assumptions will then allow us, in a later step, to derive stressed borrower PDs or stressed income components.

Table 3: Overview of Stress Scenario

This table shows the baseline and stress scenarios for the income stress test. The baseline scenario is based on the end-of-2012 forecasts by the Deutsche Bundesbank for the year 2013 (Deutsche Bundesbank, 2012a). The stress scenario for GDP growth corresponds to the period September 2008 till December 2009. The stress scenario for the interest rates should illustrate the possible impact of an inverse yield curve.

Macroeconomic variable	Baseline scenario	Stress scenario
Real GDP growth	0.5%	−3.8%
Three-month Euribor	0.2	0.8
Return on ten-year government bonds	1.6	0.7

Regarding the credit risk model, we derive sector-specific stress scenarios from the historical development of the German GDP by sectors of origin. As the data on sectoral GDP breakdown is only available as of 1991 due to the German reunification, it is difficult to estimate kernel densities on the basis of 22 years with 88 observations. In order to improve the estimation accuracy of the kernel densities according to Section 3.2, we generate an enlarged sample of yearly sectoral GDP growth rates using bootstrap methods. In this algorithm, we resample the quarterly historical sectoral GDP growth rates and construct yearly sectoral GDP growth rates from them. In doing so, we obtain a smooth sectoral GDP distribution. Compared to a flat GDP scenario assumption for all business sectors, our granular approach has the advantage that it enables us to exhibit more fine grained stress of the banks' sectoral credit portfolios, which were affected differently by the macroeconomic environment during the financial crisis. Figure 3 shows that the GDP growth rates differ only slightly between the economic sectors, but within the crisis period the differences are considerably larger. While the total GDP reduced by 3.8% during the crisis period, some sectors like automobile and parts decreased much more strongly by over 16%. Other sectors such as industrial goods and services dropped less than the total GDP, at 2.6%. There are even sectors like telecommunications that increased during the financial crisis 2008/2009. The sector private household to which the small and medium-sized banks are heavily exposed developed closely in line with the total GDP. Accordingly, the severity of the stress scenario in our approach is also specific to the GDP sectors. The sectors which showed heavily stressed growth rates during the crisis period face strongly truncated kernel densities. Automobiles and parts, for example fell below the 6.8% percentile, others like utilities and media and telecommunications came through the crisis quite well, resulting in cutoff values where the probability of falling below the threshold is close to 100% (Table 4).[11] This ensures a realistic crisis scenario and allows us to study the stress effect conditional on banks' exposures to different sectors.[12]

In the income stress test, we need to make assumptions about real GDP growth as well as the three-month and the ten-year interest rates. With respect to baseline figures for these variables, we rely on the end-of-2012 forecasts by the Deutsche Bundesbank for the year 2013 (Deutsche Bundesbank, 2012a). Turning to the stress scenario, we use the period from September 2008 to December 2009 for real GDP growth, leading to a decline of the annualized GDP growth of -3.8%. This is used as an input to stress the fee and commission income as well as the operating expenses. As mentioned above, increasing money market rates and falling German government bond yields are a reasonable scenario. Concerning interest rates, our goal is therefore to stress the reliance of small and medium-sized banks on maturity transformation for their net interest income by creating an inverse term structure within a low interest rate field. In terms of macroeconomic variables, we increase the three-month interest rate slightly by 0.6pp and reduce the long end by 0.9pp compared to the baseline scenario (Table 3).

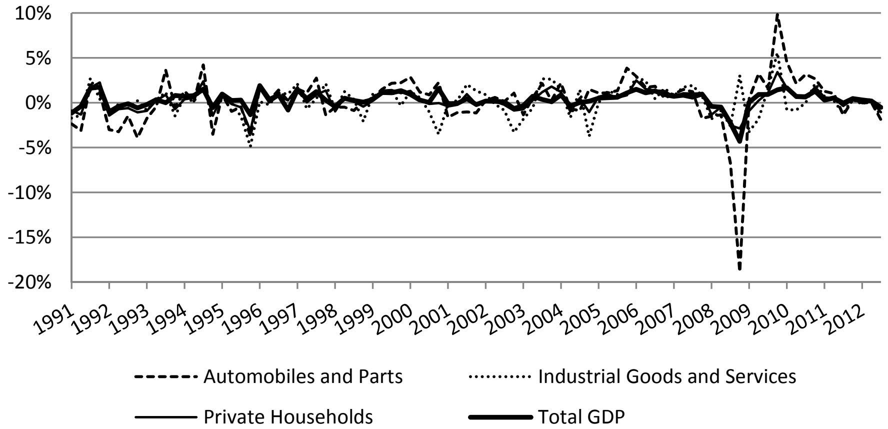
[11] There is no direct stress effect based on the cutoff values for the sectors SME retail, media, telecommunications, and utilities due to the behavior during the financial crisis. However, due to the second round effects the overall stress impact on these sectors can be significant.

