Monetary Policy and Financial (In)Stability: An Integrated Micro-Macro Approach ⋆

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Abstract

Nowadays, central banks focus on two objectives: monetary *and* financial stability. Empirical evidence on this twin objective is scarce. We aim to contribute on the issue with an integrated micro-macro approach with two core virtues. First, we measure financial stability at the bank level for Europe's largest economy: Germany. Second, we specify a VAR model with feedback between the micro- and macroeconomic model components. This enables us to assess the potential importance of interaction effects. Our results confirm the existence of a trade-off between monetary and financial stability. An unexpected tightening of monetary policy increases the mean probability of distress. This effect disappears when neglecting micro effects, underlining the crucial importance of the former. Distress responses differ across banking groups and the severity of distress events. Hence, a more detailed account of heterogeneous transmission dynamics beyond aggregate measures of financial stability is corroborated. An important policy implication is that the separation of financial supervision and monetary policy requires close collaboration among members in the European System of Central Banks and other national supervisory authorities.

Key words: financial stability, stress testing, bank distress, monetary policy
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1 Introduction

This paper investigates interactions between banking sector stability and the real economy. Thereby, we seek to contribute empirical evidence to the ongoing debate among policy makers (ECB, 2006; Deutsche Bundesbank, 2006), academics (Benink and Benston, 2005; Goodhart et al., 2006) and the public (The Economist, 2007), concerning the extent macroeconomic policies and the stability of financial systems depend on each other. Specifically, we investigate how monetary policy affects financial stability and quantify the importance of feedback mechanisms between the real and financial sector.

The twin objective of monetary and financial stability climbed the agenda of central bankers as witnessed by a rampant increase in the number of stability reports published by central banks (Oosterloo et al., 2007). This surging interest in twin stability is presumably owed to the fact that central banks have been fairly successful in conquering inflation, but are increasingly concerned with financial stability in light of globally increasing competition and integration of financial markets (Borio, 2006).

Academic research that follows suit to provide also empirical evidence on the intricate relation between monetary policy and financial stability is, however, still scarce due to a number of challenges. For starters, the definition of financial stability is surprisingly elusive (Poloz, 2006; Allen and Wood, 2006). Second, central banks' policies to ensure financial stability vary considerably across countries, thus reflecting both the term's ambiguity and related problems to measure stability (Oosterloo and de Haan, 2004). Third, a number of scholars emphasize the role of banks for financial stability (De Bandt and Hartmann, 2000; Padoa-Schioppa, 2003; Schinasi and Fell, 2005). But while the number of studies analyzing individual banks' probabilities of default is fairly abundant,[1] Jacobson et al. (2005) highlight that only few studies employ microeconomic indicators of financial stability of firms and/or banks to link it to monetary policy and resulting stability responses. Fourth, Goodhart

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[1] See for example Cole and Gunther (1995), Wheelock and Wilson (2000), Estrella et al. (2000), Shumway (2001), Gan (2004), King et al. (2005), Porath (2006).

et al. (2004, 2006) emphasize the interdependence of microeconomic agents and macroeconomic performance. Thus, allowing for feedback mechanisms is essential for models that could serve policy makers, for example for stress testing purposes (ECB, 2006).

We aim to make two core contributions. First, we develop an integrated micro-macro approach that incorporates stability indicators at the bank-level into the assessment of macroeconomic shocks and responses. Second, we allow explicitly for feedback mechanisms between both the macroeconomic stance and the microeconomic stability of banks. Contrary to extant research, our approach is agnostic about both the timing and direction of the feedback mechanisms.

To this end we use macroeconomic and individual data for all universal banks operating in Europe's largest financial system: Germany. We analyze which different types of distressed events occur more frequently following a monetary policy shock, as well as which banking groups are predominantly affected on the basis of confidential Bundesbank bank data between 1995 and 2004. Thus, we curb the measurement problem of financial stability, which most studies usually face: Financial stability is defined and measured as a bank's probability of distress according to the supervisors definition of problem banks used for supervisory policy.

Specifically, we first construct a reduced form micro-macro model which describes the convolution of bank distress probabilities at the micro-level and the macroeconomy. There are a number of reasons to combine the micro and macro perspectives. On the one hand, in a pure macro model, many potentially relevant effects are possibly obscured due to the loss of information following data aggregation. In our application we find that this effect is substantial. For example, a model based only on financial sector aggregates misleadingly suggests macro-financial feedback to be absent. Moreover, it is not always straightforward to assess how aggregate fluctuations are related to individual bank distress. On the other hand, in a pure micro approach, it is difficult to interpret movements in aggregate variables. Typical macro stress-testing exercises incorporate the real economy by specifying some unconditional distribution for aggregate variables, such as for example the macro stress-testing approach at the Dutch National Bank (van den End et al., 2006). A first drawback of such an approach is that there is no room for financial-macro feedback, also called second-round effects. Another consequence is that there is no straightforward economic interpretation of the macro fluctuations, for example in terms of structural shocks. Both seem to be desirable features of models suited for macro stress-testing (Goodhart, 2006; ECB, 2006). By focusing on monetary policy shocks, their effect on and interaction with financial stability, we aim to shed light on the policy implications of macro stress-testing analysis.

The microeconometric part of the model links bank-specific distress probabilities to both bank specific characteristics and macroeconomic variables. We then combine this model with a macro model describing the dynamics of the main macroeconomic variables, as well as their interaction with the financial sector. Subsequently, we identify monetary policy shocks in the combined micro-macro system. That is, we identify the reduced form in order to understand the effects of structural shocks. Our approach allows for macro-financial as well as financial-macro feedback dynamics. Moreover, this feedback can be both instantaneous and subject to non-linearities. Model simulations provide insight into the complex interdependence between macro shocks and microeconomic banking stability. Thus, the model allows us to measure the interactions between monetary policy and financial regulation more explicitly compared to previous studies on macroeconomic stress. In sum, our study is thus akin to Jacobson et al. (2005), who analyze interactions between the Swedish macroeconomy and the corporate sector using vector autoregressive techniques combined with probabilities of distress of individual firms derived from a hazard rate model.

We differ, however, in three important respects. First, we use confidential data provided by the Deutsche Bundesbank to estimate *bank* rather than corporate firm distress from a panel of bank-specific financial data and distress events. Therefore, we measure financial stability more directly compared to an approach that examines the financial stance by approximation of bank customers stability (Goodhart et al., 2004; Schinasi and Fell, 2005). Second, we differ substantially in the way in which we treat the combined micro-macro-system. Our study contributes methodologically by incorporating simultaneity in the macro-financial interactions. That is, we extend the VAR by a data generating process for distressed events, which is estimated on micro bank data. This combined system resembles a reduced form panel-VAR. We apply identification techniques to this combined micro-macro system (i.e. construct a SVAR), to analyze the effect of structural shocks. Importantly, we do so without imposing any a priori restrictions on the direction or the timing of interactions between the macroeconomy and the financial sector, letting the data determine their outcome. Third, we analyze the largest economy in Europe, namely Germany. To some extent, our policy implications may thus be of economic significance for the European economy as a whole.

