Monetary policy and financial (in)stability: An integrated micro–macro approach

F. De Graeve a,*, T. Kick b, c, M. Koetter b, c, d, *

a Department of Financial Economics, Ghent University, Wilsonplein 5D, 9000 Ghent, Belgium
b Deutsche Bundesbank, PO Box 10 06 02, 60006 Frankfurt a.M., Germany
c Institute for the World Economy, Düsternbrooker Weg 120, 24105 Kiel, Germany
d University of Groningen, Faculty of Economics, PO Box 800, 9700 AV Groningen, The Netherlands

Received 6 March 2007; received in revised form 30 August 2007; accepted 13 September 2007
Available online 10 October 2007

Abstract

Evidence on central banks’ twin objective, monetary and financial stability, is scarce. We suggest an integrated micro–macro approach with two core virtues. First, we measure financial stability directly at the bank level as the probability of distress. Second, we integrate a microeconomic hazard model for bank distress and a standard macroeconomic model. The advantage of this approach is to incorporate micro information, to allow for non-linearities and to permit general feedback effects between financial distress and the real economy. We base the analysis on German bank and macro data between 1995 and 2004. Our results confirm the existence of a trade-off between monetary and financial stability. An unexpected tightening of monetary policy increases the probability of distress. This effect disappears when neglecting microeffects and non-linearities, underlining their importance. Distress responses are largest for small cooperative banks, weak distress events, and at times when capitalization is low. 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 national bank supervisors.

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JEL classification: E42; E52; E58; G21; G28

Keywords: Financial stability; Stress-tests; Bank distress; Monetary policy

* Corresponding authors. Tel.: +31 50 363 3633.
E-mail addresses: ferre.degraeve@ugent.be (F. De Graeve), thomas.kick@bundesbank.de (T. Kick), m.koetter@rug.nl (M. Koetter).

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doi:10.1016/j.jfs.2007.09.003
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 a fairly successful record to control inflation, but increasing concerns regarding financial stability in light of increasing competition and financial integration (Borio, 2006). In addition, if the financial stability of individual banks differs, this is likely to affect the transmission mechanism of monetary policy, too. For example, Kishan and Opiela (2000) demonstrate that loan supply of poorly capitalized banks reacts more sensitively compared to well-capitalized peers.

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, 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 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 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 supervisor’s definition of problem banks used for supervisory policy.²

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² Note that the probability of bank distress really is a measure of a banks stability mirror image, i.e. fragility. We maintain throughout the terminology financial stability as to conform with the wording of policy makers’ objectives.
We 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. In a pure macro model, many potentially relevant effects may be obscured due to the loss of information following data aggregation. We find that this effect is substantial. 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. In turn, with a pure micro approach it is difficult to interpret movements in aggregate variables. Many macro stress-testing exercises incorporate the real economy by specifying some unconditional distribution for aggregate variables. A first drawback of this approach is to preclude financial–macro feedback, also called second-round effects. Second, there is no straightforward economic interpretation of the macro fluctuations, for example in terms of structural shocks. Both are 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 probabilities of bank distress to both bank-specific 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. This model allows us to measure the interactions between monetary policy and financial regulation more explicitly compared to previous studies on macroeconomic stress. Our study is thus akin to Jacobson et al. (2005), who analyze interactions between the Swedish macroeconomy and the corporate sector using vector autoregressive (VAR) techniques combined with probabilities of distress of individual firms derived from a hazard rate model.

We differ, however, in four 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 disaggregate our measure of distress and according responses to monetary policy shocks along two dimensions: different degrees of distress and different types of banks, respectively. Third, 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. 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, but let the data determine their outcome. Fourth, 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 result is that a contraction in monetary policy increases the average probability of distress of banks by 0.44%, which resembles a third of its 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. Moreover, the effects of monetary policy on banking sector distress are more severe when the banking sector is poorly capitalized. To the extent that banking distress carries over to banks’ lending behavior, this is in line with the bank lending channel literature. Our results suggest monetary policy transmission is intertwined with the financial health of the banking sector. In sum, the interdependency of the twin objective highlights the necessity for close collaboration between guardians of both price and 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. We use the distress database of the Bundesbank to model bank distress, which is particularly insightful for our questions of research. The German banking sector experienced substantial fluctuations in the occurrence of distressed events. The sample contains more than 1100 events and the aggregate annual frequency of distress fluctuates approximately between 2% and 7% as shown in Table 1.