[12] In the applied macroeconomic scenario the stress effect for certain sectors is limited due the development of these sectors during the considered crisis period. Thus, banks which are significantly exposed to these sectors perform better in the stress test than banks with other portfolio compositions.

Figure 3: GDP Growth Rates on Sectoral Level

This figure displays the sectoral quarterly GDP growth rates for automobiles and parts (dashed line), industrial goods and services (dotted line), private households (thin line) and the total GDP growth rate (bold line). While Figure (a) gives an overview of the entire period, Figure (b) focuses on the crisis period from September 2008 to December 2009 and includes the average annualized GDP growth rates.

(a) Entire period



(b) Crisis period

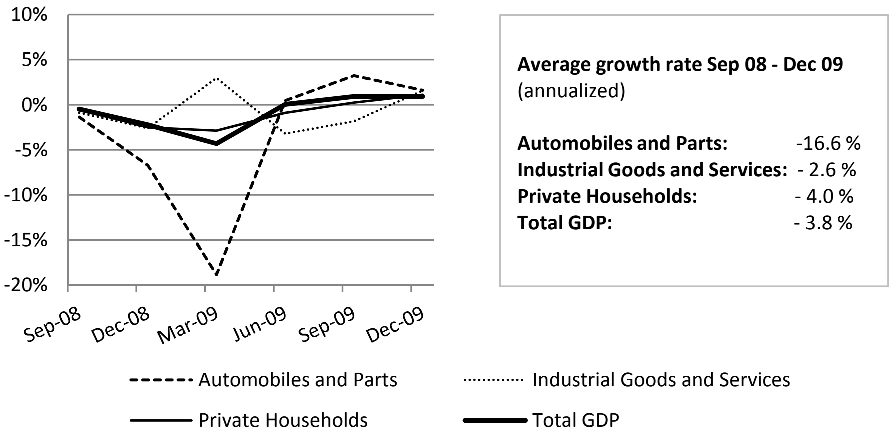


Table 4: Macroeconomic Scenario on Sectoral Level

This table provides the specification of our macroeconomic scenario used for the credit risk stress test. The first column contains the number of the economic sector, the second column refers to the ICB sector, the third column shows the asset return for each sector in the stress scenario (in %), the fourth column displays the cutoff value for the systematic factor of each sector, and the last column illustrates the probability for each sector that the return of the systematic factor is below the cutoff value (in %).

Economic Sector	ICB Sector	Asset return in stress scenario (in %)	Systematic cutoff value	Prob. of systematic factor returns below cutoff value (in %)
1	Oil and Gas	-4.3	0.3	63.6
2	Chemicals	-9.8	-1.3	9.6
3	Basic Resources	-4.0	0.2	59.0
4	Construction and Materials	-4.1	0.2	58.6
5	Industrial Goods and Services	-4.4	-0.9	18.1
6	Automobiles and Parts	-16.0	-1.5	6.8
7	Food and Beverage	-5.9	-0.3	36.6
8	Personal and Household Goods	-16.0	-1.5	6.8
9	Health Care	-6.3	-1.5	6.6
10	SME Retail	1.6	3.4	100.0
11	Media	7.6	4.3	100.0
12	Travel & Leisure	-1.8	-1.1	14.7
13	Telecommunications	7.6	4.3	100.0
14	Utilities	4.9	4.3	100.0
15	Insurance	-1.2	-0.2	43.8
16	Financial Services	-1.2	-0.2	43.8
17	Technology	-3.4	-1.1	14.5
18	Private Households	-4.1	-1.6	5.1

5 Empirical Results

In order to obtain a thorough understanding of the banking groups' resilience to the macroeconomic stress scenario, in the first step we will analyse the development of regulatory capital ratios in the baseline and stress case and quantify the shock-absorbing potential for credit, savings, and cooperative banks. In a second step, we will dissect the stress impact by assessing the development of impairments as well as the remaining income components.

5.1 Stress Impact on Capital Ratios

Starting with our overall results for the total capital ratios in Figure 4, one immediately notices the high percentage of credit banks that fall below the 8% threshold in the stress case in comparison to their peers in the other two banking groups.[13] Overall, more than 6% of all credit banks in our sample fail to reach this value, while the savings and, especially, cooperative banks prove to be considerably more resilient under stress, both with only 0.5% of the respective banking group members not achieving this target.

While one might at first suspect that this is due to a greater susceptibility of the credit banks' net income components to stress, the data show that this is not the case. The median reduction of the total capital ratio between the stress and baseline cases makes it clear that the reduction in the quality of the banks' credit portfolios only accounts for 1.41pp for credit banks. While this is above the resilient portfolio of cooperative banks (1.36pp), it is, perhaps surprisingly, the group of savings banks that loses the most, at 1.74pp. This finding is, moreover, not due to the stress effect on net interest income and net fee and commission income, as their impact on capital ratios is relatively homogeneous among the banking groups (Figure 5). The results are more driven by the considerably worse capitalization of credit banks in our sample of 13.4% (median value of banking group before stress) in comparison to 16.1% and 16.8% of savings and cooperative banks (Figure 4 and Table 1).