Our main results are threefold. First, a contraction in monetary policy increases the average probability of distress of banks by 0.44%, which resembles a third of it's annual standard deviation. Hence, the effect is economically significant and indicates a modest trade-off between monetary and financial stability. Second, allowing for feedback effects and non-linearities is crucial. Without modeling individual bank distress probabilities' reaction to the macroeconomy, a contraction of monetary policy has no significant effect on our measure of financial stability. Consequently, stability studies that neglect the integral role played by microeconomic agents may falsely fail to detect the trade-off between monetary and financial stability. Third, distinguishing different degrees of distress and banking sectors yield heterogeneous responses. Thus, a finer distinction of distress as well as alternative transmission mechanisms at work across banking sectors need to be considered when assessing financial stability.

The remainder of this paper is organized as follows. We present our data in section 2 and discuss the components of the micro-macro model subsequently in section 3. Our results in section 4 are reported for aggregate measures of distress and, in addition, according to banking group and distress level. We conclude in section 5.

2 The Data

The analysis pertains to the German economy and its banking system over the period 1995-2004. In line with previous work by the Bundesbank (Porath, 2006; Koetter et al., 2007), we use the distress database of the Bundesbank to model bank distress. The data we investigate are particularly insightful for our questions of research. The German banking sector experienced substantial fluctuations in the occurrence of distressed events. Our sample contains more than 1,100 such events, with the aggregate annual frequency of distressed events fluctuating approximately between 2 and 7% as depicted in table 1.

Table 1
Distressed event frequency over time according to banking group and distress category

Year	**All**	**Banking groups**			**Distress categories**			
		Com'cl	*Sav's*	*Coop's*	*I*	*II*	*III*	*IV*
1995	1.9%	2.2%	0.3%	2.3%	0.1%	0.4%	0.8%	0.6%
1996	2.5%	4.9%	0.8%	2.8%	0.1%	0.4%	1.2%	0.7%
1997	3.4%	6.3%	0.9%	4.0%	0.1%	0.7%	0.9%	1.7%
1998	4.7%	7.5%	2.1%	5.3%	0.1%	1.4%	1.3%	1.9%
1999	5.6%	4.4%	0.7%	7.2%	0.2%	2.4%	0.9%	2.1%
2000	5.0%	5.0%	1.6%	6.1%	0.1%	2.2%	1.0%	1.7%
2001	6.9%	9.2%	2.2%	8.3%	0.8%	3.1%	1.1%	1.9%
2002	7.0%	4.4%	3.4%	8.7%	1.2%	3.3%	0.9%	1.6%
2003	6.6%	4.7%	1.8%	8.8%	0.8%	3.4%	1.1%	1.3%
2004	4.1%	0.8%	1.1%	5.8%	0.5%	2.5%	0.8%	0.3%
Obs	26,012	1,509	5,569	18,736	24,967	25,325	25,131	25,226

We observe differences between banking sectors and across distress categories in our sample period. Therefore, we disentangle below responses of probabilities of distress to monetary shocks according to both dimensions and depict next to the aggregate distress frequencies according splits in table 1, too.

The cross-sectional dispersion in the data is substantial. The different evolution of distress frequencies across banking groups reflects the partition of German banking into three distinct sectors that pursue different business strategies and face accordingly different risks (Hackethal, 2004). For example, the group of small commercial banks exhibits especially during the times of stock market turmoil at the turn of the century exceptionally high frequencies of distressed events. This may reflect the larger dependence of these banks on non-interest income and financial markets exposure (Koetter et al., 2006). Likewise, especially small cooperative banks experienced distress in the wake of increasingly fierce competition and consolidation pressure (Lang and Welzel, 1999). The pillar-specific pattern of distressed events thus suggests that structural shocks may affect the stability of these banking groups differently, which we investigate below.

Regarding different distress categories, Oshinsky and Olin (2006) point out that banks hardly ever face only a dichotomous destiny of either failure or survival. Instead, a number of different shades of distress can occur to a bank. Based on detailed data on approximately 60 different possible events collected by the Bundesbank, we distinguish four increasingly severe classes of distress labeled I through IV in table 1.[2] The first group of weakest events includes three incidents. First, compulsory notifications by banks about events that may jeopardize the existence of the bank as a going concern according to §29(3) of the German Banking act (*"KWG"*). Second, a notification by banks of losses amounting to 25 percent of liable capital according to §24(1)5 *KWG*. Third, weak measures like letters of warning. The second distress category captures measures taken by the Federal Financial Supervisory Authority (*"BaFin"*) representing official warnings, admonishment hearings, disapproval, warnings to the CEO, and serious letters. None of these measures imply an active intrusion into the ongoing operations of the bank. In turn, category III represents corrective actions against the bank such as orders to restructure operations, restrictions to lending, deposit taking, equity withdrawal or profit distribution or the dismissal of management. The fourth (and worst) distress category comprises takeovers classified by the Bundesbank as restructuring mergers and enforced closures of banks initiated by the BaFin, which are extremely rare. The pattern depicted in table 1 highlights that in particular weaker distress events occurred more often in recent years. Potentially, temporary policy shocks have different effects to trigger increasingly worse kinds of bank in-

[2] Next to the annual distress database of the Bundesbank, we also use three subset databases with exact dates ("measures", "incidents" and "mergers") to construct below a quarterly series of the distress indicator for reasons explained in section 3.2. A detailed discussion of distress events can be found in Kick and Koetter (2007).

stability. For example, weaker incidents may be more likely during monetary contraction but structural distress, such as market exit through mergers, may not be affected by such temporary phenomena but depend on fundamental deficiencies of the bank. We therefore test below if responses do differ across distress categories.

Often, macro stress-tests focus on credit risk alone. According to Aspachs et al. (2007), the probability of distress is a much more appealing statistic to measure financial (in)stability. Theoretically, it provides a sufficient statistic for the relation between individual banks' probability of distress, their exposure to various measures of risk, and the macroeconomic stance. Thus, the probability of distress provides a more exhaustive picture of stress borne by the banking system and considers, in contrast to other stability studies, all types of risk.

3 Methodology and auxiliary results

We first introduce our approach to measure financial stability at the bank level with a hazard rate model. Subsequently, we discuss the macro model and the link between the two that allows for feedback effects between monetary and financial stability policies.

3.1 A microeconomic measure of financial stability

The microeconomic component of our integrated model captures the driving forces of the aggregate probability of distress (PD) among banks more succinctly. In particular, the model estimates the effect of bank-specific and macroeconomic variables on the probability of distress.

$$PD_{it} = \frac{e^{\beta X_{it-1} + \pi Z_{t-1}}}{1 + e^{\beta X_{it-1} + \pi Z_{t-1}}}. \tag{1}$$

Here, PD_{it} denotes the probability that bank i will default in year t. It is estimated from a set of covariates X_{it-1} observed for bank i in period $t-1$ and, additionally, a set of macroeconomic covariates Z_{t-1}, where β and π are parameters to estimate. Put differently, the micro model transforms a set of bank-specific and macroeconomic covariates observed in year $t-1$ into bank-specific $PD's$ with an appropriate link function, in our case a logit link function. [3]

[3] The link function transforms the variables' effects into probabilities. The particular choice for a logit essentially leaves our results unaffected (see also Porath, 2006). Based on standard lag selection criteria, we use one year lags for all variables.