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 a larger dependence on non-interest income and financial market 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 distress suggests that 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 a dichotomous destiny of either failure or survival. Instead, a number of different
Table 1
Annual distress frequency according to banking group and distress category

<table>
<thead>
<tr>
<th>Year</th>
<th>All</th>
<th>Banking groups</th>
<th>Distress categories</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Com’cl</td>
<td>Sav’s</td>
</tr>
<tr>
<td>1995</td>
<td>1.9%</td>
<td>2.2%</td>
<td>0.3%</td>
</tr>
<tr>
<td>1996</td>
<td>2.5%</td>
<td>4.9%</td>
<td>0.8%</td>
</tr>
<tr>
<td>1997</td>
<td>3.4%</td>
<td>6.3%</td>
<td>0.9%</td>
</tr>
<tr>
<td>1998</td>
<td>4.7%</td>
<td>7.5%</td>
<td>2.1%</td>
</tr>
<tr>
<td>1999</td>
<td>5.6%</td>
<td>4.4%</td>
<td>0.7%</td>
</tr>
<tr>
<td>2000</td>
<td>5.0%</td>
<td>5.0%</td>
<td>1.6%</td>
</tr>
<tr>
<td>2001</td>
<td>6.9%</td>
<td>9.2%</td>
<td>2.2%</td>
</tr>
<tr>
<td>2002</td>
<td>7.0%</td>
<td>4.4%</td>
<td>3.4%</td>
</tr>
<tr>
<td>2003</td>
<td>6.6%</td>
<td>4.7%</td>
<td>1.8%</td>
</tr>
<tr>
<td>2004</td>
<td>4.1%</td>
<td>0.8%</td>
<td>1.1%</td>
</tr>
<tr>
<td>Observations</td>
<td>26012</td>
<td>1509</td>
<td>5569</td>
</tr>
</tbody>
</table>

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. 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% of liable capital according to §24(1) 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, weaker incidents are 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.

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4 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.
3. Methodology and auxiliary results

We first introduce our approach to measure financial stability at the bank level with a hazard rate model. The particular model deployed is a logit model that relates bank-specific probabilities of distress to bank-specific as well as macroeconomic conditions. Subsequently, we discuss our specification of the reduced form macro model. The macro model is a VAR for key macroeconomic aggregates. Up to this point, our methodology is very similar to the one of Jacobson et al. (2005). The latter identify a monetary policy shock in the macro model and verify its impact on the micro financial model. The financial impact then may affect macro developments in a subsequent period. In a third subsection we lay out the way we combine the reduced form micro and macro models, which is different from that in Jacobson et al. (2005). In particular, we combine the reduced form micro and macro models in one integrated system. We then identify shocks in the combined micro–macro-system. This has two virtues relative to the approach of Jacobson et al. (2005). First, the identification of the shock takes into account the financial effect, as well as possible non-linearities. Second, we do not need to make assumptions about the timing of real–financial interactions. We regard this as an important feature of models analyzing stability in the financial sector. Specifically, since a broad consensus on theoretical models of financial stability does not exist yet, somewhat contrary to monetary policy models, imposing restrictions on financial sector interactions with the real economy is harder to defend.

3.1. A microeconomic measure of financial stability

The microeconomic component of our integrated model captures the driving forces of the probability of distress (PD) among banks. In particular, we estimate the conditional probability of distress with a logit model:

\[ PD_{it} = \frac{e^{\beta X_{it-1} + \pi Z_{t-1}}}{1 + e^{\beta X_{it-1} + \pi Z_{t-1}}} \]  

(1)

Here, \( PD_{it} \) denotes the probability that bank \( i \) will face distress 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 \( \beta \) and \( \pi \) are parameters to estimate. 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.\(^5\)

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., 2006).\(^6\) Within each category we conduct univariate tests to identify a shortlist of covariates that maximize explanatory power.\(^7\) Ultimately, we select a 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 A.1 in the Appendix A.

\(^5\) 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 1 year lags for all variables.

\(^6\) CAMEL: capitalization, asset quality, management, earnings, liquidity.

\(^7\) For a more detailed description of model selection for Bundesbank data see Porath (2006), Koetter et al. (2007) and Kick and Koetter (2007).
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 included to establish the link with the macroeconomic VAR model. Moreover, the evolution of both bank-specific and macroeconomic covariates over time, depicted in Fig. A.1 in the Appendix A, shows that no individual model component alone appears to perfectly coincide with observed distress events.\(^8\) This corroborates Porath’s (2006) point that macroeconomic and bank-specific covariates are jointly relevant to predict bank distress.

Consider first the hazard rate model in Eq. (1) for the sample pooled across banking groups and distress categories depicted in Table A.2. This hazard rate model exhibits a good fit as witnessed by a pseudo-\(R^2\) of approximately 11%. This is on the low side compared to Jacobson et al. (2005), who report aggregated (Laitila) pseudo-\(R^2\)s calculated for the full sample between 16% and 39%.\(^9\) While these are in line with results reported in other corporate failure studies, our goodness of fit measure is fairly well in line with international bank failure studies (see for example Ramirez, 2003 reporting \(R^2\) between 6% and 13%) and previous studies on German bank distress.\(^10\) Hence, the difference of these measures may merely reflect the different hazard rate models, namely corporate versus bank distress, respectively.