In order to obtain a better understanding of the movement of the baseline and stressed capital ratios, we need to disentangle the stress impact that impairments, net interest rate income, net fee and commission income and operational expenditures have. From Figure 5 we see that, across all three banking groups, the influence of the change in impairments from the baseline to the stress case is the dominant factor for the stress effect of the capital ratios compared to the other income components. In this context, the stress effect on the impairments is especially pronounced for savings banks.

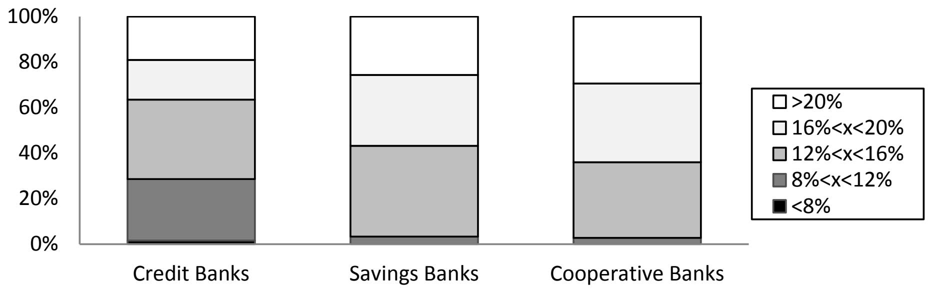
Table 5 gives an overview of average income components relative to total assets. For the stress scenario we find a decline of the interest margin by 0.16pp (6.8%) on average compared with the baseline scenario. The fee income margin shows a reduction of 6pp (9%) compared with the baseline scenario. Administrative costs increase slightly since

[13] In a robustness analysis we estimate the capital ratios under the baseline and the stress scenario under the assumption of infinitely granular credit portfolios using the Vasicek approach (Vasicek, 1987, 1991; Gordy, 2003). These results indicate that our findings are robust as only slight differences between the two approaches are obtained.

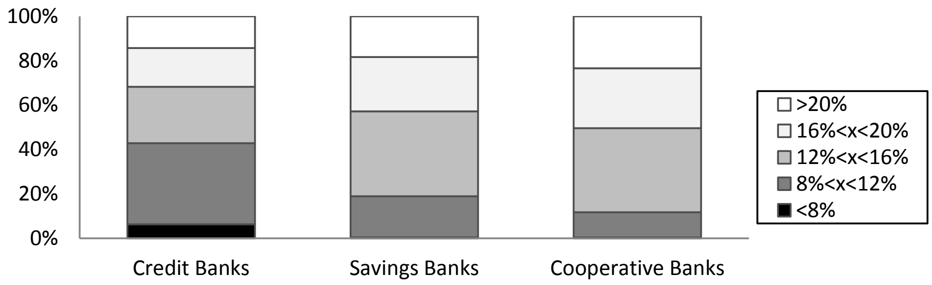
Figure 4: Total Capital Ratio in Baseline and Stress Case

This figure displays the distribution of the total capital ratio for the baseline and stress cases for credit, savings and cooperative banks as a percentage of the banking group subsample. The colour marking indicates banks with the following total capital ratios: black= below 8%, dark grey= between 8% and 12%, grey= between 12% and 16%, light grey= between 16% and 20% and white= above 20%.

(a) Baseline



(b) Stress



GDP decline is accompanied with higher operating expenses per total assets. Other non-interest income is assumed to stay constant as we took three-year averages of this variable. After subtracting administrative costs, the average net income to total assets ratio is 0.25pp lower in the stress case. The aggregated net income under stress is 23% lower than under the baseline. This reduction is based in large parts on the interest income reduction. Although only a vanishingly small number of banks (less than one per cent) have to take a negative net income (excluding impairments), the income decline is quiet noticeable especially given that this net interest income has to absorb losses in lending business.

Moving on to the change of impairments for each banking group in our stress approach (Figure 5), we can see that the sample of savings banks shows the highest stress impact on impairments which amounts to a reduction of 2.2pp of the total capital ratio and 83 per cent of the overall stress effect.[14] This shows that the impairments cover the main part of the stress impact and the income stress is both moderate and equally distributed across the banking groups. Cooperative banks as well as credit banks are impacted on a lower level by the stressed impairments reaching values of about 1.6pp and 1.7pp of the

[14] Also striking is the higher heterogeneity of the savings banks' credit portfolios, which show a resilience to the stress scenario which is very different from that of the other two banking groups.

Figure 5: Change of Impairment/RWA and other Net Income/RWA (in pp)

This figure compares the stress-baseline change of impairments by RWA (black) and stress-baseline change of net income (excluding impairments) by RWA (grey) for credit, savings, and cooperative banks in percentage points with respect to the median. The other net income components consist of the net interest income, net fee and commission income, other non-interest income, and operational expenditures.