Since the number of bank-specific covariates to include in X is possibly immense, we follow the procedure suggested in Hosmer and Lemshow (2000) and pre-select an economically meaningful long-list of around 150 covariates. We orient ourselves at the rating practices followed by supervisory authorities, which use the so-called CAMEL taxonomy (King et al., 2005).[4] Within each category we conduct univariate tests to identify a shortlist of covariates that maximize explanatory power.[5] Ultimately, we select the final vector of seven bank-specific and three macroeconomic variables by means of stepwise regression. Descriptive statistics according to banking group and distress category are provided in table 3 in the appendix.

More importantly in the light of our study is the inclusion of three macroeconomic covariates ($Z_t = (Y, P, R)_t'$, denoting respectively output growth, inflation and the interest rate) as an additional category of its own. These are necessary to establish the link with the macroeconomic VAR model. We estimate the hazard rate model in equation (1) and focus first on the sample pooled across banking groups and distress categories. This hazard rate model exhibits a good fit as witnessed by a pseudo-R^2 of approximately 11 percent. To evaluate the discriminatory power of the model over the range of alternative cutoff levels between zero and one, we employ the area under the Receiver Operating Characteristics (ROC) curve. The area under the ROC curve (AUR) measures the percentage of correctly classified events (sensitivity) versus one minus the percentage of correctly classified non-events (specificity). According to Hosmer and Lemshow (2000), the reported AUR values of around 77 percent indicate a good ability of this model to discriminate successfully between distressed and non-distressed events. Even though our prime interest is not in individual parameter estimates, it is nonetheless comforting that virtually all coefficients are significantly different from zero and exhibit signs and magnitudes in line with other bank failure studies. Finally, we depict parameter estimates for group-specific logit models in the right-hand panels in table 4. Like the aggregate model, each specification exhibits fairly high AUR values. Since our prime focus in this paper is to assess the effects of monetary policy on financial stability, we refrain from further inference and turn next to the macroeconomic component of the model and it's conciliation with bank stability.

Table 2 sheds light on the importance of incorporating the macroeconomic variables in the micro model. The table compares two measures of fit across

[4] CAMEL: Capitalization, Asset quality, Management, Earnings, Liquidity.

[5] For a more detailed description of model selection for Bundesbank data see Porath (2006), Koetter et al. (2007) and Kick and Koetter (2007).

our baseline model with and without macro covariates.[6] For completeness, we also provide coefficient estimates for the model without macro variables in table 5 in the appendix.

Table 2
Hazard model fit with and without macroeconomic covariates

	All	**Banking groups**			**Distress category**			
		Com'cl	*Sav's*	*Coop's*	*I*	*II*	*III*	*IV*
A-RMSE								
no macro	0.049	0.077	0.025	0.053	0.010	0.031	0.007	0.018
macro	0.035	0.049	0.022	0.042	0.006	0.026	0.005	0.011
reduction (%)	28.45	36.17	12.79	21.67	43.12	14.41	27.92	40.44
AUR								
no macro	0.766	0.623	0.839	0.772	0.826	0.723	0.850	0.784
macro	0.774	0.664	0.844	0.780	0.835	0.740	0.850	0.796
gain (%)	1.044	6.648	0.680	0.945	1.089	2.296	0.000	1.621

Notes: A-RMSE: Aggregate root mean squared error;

AUR: Area under the Receiver Operating Characteristics curve.

Including macro variables helps the model in two important ways. First, consider the aggregate root mean-squared errors (A-RMSE). This measure reflects the success of both models in capturing the aggregate rate of distress over time. Macro variables reduce projection errors by at least ten and up to forty percent. Second, table 2 also contains a measure that reflects the cross-sectional fit of the model with and without macro variables: the AUR. Here, we also see that incorporating macro covariates improves the cross-sectional success of the model substantially. In particular, we observe a gain in AUR of up to six percent for commercial banks.

The implication of this model comparison exercise is twofold. First, the macro variables improve the estimation of the marginal effects of the default model. Importantly, the identification of macro effects requires both the micro (cross-section) and macro (time series) dimension (Porath, 2006). This reduces potential concerns with respect to the fairly short time-series dimension of the data. Second, the success of the model in reproducing the aggregate distress rate is intimately tied to the inclusion of macroeconomic information. This result is in line with Jacobson et al. (2005), who also highlight the crucial im-

[6] We present two measures that do not necessarily improve when including more covariates (such as e.g. R-squared), because failing to do so would automatically favor the model including macro variables.

portance to include macro variables when fitting a default model for Swedish firms to capture aggregate movements.

3.2 The macroeconomic model

The macro block of the model is a standard vector autoregression (VAR), describing the convolution of the most important macroeconomic aggregates. We incorporate financial-macro feedback by allowing these macro variables to depend on our measure of financial stability. We favor a VAR approach for a number of reasons. First, reduced form VARs typically perform very well in capturing the data generating process of macro-aggregates, and the German data are no exception. Second, the interactions between financial stability and the real economy have not been rigorously identified theoretically. Goodhart et al. (2006) is a very important contribution toward this goal. However, a consensus view on these interactions has yet to emerge. The contemporaneous and lagged intricate relation between the real economy and the banking sector is hardly to be measured with a theory based approach without either heroic assumptions or sole focus on single market segments, such as for example aggregate lending.

We therefore aim to impose as little a priori theorizing as possible. Structural VARs render the most flexible way to do so.[7] We identify a monetary policy shock using sign restrictions. This allows us to remain agnostic with respect to the response of the financial sector. Moreover, this approach naturally extends into considering other types of structural shocks, such as demand and supply shocks (Peersman, 2005).

Specifically, the macroeconomic model consists of a quarterly vector autoregression of GDP growth (Y), inflation (P) and the interest rate (R). Any macro analysis of monetary policy issues typically includes (at least) these three variables. Here, in view of the interest in financial stability, the probability of bank-distress (measured by the frequency of distressed events) is incorporated as an additional explanatory variable. The reduced form macro

[7] Though complete structural models also have a VAR representation, they comprise many more cross-equation restrictions. Precisely because of the lack of consensus on such restrictions, we refrain from imposing them.

model thus has the following structure: [8]

$$Z_q = \begin{bmatrix} Y \\ P \\ R \end{bmatrix}_q = \Pi^{MM} \begin{bmatrix} Y \\ P \\ R \end{bmatrix}_{q-1} + \Pi^{MF} PD_{q-1} + u_q \tag{2}$$

Where the Π matrices capture the reduced form feedback coefficients from macro to macro (Π^{MM}, dimension 3×3) and from the financial sector to the macro side (Π^{MF}, 3×1), respectively. Note that we fit the VAR with quarterly data, which is available for GDP, inflation and the interest rate and reduces prohibitive low degrees of freedom in an annual setting. Thus, the macro model is estimated on quarterly data but rewritten below in annual form. The two models are then combined at the lowest frequency. In principle, this could be done at the quarterly frequency, too, yet far more time-series data would be required, which are not available.

This requires us to break down the annual distress measure to a quarterly series by employing an according indicator. This indicator series is created by exploiting three sub-databases of the annual distress catalogue of the Bundesbank, which indicate specific dates for individual measures (*"Maßnahmen"*), incidents (*"Vorkomnisse"*) and (distressed) mergers. While these subsets cover around 75 percent of all events specified in equation 1, the quarterly distress indicator is thus an approximation. [9] Akin to Hoggarth et al. (2005), we use the former as a weighting scheme to distribute the annual distress series to quarters. In a second step the quarterly series is smoothed by interpolation. This approach seems sufficiently robust for two reasons. First, any uncertainty in the quarterly series about exact timings is likely to be random rather than systematic. Second, our results for impulse response functions reported are insensitive towards different smoothing techniques. [10]

3.3 The integrated micro-macro model

After describing both the micro and macro blocks of the model, we now focus on the combined model. Note that the model in equation (2) is a plain

[8] For expositional purposes, we write the system as a first order VAR.

[9] For example, a category III event contains capital injections, which could not be included in the quarterly series since data are only available annually. Likewise, the exact distribution of mergers to quarters is subject to caution, since it is conceptually non-trivial when to consider a merger process to be ultimately completed.

[10] Different periodicity in macroeconomic studies is a frequently encountered problem. See Schumacher and Breitung (2006) for a discussion and a suggested remedy.

VAR augmented with a measure of financial stability as an additional explanatory variable. Put differently, this model does not incorporate any feedback mechanism between financial stability and real macroeconomic conditions. Therefore, we first rewrite the VAR model as an annual one and expand the macro system with one equation, namely the data generating process for the aggregate probability of distressed events originating from the micro model. Consequently, impulse response functions are also annual, which is due to the annual frequency of the bank-specific variables.

$$\begin{bmatrix} Y \\ P \\ R \\ PD \end{bmatrix}_t = \begin{pmatrix} \Pi^{MM} \\ \Pi^{FM} \end{pmatrix} \begin{bmatrix} Y \\ P \\ R \end{bmatrix}_{t-1} + \begin{pmatrix} \Pi^{MF} \\ \Pi^{FF} \end{pmatrix} PD_{t-1} + \varepsilon_t \tag{3}$$

Put differently, the fourth equation of the combined model describes the relation between the probability of distress and the macro variables. The bank-specific variables are considered as exogenous for the combined model. [11] They do, however, retain an important role in the model. That is, the coefficients Π^{FM} are the marginal effects of the macro variables on the financial sector, i.e. the frequency of distressed events. These marginal effects depend on the level of each of the variables in the micro model. For example, the elasticity of distress with respect to output depends, among other CAMEL covariates, on the bank capitalization. The same holds for all variables in the system. Moreover, as output changes, all the marginal effects dynamically change along. Thus, the model allows for the possibility of state-dependent coefficients, such as dependence on the stance of the business cycle or the balance sheet of the financial sector.

Note the following about the structure of the combined micro-macro model. First, the model is a reduced form model. It combines two lower layer reduced form models, in which no contemporaneous relations among the variables exist. The absence of such interactions is what crucially distinguishes this model from a structural model. Second, the model fits into a panel-VAR type framework. That is, all variables are explained in terms of lags of themselves and all other variables in the system. In fact, the model is a mixed panel-VAR since the macro variables are measured in the aggregate, while the probability of distress at the cross-sectional bank-level.

Acknowledging this structure of the combined model, one can transform this reduced form into a structural form using standard identification techniques. Similar to transforming a reduced form VAR to a structural one (SVAR), one

[11] Therefore, they do not appear as separate variables in the combined dynamic system. We aim to endogenize banks' balance sheets in future research.

can identify the above combined micro-macro system. A complete structural model, as in equation (4) below, describes the entire set of relations (both contemporaneous (A, 4×4) and lagged (B, 4×4)) between all variables in the system, and thus the response to each possible structural shock s_t (4×1).

$$A \begin{bmatrix} Y \\ P \\ R \\ PD \end{bmatrix}_t = B \begin{bmatrix} Y \\ P \\ R \\ PD \end{bmatrix}_{t-1} + s_t \tag{4}$$

We partially identify the combined micro-macro system. In particular, we identify a monetary policy shock. Intuitively, we look for all possible structural models that satisfy, first, the reduced form combined micro-macro model in equation (3) and, second, what we "know" happens after a monetary policy shock. Regarding the latter, we define a policy shock as one which contemporaneously (within the year) has a positive effect on the interest rate, while neither increasing growth nor inflation ($R \uparrow, Y \downarrow, P \downarrow$). This is a common set of restrictions in the macro literature (Peersman, 2005). Importantly, we remain agnostic with respect to the response of the financial sector to monetary policy shocks.

4 Results

We first analyze the effects of monetary policy shocks on financial distress in the combined micro-macro system. This gives an indication of the average historical interrelation between monetary policy stance and the degree of financial stability. Then, we disaggregate the financial response in two insightful ways. We check how different types of distress react and whether all types of banks are equally resilient to the incidence of monetary policy shocks.

4.1 The Aggregate Response

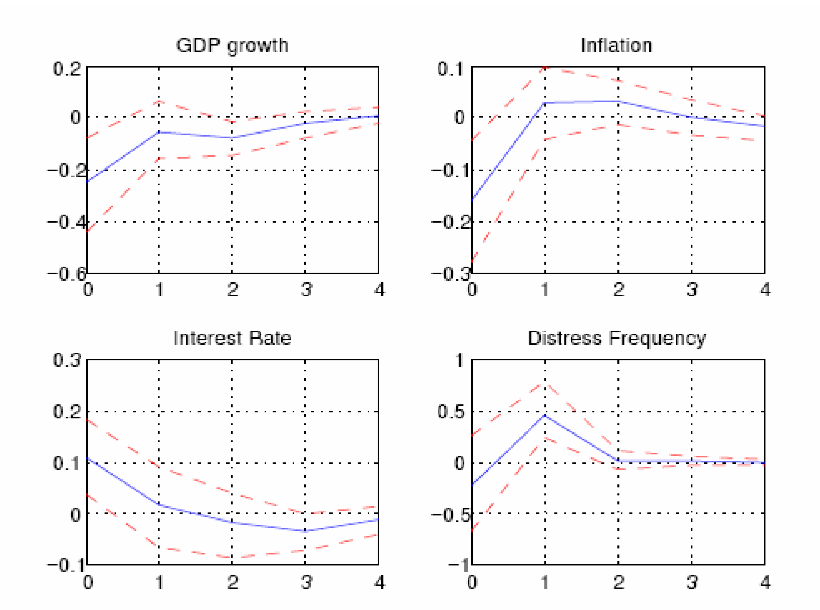
Figure 1 plots the median impulse response functions and corresponding confidence intervals of all variables in the system to a monetary policy shock. The impulse responses are annual. [12] Therefore, a one standard deviation increase of the interest rate of around 0.125%, is compatible with, e.g., a two quarter increase of 25 basis points, or a one quarter increase of 50 basis points. On

[12] Recall that the macro model is estimated quarterly but rewritten in annual form, in order to align its frequency with that of the micro data.

the macro side, this reduces GDP growth and inflation with 0.2 and 0.15%, respectively, during the first year. These magnitudes lie in the ballpark of those in other monetary VARs. For instance, Smets and Wouters (1999) report for Germany point estimates virtually identical to ours. We now look at the response of the financial sector more closely.