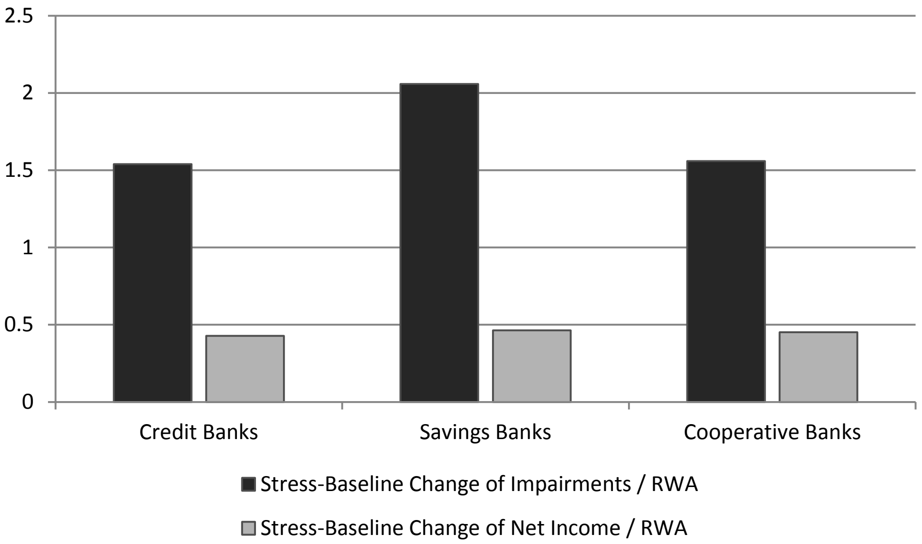


Table 5: Overview of Average Income Components

This table shows the descriptive statistics of the results for the income stress tests for net interest income, net fees and commissions, administrative costs, other non-interest income, and net income (excluding impairments) as a percentage of total assets.

Income component		Baseline scenario	Stress scenario
Net interest income to total assets	Means	2.38	2.22
	Median	2.39	2.23
Fees and commissions to total assets	Means	0.76	0.71
	Median	0.70	0.64
Operating expenses to total assets	Means	2.21	2.24
	Median	2.12	2.16
Other non-interest income to total assets	Means	0.075	0.075
	Median	0.020	0.020
Net income (excl. impairments)	Means	1.01	0.75
	Median	1.02	0.76

total capital ratio which accounts for 79 per cent of the entire stress for each banking group.

5.2 Drivers of stressed impairments

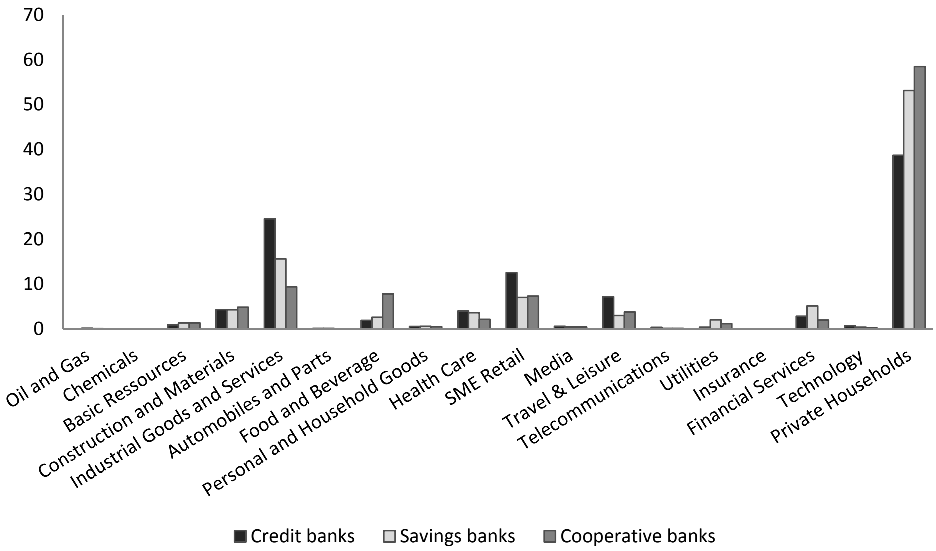
In order to obtain a deeper understanding of the factors that contribute to stress effect on the impairments, we have to look at the parameters which determine the impairments. According to Equation (14) the impairments are mainly quantified by the credit exposure as well as the PD. As the LGD is stressed for all banks in the same manner, LGDs do not, in the stressed case, drive the differences between the banking groups. Beyond we look at the sectoral distribution of credit exposures and then assess the behavior of the PDs.