While the instantaneous response of the probability of distress is insignificant, our results indicate a significant deterioration of financial stability in response to restrictive monetary policy after one year. Note that this result is by no means due to the methodological setup imposed but solely a reflection of the data -in contrast to other financial stability studies, for example Jacobson et al. (2005). Quantitatively, the period 1 median response is 0.44%. Though this may seem small at first sight, it amounts to about one third of the annual standard deviation of the distress frequency. This is an important result since it shows that monetary policy affects the stability of the financial sector. The increase in the average probability of distressed events following a restrictive monetary policy shock suggests that curbing inflation comes at the cost of lowering financial stability. Hence, we find evidence in support of the existence of a trade-off between the two main goals of central banks.

Figure 1. Financial stability response to monetary shock with feedback



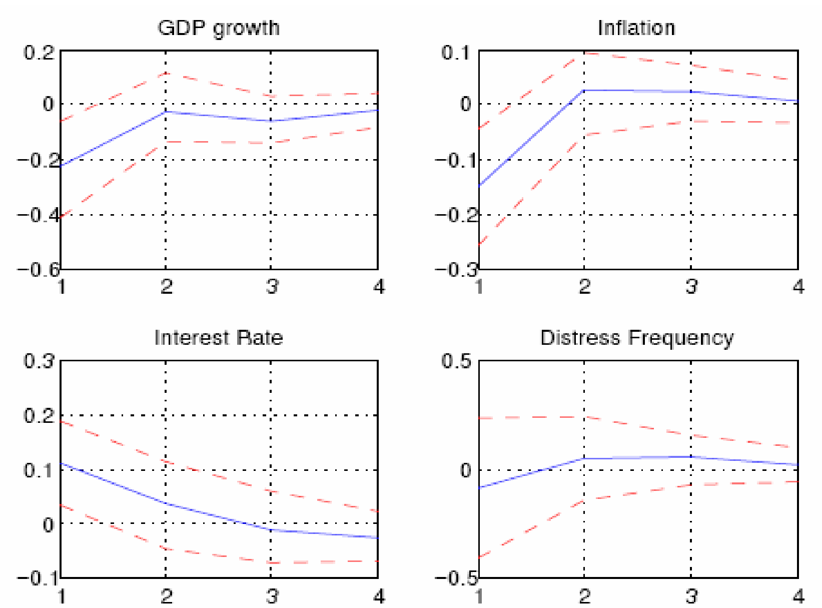
Given the institutional dichotomy between national supervisory authorities, usually central banks and/or other government agencies (Barth et al., 2001; Carletti et al., 2006), and the European Central Bank's mandate to conduct monetary policy in the European Monetary Union, the presence of a trade-off between the two goals underlines the importance of intensive supra-national coordination between policy makers. Hence, the need for a harmonized definition of financial stability paired with concerted efforts by members of the European System of Central Banks forwarded by, for example, Allen and Wood (2006) or Borio (2006) are corroborated by our findings.

4.2 Feedback Effects

Importantly, the identified trade-off between monetary and financial stability does not emerge in a macro VAR limited to the specification of the mean probability of distress as an additional endogenous variable. The absence of a significant change in financial stability is shown in figure 2.

With a pure macro model as depicted in equation (3), which does neither account for micro data nor non-linearities, we find no effect of the policy shock on the frequency of distress. The deceptive absence of a response of financial stability is in line with Jacobson et al. (2005), who also report no impact of a policy shock on firm defaults when ignoring the micro side of the data. Our result underlines the importance to allow for possible repercussions of monetary policy at the *bank*-level, as stated in many central banks' wishlists for macro-stress testing analyses (ECB, 2006).

Figure 2. Financial stability response without feedback



The importance of feedback effects is not only intuitively appealing, but also economically reasonable. While bank PDs may depend to some extent on macroeconomic conditions, too, most of the historical distress incidents are explained by bank-specific factors such as capitalization, profitability and asset quality. Direct effects of temporary and moderate changes in monetary policy are thus unlikely to affect aggregate bank PDs significantly. However, a monetary contraction's well-documented depression of output may very well affect banks' financial accounts through it's effect on borrowers and financial markets in subsequent feedback effects. In an environment of stable inflation and growth, Borio (2006) cautions that a process can unfold where demand side pressure paired with a misperception of risk and wealth as well as looser credit constraints foster the build-up of financial imbalances of firms and households. Excessive demand side pressure may then entail failure of financial institutions to build up sufficient buffers but to rely, for example on financial markets to hedge risks (Driffill et al., 2006). These may shield banks from instantaneous effects in response to efforts by central banks to control inflation. But their customers' imbalances will dynamically lead to deteriorating determinants of bank distress in subsequent periods. The crucial importance of such dynamic effects (and potential non-linearities) has also been raised by Poloz (2006), who cautions that failure to account for the former, as in the majority of twin stability studies, may render inference futile.

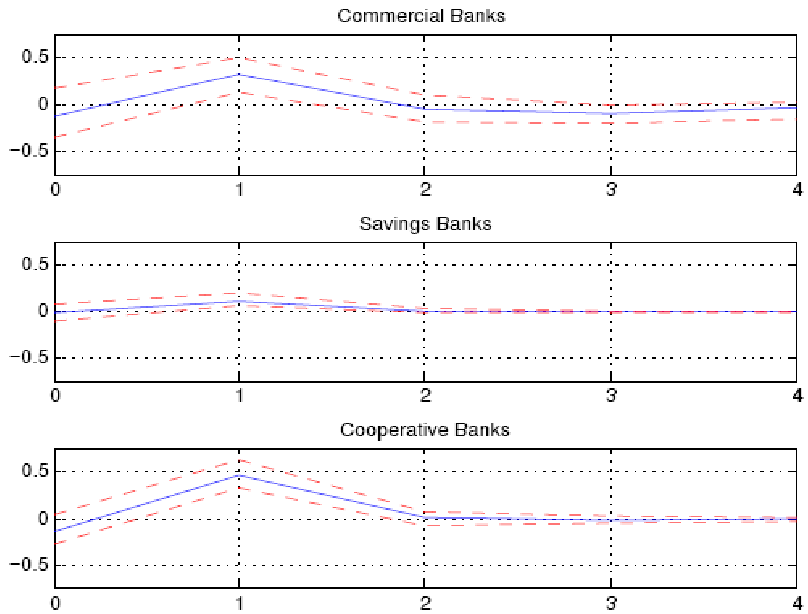
4.3 Dissecting the Evidence: Types of Banks

Banks differ considerably in Germany's so-called three pillar system in terms of both funding structure and investment portfolios (Koetter et al., 2006). Financial stability responses are therefore likely to differ across banking sectors and therefore we also disaggregate our results accordingly (Eickmeier et al., 2006). In figure 3, we present the impulse response functions of three types of local banks: commercial, savings and cooperative banks. [13]

Most of the differences of banking group responses rest to a lesser extent with the dynamics, but rather in the quantitative reactions. The response of savings banks is significant, though relatively small at 0.1% compared to the aggregate response. The median response of the commercial banks is substantially higher. The largest response is the increase in the distress probability of cooperative banks. Commercial and cooperative banks react, respectively, about three and more than four times as much as savings banks.

[13] The focus on local banks originates in the lack of data on distressed events for the large nationwide banks. In a sense, this lack of data in itself presents the result for these large banks: they faced no distressed events during the observation period.

Figure 3. Financial stability responses per banking group



One possible explanation for the fairly low response of local savings banks is related to the two-tier structure of this banking sector. Funding-wise, local savings banks rely to a considerable extent on the respective central savings bank (*"Landesbanken"*) they are associated with. The latter, in turn, raise funds in international bond markets. This two layer structure may shield local savings from interest rate changes due to tighter monetary policy if central savings do not pass through interest rate changes to the full extent. Furthermore, the most important funding source of local savings banks are customer deposits, of which many are in fact savings deposits of households serving as a storage of wealth. These appear to be rather inelastic with respect to a decline in aggregate income and raising opportunity cost due to a hike in nominal interest rates.

While cooperative banks exhibit a similar two-tier structure and also rely extensively on customer deposits as a source of funding, their typical customer portfolio differs considerably from that of an average savings bank. Specifically, these banks are very small and serve historically agricultural and small trade SMEs in rural areas (Hackethal, 2004). The mutual ownership structure of these banks implies that most customers are also members and thus owners of the bank (Altunbas et al., 2001). Consequently, changing interest rates maybe difficult to translate into higher yields on new credits to these member-customers, who however may very well press for more favorable rewards on their deposits. Likewise, the dispersed ownership of these mutual banks could imply poor incentives to monitor managers, who in turn have lower incentives to insulate the bank against excessive risks. Finally, these smallest banks in

Germany's industry may employ relatively unsophisticated risk management systems.[14] Then, a change in the monetary stance may affect funding cost much more directly compared to larger banks if asset-liability management practices are conducted without the adequate use of financial instruments.

These two-tier structures contrast with that of local commercial banks, which have no head institution. This may imply substantial costs to evaluate risks as well as in constructing hedged positions. However, the lower response of local commercials compared to cooperatives could be due to the different ownership structure. In contrast to the latter, local commercial banks have shareholders similar to firms in the corporate sector. These may impose a sufficient degree of discipline on the bank's management. The relative resilience of commercial banks is consistent with shareholders whose quest for profit maximization requires them to at least partially hedge various risks. By contrast, the relatively high exposure to risk of cooperative banks is compatible with a group of shareholders for whom monitoring is less evident.

4.4 Dissecting the Evidence: Types of Distress

Finally, we acknowledge here an argument raised by Oshinsky and Olin (2006) that banks hardly ever face only two options: to fail or not to fail. In contrast, the nature of events that we observe describes diverse degrees of distress. We investigate how the four increasingly severe subcategories of financial strain defined in section 2 are affected by policy shocks. The categories we consider are labeled as "automatic signals" (category I), "warnings by the financial authority" (category II), "measures by the financial authority" (category III) and "defaults and acquisitions" (category IV) in figure 4. We plot how each of these categories respond to monetary policy shocks.

Only events of the relatively weak category II "warnings by the financial authority" respond significantly. This response closely resembles the aggregate response of figure 1. Thus, following a monetary restriction, about 0.40 percent of banks run into difficulties, causing an official warning. 80% of the events within this category comprise admonishment hearings, disapproval, serious letters and warnings to the CEO.

The other categories do not seem to respond significantly. The response of the automatic signals may underestimate the actual impact, because in the case of

[14] The observation that this banking group exhibits the lowest off-balance sheet activities, which contain also financial instruments for e.g. hedging purposes, serves as circumstantial evidence.

Figure 4. Financial stability responses across types of distress

simultaneous events, only the most severe event is registered. The most severe categories III "measures by the financial authority" and IV "defaults and acquisitions" show no systematic reaction to the stance of monetary policy. [15]

This result suggests two implications. First, monetary policy shocks alone do not cause the supervisor to prohibit the bank certain activities, or worse, close the bank. Ultimately, this is not too surprising: the more severe corrective actions seem to be closer related to structural deficiencies of a bank rather than an unexpected change in the monetary stance. Second, and related, a number of banks appear to have entered business activities that brought the bank to the verge of early indications of distress. Put differently, while monetary shocks are unlikely to take a bank out of business entirely due to outright failure, an increasingly competitive environment could have induced managers to exhaust the risk-taking capacities of their business just before catching regulatory attention. However, a monetary shock induces a fairly large portion of institutes to tumble over the rim and be put on the watchlist of financial stability guardians.

[15] Note that since these categories are the most severe, and the severest is always recorded, their non-response is not potentially underestimated.

5 Conclusion

We provide in this study empirical evidence on the nexus between financial and monetary stability. Our approach rests on an integrated micro-macro model. Two main contributions are to our knowledge the first of their kind in financial stability analysis. First, we measure the financial stability directly at the bank level as the probability of distress. Second, we combine this microeconomic model with a structural macroeconomic VAR model that both allows for feedback effects and non-linearities. Our analysis is based on German bank and macro data between 1995 and 2004. Our main findings are fourfold.

First, we find evidence of a trade-off between the two main objectives of central banks: monetary and financial stability. An unexpected tightening of monetary policy by one standard deviation increases the average probability of bank distress by 0.44% after one year.

Second, this significant disturbance of financial stability can not be identified if we employ a model that fails to account for feedback effects. Hence, the necessity to model the intricate dynamics between macroeconomic measures targeted for (monetary) policy making and microeconomic measures of financial stability measured more directly at the bank level is confirmed.

Third, the distinction of responses for different banking sectors exhibits heterogeneous dynamics, which may reflect respectively alternative business models. Publicly owned savings banks react not significantly to a policy shock, potentially due to the refunding function fulfilled by central savings that dampens the immediate impact of monetary shocks. Instead, especially small cooperative banks exhibit pronounced responses. Since these small banks bore the brunt of recent consolidation and competitive pressure, they appear most sensitive to unexpected changes in the monetary stance. The disaggregation of four increasingly severe distress events further suggests that absorbing failure events, such as restructuring mergers or outright closures of banks, are unlikely triggered by monetary shocks. In turn, the significant increase in the likelihood of weaker distress events underpins that monetary shocks can put banks that stretched the riskiness of their business already considerably onto regulator's watchlists.

Finally, the presence of a trade-off between monetary and financial stability has important implications. Among members of the European Monetary Union the mandates for financial supervision and monetary policy are separated between national central banks and the European Central Bank, respectively. Hence, the importance of harmonized definitions of distress and, more importantly, concerted policies in the European System of Central Banks stressed by, for example Allen and Wood (2006) and Borio (2006), is corroborated.

References

Allen, W. A. and G. Wood (2006). Defining and achieving financial stability. *Journal of Financial Stability 2*, 152–172.

Altunbas, Y., L. Evans, and P. Molyneux (2001, November). Bank Ownership and Efficiency. *Journal of Money, Credit, and Banking 33*(4), 926–954.

Aspachs, O., C. A. E. Goodhart, D. P. Tsomocos, and Z. L. (2007). Towards a measure of financial fragility. *Annals of Finance 3*(1), 37–74.

Barth, J., G. Caprio, and R. Levine (2001). The Regulation and Supervision of Banks around the World: A New Database. *World Bank Working Paper* (2588).