The sectoral portfolio composition plays a substantial role explaining different stress levels of credit risk for each banking group. However, the credit exposures are fixed, which means they are not stressed in our one-period approach. Figure 6 mainly explains the role of credit exposures in our stress test and shows that the sectoral distribution of the credit exposures varies strongly across both sectors and banking groups. As we are considering small and medium-sized banks, their credit portfolios also differ strongly from the ones of large banks (e.g. Duellmann and Kick, 2014). The main part of the credit exposures belongs to the sector private households. Beyond this sector, only the industrial goods and services sector as well as SME retail represent a significant part of the banking groups' credit portfolios. By aggregating the exposures of these three sectors, the major part of the credit portfolios of each banking group is covered at about 75 per cent. In contrast to large banks, the financial services sector plays only a minor role. Within these major sectors, it is possible to identify significant differences across the groups of banks in terms of what drives the stress impact. Savings and cooperative banks hold more than one-half of their total exposures in the private household sector, whereas credit banks are less exposed to this sector at about 40 per cent of their total exposure. Furthermore, cooperative banks' exposure to private households is, in fact, five percentage points higher than that of the savings banks. At a lower absolute level, the order is reversed in case of exposures to the industrial goods and services sector. With respect to the SME retail sector, both savings and cooperative banks have approximately the same exposure. Only credit banks' exposure is at a level which is almost twice as high.

Beyond the credit exposures, PDs are the other main factor which determines the impairments. This effect is twofold. First, there is an absolute effect based on the absolute value of the PDs in the baseline scenario. Second, the PDs are increased in the stress scenario which represents a core figure for the stress impact. Starting with the distribution of the PDs in the baseline and stress case in Figure 7, we see that the distribution of PDs differs considerably across sectors and banking groups. In the baseline case, the PDs for the sector private households is comparatively low at less than one per cent. The other main important sectors of industrial goods and services as well as SME retail face PDs of about two per cent. The change in the PDs between baseline and stress scenario is heterogeneous overall, ranging from an increase of, on average, 250% for telecommunications, to about 900% for private households. These changes are for the industrial goods and services sectors as well as SME retail on a relative basis below the average at around 450 per cent, but in percentage point changes these stress impacts are significant at roughly 7pp for industrial goods and services as well as more than 7.5pp for SME retail. The comparatively strong relative movement of the private household sector PDs is mainly

Figure 6: Credit Exposure according to ICB Class (in per cent)

This figure shows the sectoral distribution of credit exposures for credit (black), savings (light grey) and cooperative banks (grey) in % for each of the 18 industry sectors. With the exception of the private household sector, their definitions follow the ICB scheme.



explained by the high percentage of employees subject to social insurance contributions working in manufacturing, other economic services, and the health and social care field, which all feed into sectors which are highly distressed in our "financial crisis" scenario. As the stress impact on the capital ratios is determined by the percentage point changes and not by the percentage changes from the baseline to the stress case, it is clear that, despite its high percentage increase, a high exposure to the private household sector will lead to a greater stress resilience compared to industrial goods and services.

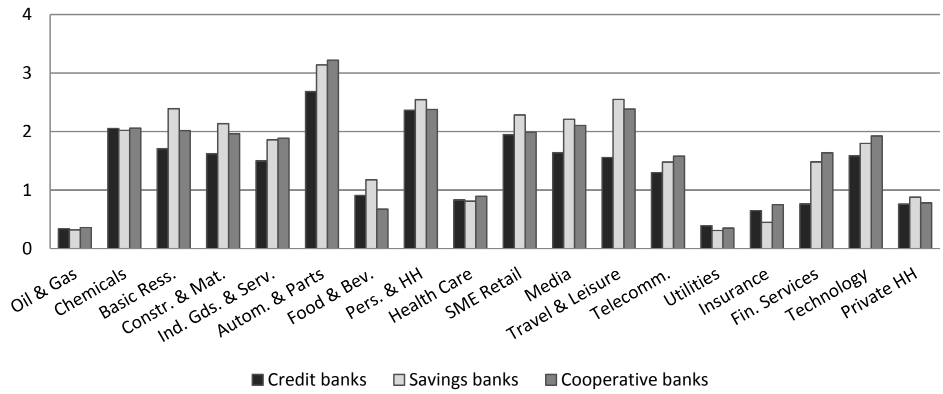
The baseline and stressed PDs are driven mainly by the following three factors: the default thresholds, the cutoff values of the systematic factors, and the systematic factor correlations. The first components, displayed in Table 4, are the default barriers for the banks' sectoral portfolios. As these are derived by applying the inverse of the standard normal distribution on the single sector baseline PDs, an inherent link between the default barrier (and thus the stressed PDs) and the baseline PDs is created, and the same observation patterns mentioned for the baseline PDs still hold true here. The other two components are the direct sectoral stress obtained from the systematic factor cutoff values and the indirect sectoral stress via the systematic factor correlations, which capture inter-sectoral spill-over effects. As already discussed in Section 4, not all sectors were equally stressed during the financial crisis (Table 4). In the case of the three most relevant sectors, we find that especially the private household sector (the probability of systematic factor returns falling below cutoff value is 5.1%) was heavily stressed, followed closely by that for industrial goods and services (probability of 18.1%), while SME retail remained unstressed.