Benink, H. and G. Benston (2005). The Future of Banking Regulation in Developed Countries: Lessons from and for Europe. *Financial Markets, Institutions & Instruments 14*(5), 289–328.

Borio, C. (2006). Monetary and financial stability: Here to stay? *Journal of Banking & Finance 30*, 3407–3414.

Carletti, E., P. Hartmann, and S. Ongena (2006). The Economic Impact of Merger Control: What Is Special About Banking? *EFA 2006 Zurich Meetings*.

Cole, R. and J. Gunther (1995). Separating the Likelihood and Timing of Bank Failure. *Journal of Banking & Finance 19*, 1073–1089.

De Bandt, O. and P. Hartmann (2000). Systemic risk: A survey. *European Central Bank Working Paper 35*.

Deutsche Bundesbank (2006, November). *Financial Stability Review*. Frankfurt a.M.: Deutsche Bundesbank.

Driffill, J., Z. Rotondi, P. Savona, and C. Zazzara (2006). Monetary policy and financial stability: What role for the futures market? *Journal of Financial Stability 2*, 95–112.

ECB (2006). Country-Level Macro Stress-Testing Practices. In *Financial Stability Report*, pp. 147–154. European Central Bank.

Eickmeier, S., B. Hofmann, and A. Worms (2006). Macroeconomic fluctuations and bank lending: evidence for Germany and the euro area. *Deutsche Bundesbank Discussion Paper Series 1 34*.

Estrella, A., S. Park, and S. Peristiani (2000). Capital ratios as predictors of bank failure. *Federal Reserve Bank of New York: Economic Policy Review*, 33–52.

Gan, J. (2004). Banking market structure and financial stability: Evidence from the texas real estate crisis in the 1980s. *Journal of Financial Economics 73*.

Goodhart, Charles, A., P. Sunirand, and D. P. Tsomocos (2004). A Model to Analyse Financial Fragility: Applications. *Journal of Financial Stability 1*, 1–30.

Goodhart, C. A. E. (2006). A Framework for Assessing Financial Stability. *Journal of Banking & Finance 30*, 3415–3422.

Goodhart, C. A. E., P. Sunirand, and D. P. Tsomocos (2006). A Model to

Analyse Financial Fragility. *Economic Theory 27*, 107–142.

Hackethal, A. (2004). German banks and banking structure. In J. Krahnen and R. Schmidt (Eds.), *The German Financial System*, pp. 387–424. Oxford: Oxford University Press.

Hoggarth, G., A. Logan, and L. Zicchino (2005). Macro stress tests of UK banks. *BIS Paper 22*.

Hosmer, D. W. and S. Lemshow (2000). *Applied Logistic Regression* (2nd ed.). New York: Wiley.

Jacobson, T., J. Lindé, and K. Roszbach (2005). Exploring Interactions between Real Activity and the Financial Stance. *Journal of Financial Stability 1*, 308–341.

Kick, T. and M. Koetter (2007). Slippery Slopes of Stress: Ordered Failure Events in German Banking. *Journal of Financial Stability forthcoming*.

King, T. B., D. A. Nuxoll, and T. J. Yeager (2005). Are the Causes of Bank Distress Changing? Can Researchers Keep Up? *FDIC Center for Financial Research Working Paper 3*.

Koetter, M., J. W. B. Bos, F. Heid, J. W. Kolari, C. J. M. Kool, and D. Porath (2007). Accounting for Distress in Bank Mergers. *Journal of Banking & Finance forthcoming*.

Koetter, M., T. Nestmann, S. Stolz, and M. Wedow (2006). Still Overbanked and Unprofitable? Two Decades of German Banking. *Kredit und Kapital 39*(4), 497–511.

Lang, G. and P. Welzel (1999). Mergers Among German Cooperative Banks: A Panel-Based Stochastic Frontier Analysis. *Small Business Economics 13*(4), 273–86.

Oosterloo, S. and J. de Haan (2004). Central banks and financial stability: a survey. *Journal of Financial Stability 1*, 257–273.

Oosterloo, S., J. de Haan, and R. Jong-a Pin (2007). Financial stability reviews: A first empirical analysis. *Journal of Financial Stability 2*, 337–355.

Oshinsky, R. and V. Olin (2006). Troubled Banks: Why Don't They All Fail? *FDIC Banking Review 18*(1), 23–44.

Padoa-Schioppa, T. (2003). Central banks and financial stability: exploring a land in between. In V. Gaspar, P. Hartmann, and O. Sleijpen (Eds.), *The Transformation of the European Financial System*, pp. 147–154. European Central Bank.

Peersman, G. (2005). What caused the early Millennium Slowdown? Evidence based on Vector Autoregressions. *Journal of Applied Econometrics 20*, 185–207.

Poloz, S. S. (2006). Financial stability: A worthy goal, but how feasible? *Journal of Banking & Finance 30*, 3423–3427.

Porath, D. (2006). Estimating Probabilities of Default for German Savings Banks and Credit Cooperatives. *Schmalenbach Business Review 58*, 214–233.

Schinasi, G. and J. Fell (2005). Assessing financial stability: Exploring the boundaries of analysis. *National Institute Economic Review 192*(1), 102–

117.

Schumacher, C. and J. Breitung (2006). Real-time forecasting of GDP based on a large factor model with monthly and quarterly data. *Deutsche Bundesbank Discussion Paper Series 1: Economic Studies 33*.

Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *Journal of Business 74*, 101–124.

Smets, F. and R. Wouters (1999). The Exchange Rate and Monetary Transmission in Germany. *De Economist 147*(4), 489–521.

The Economist (2007). Fretting about financial stability. *The Economist February 1st*.

van den End, J., M. Hoeberichts, and M. Tabbae (2006). Modelling Scenario Analysis and Macro Stress-testing. *De Nederlandsche Bank Working Paper 119*.

Wheelock, D. C. and P. W. Wilson (2000). Why Do Banks Dissapear? The Determinants of U.S. Bank Failures and Acquisitions. *The Review of Economics and Statitistics 82*, 127–138.

Appendix

Table 3
Mean CAMEL covariates per banking group and distress category

Variable		All	Banking groups			Distress category			
			Com'cl	*Sav's*	*Coop's*	*I*	*II*	*III*	*IV*
Equity ratio	c_1	8.45	14.67	7.64	8.20	9.98	7.77	7.54	8.22
Total reserves	c_2	0.93	0.21	1.39	0.86	0.48	0.72	0.36	0.44
Customer loans	a_1	11.13	13.12	11.13	11.03	13.58	12.98	15.38	13.83
Off-balance sheet	a_2	3.14	6.49	2.78	2.96	3.00	3.07	3.96	3.62
Size	a_3	19.22	20.16	20.68	18.65	19.63	19.20	19.24	19.03
RoE	e_1	14.80	7.68	19.08	14.18	1.08	7.30	1.46	2.99
Liquidity	l_1	6.70	11.35	4.43	7.04	8.71	7.69	7.92	7.63
Change in real GDP	m_1	1.70	1.67	1.66	1.72	1.56	1.56	1.73	1.79
Inflation	m_2	0.92	0.95	0.91	0.92	0.82	0.68	0.89	0.65
Interest (3 months)	m_3	3.79	3.80	3.77	3.80	3.84	3.59	3.78	3.69
Observations		26,012	1,509	5,569	18,736	88	446	252	347