Furthermore, the impact of spill-over effects between the sectors plays an important role

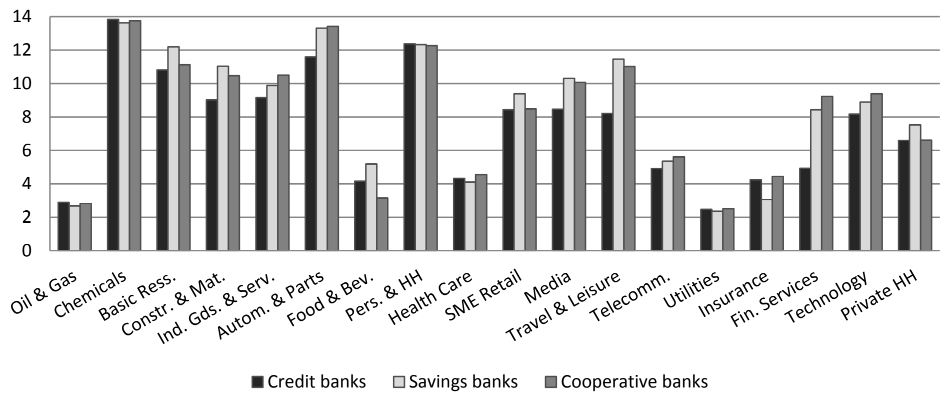
Figure 7: Median PD by Banking and Economic Sector

This figure shows the sectoral distribution of the PDs for credit (black), savings (light grey), and cooperative banks (grey) in % for each of the 18 industry sectors. With the exception of the sector for private households, their definitions follow the ICB scheme.

(a) Baseline



(b) Stress

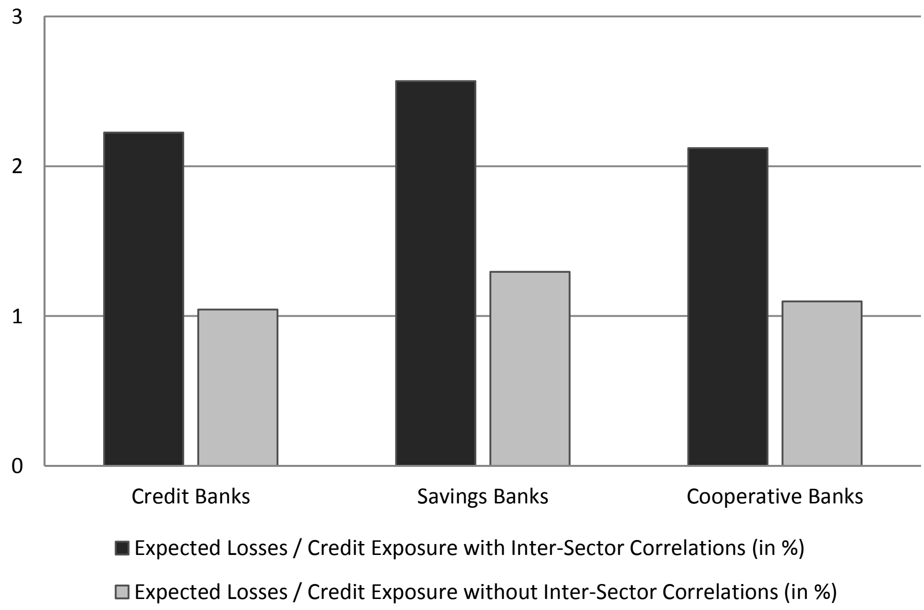


as correlations increase considerably in bear markets (e.g. Engle and Rangel, 2009; Junior and Franca, 2012; Sensoy, Yuksel, and Erturk, 2013). It is therefore not surprising that, looking at the systematic factor correlations, we find that they lie, at an average value of 62.6% (Table 6), above the period outside the financial crisis. Therefore, even sectors that are only moderately stressed via their cutoff values exhibit significant increases in their stressed PDs due to spill-overs from highly stressed sectors with which they are correlated. The significant influence of this spill-over effect can easily be observed in Figure 8 for the stress case. A simulation of the stressed expected losses without spill-over effects would result in an average decline of the impairments between all banking groups of around 50%, which underlines the importance of obtaining reliable correlation estimates.

For instance, we can explain the comparatively high relative PD increase (in %) under stress for the private household sector by its very low systematic cutoff value in combination with its high correlation with other sectors that exhibit low truncation values. Despite this combination of these factors, the comparatively small default barrier will still

Figure 8: Influence of Inter-sectoral Correlations

This figure compares baseline and stress expected losses by credit exposures with (black) and without (grey) inter-sectoral correlations for credit, savings, and cooperative banks in %. Inter-sectoral correlations are derived from Eurostoxx net index log returns from August 2007 until May 2010.



lead to stressed PD levels that fall below the stressed PDs of the SME retail and industrial goods sector.

With respect to the earlier discussion, the sectoral distribution of impairments both in the baseline and in the stress scenario in Figure 9 explains the overall stress impact on the impairments. From the baseline scenario impairments, it is apparent that private household sector impairments make up a particularly high proportion for cooperative banks (30%), while especially credit banks, but also to a lesser degree savings banks, have the highest impairments in industrial goods and services (37% and 31%). Moving on to the transition of the proportions under stress, we see that the impairments attributed to private households increase particularly strongly in the stress case at the expense of SME retail and the other 16 sectors. The industrial goods and services sector, on the other hand, reduces its impairments slightly at the same time. The reason for this transition lies in the percentage changes in the sectoral PDs between the baseline and the stress case as discussed above.

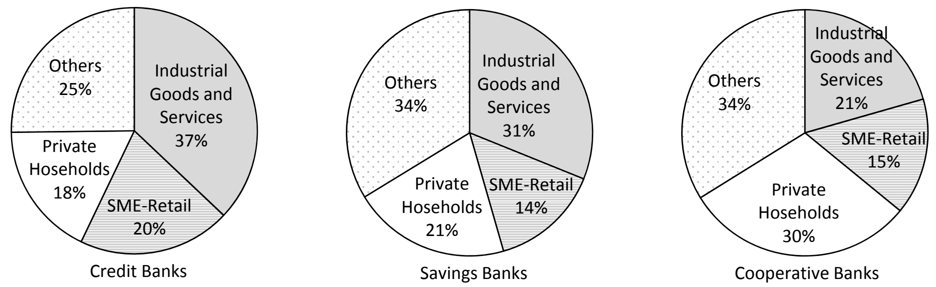
6 Conclusion

We have introduced a macroeconomic stress test for small and medium-sized banks and applied the framework to analyse the resilience of German credit, savings, and cooperative banks. On the one hand, we have stressed the banks' credit portfolios by using a multi-sectoral stress scenario which captures the decline of GDP during the financial crisis

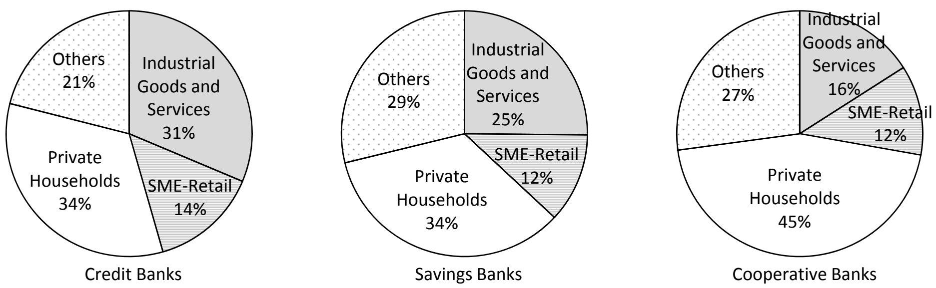
Figure 9: Sectoral Distribution of Impairments

This figure shows the baseline and stress median distribution of impairments for credit, savings and cooperative banks in % for each of the 18 industry sectors.

(a) Baseline



(b) Stress



on a sectoral basis. We link the stressed GDP sector growth rates to a multi-factor portfolio model by truncating the distributions of the systematic factors, which allows us to simulate, in the first step, stressed PDs, and, in the second step, stressed impairments. On the other hand, we employ a dynamic panel data model to generate stress for net income components. Using the average overall decline in GDP during the financial crisis as well as twisting the term structure, we are able to forecast the changes in net interest income and net fee and commission income. Taken together, this allows us to simulate the one-period change in net income and the stress impact on the banks' capital ratios for German small and medium-sized banks.

Our results show that, with respect to total capital ratio, savings, and especially cooperative banks prove to be very resilient to our extreme macroeconomic stress scenario. Both banking groups benefit from a very solid capital base, in addition to a comparatively low credit risk for cooperative banks. Credit banks display greater heterogeneity, but a portion of more than 6% falls below 8% of total capital in the stress case, mainly due to a smaller cushion of capital.

The split between impairments and other net income components reveals that, for all banking groups, credit impairments are by far the most important driver of stress. Looking at the impairments more closely, we see that they stem mainly from the private households, industrial goods and services, as well as SME retail sectors, as these are the main sectors that receive credits. We also find that modelling spill-over effects correctly is of particular importance, as they increase the direct stress effect by around 100% in our set-up, where we account for them via inter-sectoral correlations.

With respect to the income stress test, we show that net interest income has a higher stress impact than net fee and commission income. After subtracting operative expenses, which increase slightly in the stress scenario, net operating income decreases by 23% under stress, which is a substantial reduction.