Notes: All variables measured in percent except size; c_1: Core capital to risk-weighted assets;

c_2: reserves to total assets; a_1: Customer loans to total assets; a_2: Off balance sheet activities to total assets

a_3: log of total assets; e_1: Return on equity; l_1: Net interbank assets and cash to total assets

Table 4
Logit model parameters per banking groups and distress categories

	All	Banking groups			Distress categories			
Variable		*Com'cl*	*Sav's*	*Coop's*	*I*	*II*	*III*	*IV*
Equity ratio	-0.0787***	0.0174	-0.1949**	-0.1320***	0.0130	-0.1346***	-0.1536***	-0.0608**
	(0.0173)	(0.0119)	(0.0983)	(0.0247)	(0.0234)	(0.0274)	(0.0367)	(0.0266)
Total reserves	-0.7558***	-0.6941*	-0.8506***	-0.6644***	-0.9732***	-0.2981***	-1.5298***	-1.2238***
	(0.0859)	(0.4134)	(0.2007)	(0.1067)	(0.2734)	(0.0756)	(0.4497)	(0.1549)
Customer loans	0.0224***	0.0053	0.0465***	0.0203***	0.0166*	0.0210***	0.0292***	0.0193***
	(0.0028)	(0.0070)	(0.0130)	(0.0036)	(0.0086)	(0.0046)	(0.0054)	(0.0048)
Off-balance sheet	-0.0038	-0.0247	0.0192	-0.0010	-0.0727*	-0.0361**	0.0181	0.0124
	(0.0095)	(0.0205)	(0.0737)	(0.0138)	(0.0389)	(0.0184)	(0.0164)	(0.0131)
Size	-0.0547***	0.0117	-0.1688	0.1595***	0.1462**	-0.0558*	-0.0614	-0.1516***
	(0.0212)	(0.0916)	(0.1408)	(0.0343)	(0.0622)	(0.0325)	(0.0378)	(0.0404)
RoE	-0.0411***	-0.0108**	-0.0598***	-0.0443***	-0.0354***	-0.0327***	-0.0377***	-0.0377***
	(0.0022)	(0.0054)	(0.0091)	(0.0030)	(0.0047)	(0.0026)	(0.0037)	(0.0029)
Liquidity	0.0286***	-0.0005	0.1110***	0.0380***	0.0161	0.0363***	0.0327***	0.0156*
	(0.0052)	(0.0085)	(0.0382)	(0.0080)	(0.0124)	(0.0074)	(0.0092)	(0.0095)
Change in real GDP	-0.2988***	-0.0016	-0.3749	-0.2584***	-1.4865***	-0.5429***	0.0953	-0.0295
	(0.0800)	(0.3148)	(0.3436)	(0.0865)	(0.2825)	(0.1219)	(0.1679)	(0.1447)
Inflation	-0.5222***	-0.4397	-0.7368***	-0.4378***	-1.4000***	-0.7782***	-0.0323	-0.4512***
	(0.0731)	(0.2735)	(0.2859)	(0.0806)	(0.2565)	(0.1112)	(0.1591)	(0.1259)
Interest (3 months)	0.2117**	0.2068	0.3133	0.1491	1.9196***	0.3566**	-0.2239	-0.0538
	(0.1035)	(0.3801)	(0.4522)	(0.1109)	(0.4018)	(0.1624)	(0.2157)	(0.1797)
Constant	-0.7354	-3.7112*	1.1132	-4.2133***	-11.3544***	-1.4457*	-0.8691	0.5311
	(0.5122)	(2.1470)	(3.1157)	(0.7673)	(1.6585)	(0.7953)	(0.9941)	(0.9161)
Observations	26012	1509	5569	18736	24967	25325	25131	25226
R-squared	0.1133	0.0405	0.2031	0.1206	0.1218	0.068	0.1515	0.1199
AUR[1)]	0.7741	0.6641	0.8443	0.7796	0.8354	0.7395	0.8501	0.7963

Notes: Robust standard errors in parentheses; ***,**,* denote significant at the 1,5,10 percent level, respectively.
For variable descriptions see table 3. [1)] Area under the Receiver Operating Characteristics curve (Hosmer and Lemshow, 2000).

Table 5
Logit model neglecting macroeconomic covariates

	All	**Banking groups**			**Distress categories**			
Variable		*Com'cl*	*Sav's*	*Coop's*	*I*	*II*	*III*	*IV*
Equity ratio	-0.0751***	0.0176	-0.2346**	-0.1246***	0.0107	-0.128***	-0.1497***	-0.0562**
	(0.0171)	(0.0117)	(0.1005)	(0.0245)	(0.0241)	(0.0267)	(0.0367)	(0.0257)
Total reserves	-0.6885***	-0.7207*	-0.7636***	-0.5939***	-0.8495***	-0.2148***	-1.4978***	-1.1476***
	(0.0827)	(0.4097)	(0.1903)	(0.103)	(0.2674)	(0.0726)	(0.4379)	(0.1476)
Customer loans	0.0188***	0.0059	0.0306**	0.0164***	0.0144	0.0158***	0.0274***	0.0156***
	(0.0028)	(0.0072)	(0.0125)	(0.0035)	(0.0088)	(0.0047)	(0.0054)	(0.0048)
Off-balance sheet	-0.0108	-0.0294	0.0149	-0.0067	-0.0935**	-0.0476**	0.0153	0.0065
	(0.0101)	(0.0205)	(0.0733)	(0.0145)	(0.0432)	(0.0196)	(0.0168)	(0.0137)
Size	-0.0315	0.016	-0.167	0.199***	0.191***	-0.0206	-0.052	-0.1309***
	(0.0206)	(0.0916)	(0.1363)	0.0334	(0.0608)	(0.0312)	(0.0369)	(0.0387)
RoE	-0.043***	-0.008	-0.0621***	-0.0466***	-0.0387***	-0.0354***	-0.0382***	-0.0387***
	(0.0022)	(0.0051)	(0.009)	(0.0029)	(0.0043)	(0.0024)	(0.0035)	(0.0028)
Liquidity	0.0287***	-0.0008	0.102***	0.039***	0.0224**	0.0382***	0.0313***	0.012
	(0.0052)	(0.0085)	(0.0398)	(0.0078)	(0.0109)	(0.0073)	(0.0092)	(0.0098)
Constant	-1.3072**	-3.3692	1.5279	-5.2177***	-8.5205***	-2.3024***	-1.764*	-0.4521
	(0.5122)	(2.147)	(3.1157)	(0.7673)	(1.6585)	(0.7953)	(0.9941)	(0.9161)
Observations	26,012	1,509	5,569	18,736	24,967	25,325	25,131	25,226
R-squared	0.103	0.024	0.188	0.113	0.095	0.051	0.149	0.106
AUR	0.766	0.623	0.839	0.772	0.826	0.723	0.850	0.784

Notes: Robust standard errors in parentheses; ***,**,* denote significant at the 1,5,10 percent level, respectively.
For variable descriptions see table 3. 1)Area under the Receiver Operating Characteristics curve (Hosmer and Lemshow, 2000).