A Appendix

A.1 Correlation Matrix

Table 6: Correlation Matrix of the Sector Indices

This table shows inter-sectoral correlations of 17 sector indices following the ICB sector classification and the private household sector. The correlations were estimated from weekly Eurostoxx Net Index Returns from August 2007 until May 2010.

	Sector	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	Oil and Gas	1	0.80	0.78	0.72	0.81	0.52	0.60	0.76	0.48	0.60	0.69	0.61	0.60	0.81	0.68	0.78	0.64	0.82
2	Chemicals	0.80	1	0.85	0.77	0.86	0.58	0.60	0.82	0.47	0.59	0.71	0.73	0.62	0.81	0.79	0.82	0.71	0.89
3	Basic Resources	0.78	0.85	1	0.78	0.64	0.64	0.53	0.79	0.33	0.60	0.68	0.71	0.47	0.69	0.72	0.78	0.75	0.87
4	Construction and Materials	0.72	0.77	0.78	1	0.91	0.72	0.53	0.86	0.34	0.72	0.78	0.84	0.53	0.65	0.82	0.87	0.78	0.90
5	Industrial Goods and Services	0.81	0.86	0.86	0.91	1	0.62	0.58	0.90	0.39	0.70	0.80	0.85	0.60	0.75	0.84	0.90	0.81	0.95
6	Automobiles and Parts	0.52	0.58	0.64	0.72	0.62	1	0.39	0.60	0.26	0.54	0.53	0.55	0.20	0.40	0.58	0.60	0.57	0.67
7	Food and Beverage	0.60	0.60	0.53	0.53	0.58	0.39	1	0.70	0.53	0.66	0.63	0.56	0.59	0.61	0.53	0.64	0.54	0.68
8	Personal and Household Goods	0.76	0.82	0.79	0.86	0.90	0.60	0.70	1	0.46	0.81	0.81	0.83	0.62	0.72	0.79	0.88	0.79	0.93
9	Health Care	0.48	0.47	0.33	0.34	0.39	0.26	0.53	0.46	1	0.44	0.48	0.42	0.48	0.49	0.38	0.43	0.40	0.58
10	SME Retail	0.60	0.59	0.60	0.72	0.70	0.54	0.66	0.81	0.44	1	0.71	0.71	0.52	0.57	0.62	0.75	0.63	0.80
11	Media	0.69	0.71	0.68	0.78	0.80	0.53	0.63	0.81	0.48	0.71	1	0.80	0.62	0.68	0.73	0.77	0.74	0.85
12	Travel and Leisure	0.61	0.73	0.71	0.84	0.85	0.55	0.56	0.83	0.42	0.71	0.80	1	0.54	0.60	0.80	0.80	0.77	0.86
13	Telecommunications	0.60	0.62	0.47	0.53	0.60	0.20	0.59	0.62	0.48	0.52	0.62	0.54	1	0.66	0.59	0.65	0.54	0.63
14	Utilities	0.81	0.81	0.69	0.65	0.75	0.40	0.61	0.72	0.49	0.57	0.68	0.60	0.66	1	0.68	0.74	0.63	0.78
15	Insurance	0.68	0.79	0.72	0.82	0.84	0.58	0.53	0.79	0.38	0.62	0.73	0.80	0.59	0.68	1	0.84	0.70	0.83
16	Financial Services	0.78	0.82	0.78	0.87	0.90	0.60	0.64	0.88	0.43	0.75	0.77	0.80	0.65	0.74	0.84	1	0.75	0.90
17	Technology	0.64	0.71	0.75	0.78	0.81	0.57	0.54	0.79	0.40	0.63	0.74	0.77	0.54	0.63	0.70	0.75	1	0.83
18	Private Households	0.82	0.89	0.87	0.90	0.95	0.67	0.68	0.93	0.58	0.80	0.85	0.86	0.63	0.78	0.83	0.90	0.83	1

A.2 Descriptive Statistics

Table 7: Descriptive Statistics

This table shows the summary statistics for the variables in the income stress test models. Abbreviations/variable definitions: llp = loan loss provisions; rwa = risk-weighted assets; funding gap = difference between customer credits and liabilities as a percentage of total assets; ln(TA) = total assets in logarithm.

Variable	Mean	Std	Min	Max
Net interest income as % of total assets	2.62	0.55	0.25	8.61
Net fee income as % of total assets	0.69	0.88	−0.19	21.91
Operating costs as % of total assets	2.44	1.04	0.35	20.54
Other non-interest income as % of total assets	0.12	0.44	−0.46	6.40
Funding gap	−14.91	18.80	−81.73	78.25
Llp to customer loans	0.69	0.62	0	6.73
Customer loans to total assets	58.40	12.83	0.34	99.92
Equity to risk weighted assets	10.33	5.05	4.65	96.46
ln(TA)	19.73	1.35	16.02	24.18

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