Finally, Wooldridge (2002) and Hosmer and Lemshow (2000) caution not to over-emphasize pseudo-\(R^2\)s to assess the adequacy of limited dependent variable models. In fact, the ability of hazard rate models to correctly discern events from non-events is crucial. The classification of predicted events depends on the probability cutoff level beyond which an observation is assigned to either one of these classes. In contrast to studies reporting types I and II classification errors (Kolari et al., 2002), we follow Hosmer and Lemshow (2000) and evaluate the discriminatory power of the model over the range of alternative cutoff levels between zero and one by means of the area under the Receiver Operating Characteristics (ROCs) curve. The area under the ROCs curve (AUR) measures the percentage of correctly classified events (sensitivity) versus one minus the percentage of correctly classified non-events (specificity). It is thus more general and informative compared to types I and II errors or \(R^2\).

According to Hosmer and Lemshow (2000), the reported AUR values of around 77% 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 comforting that virtually all coefficients are significantly different from zero and exhibit signs and magnitudes in line with other bank failure studies. We also depict parameter estimates for group-specific logit models in the right-hand panels of Table A.2. 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 its relation to bank stability.

Table 2 sheds light on the importance of incorporating macroeconomic variables in the micro model. The table compares two measures of fit across our baseline model with and without macro covariates.\(^11\)

Including macro variables helps the micro model in two important ways. First, consider the aggregate root mean-squared errors (A-RMSE). This measure reflects the success of both models

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\(^8\) We discuss the respective contribution to the discriminatory power of the micro model in more detail below.

\(^9\) We check if this could be attributed to our choice of 1 year lags for all covariates in the bank hazard model, i.e. including macro covariates, which differs from the contemporaneous specification of macro terms in Jacobson et al. (2005). This turns out to be not the case since \(R^2\) declines to 10.6% in the latter specification.

\(^10\) For example, Koetter et al. (2007) and Kick and Koetter (2007) report \(R^2\) between 11% and 13%, respectively.

\(^11\) Parameter estimates without macro variables are in Table A.3 in the Appendix A.
in capturing the aggregate rate of distress over time. Macro variables reduce projection errors by at least 14% and up to 40%. 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. In particular, we observe a gain in AUR of up to 6% for commercial banks.

This model comparison exercise implies, first, that the macro variables improve the estimation of the marginal effects of the hazard 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 importance 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 autoregressive model (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 as pointed out by, for instance, the ECB (2005). 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. VARs render the most flexible way to do so.12

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Notes: A-RMSE: aggregate root mean squared error; AUR: area under the Receiver Operating Characteristics curve.

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Table 2
The contribution of macro covariates to discern bank-specific distress

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Banking groups</th>
<th>Distress category</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Com’cl</td>
</tr>
<tr>
<td>A-RMSE</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Micro only</td>
<td>0.015</td>
<td>0.024</td>
<td>0.008</td>
</tr>
<tr>
<td>Micro and macro</td>
<td>0.011</td>
<td>0.016</td>
<td>0.007</td>
</tr>
<tr>
<td>Reduction (%)</td>
<td>28.45</td>
<td>36.17</td>
<td>12.79</td>
</tr>
<tr>
<td>AUR</td>
<td></td>
<td></td>
<td>0.77</td>
</tr>
<tr>
<td>Micro only</td>
<td>0.77</td>
<td>0.66</td>
<td>0.84</td>
</tr>
<tr>
<td>Micro and macro</td>
<td>0.77</td>
<td>6.65</td>
<td>0.68</td>
</tr>
<tr>
<td>Gain (%)</td>
<td>1.04</td>
<td>6.65</td>
<td>0.68</td>
</tr>
</tbody>
</table>

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12 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 within a framework for financial stability, we refrain from imposing them.
Specifically, the macroeconomic model consists of a quarterly VAR for 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 model thus has the following structure:

$$Z_t = \begin{bmatrix} Y \\ P \\ R \end{bmatrix}_t = \Pi_{MM} \begin{bmatrix} Y \\ P \\ R \end{bmatrix}_{t-1} + \Pi_{MF} PD_{t-1} + u_t$$

where the $\Pi$ matrices capture the reduced form feedback coefficients from macro to macro ($\Pi_{MM}$, dimension $3 \times 3$) and from the financial sector to the macro side ($\Pi_{MF}$, $3 \times 1$), respectively.

### 3.3 The integrated micro–macro model

#### 3.3.1 The reduced form

After describing both the micro and macro blocks of the model, we now focus on the combined model. Note that the model in Eq. (2) is a plain VAR augmented with a measure of financial stability as an additional explanatory variable. Put differently, this model does not incorporate any feedback mechanism from macroeconomic conditions to the financial sector. Therefore, we expand the macro system with one equation, namely the data generating process for the aggregate probability of distressed events originating from the micro model.

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

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. They do, however, retain an important role in the model. That is, the coefficients $\Pi_{FM}$ 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 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 balance sheet of the financial sector, an experiment we conduct in Section 4.6.

Considering the micro component in the integrated VAR improves the fit considerably as shown by the improvement of aggregate RMSE in Table 3. Note that, in contrast to the comparison of hazard rate models before, we compare here the integrated model relative to a plain VAR merely augmented with the frequency of distress as an additional endogenous variable. The improvement

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13 For expositional purposes, we write the system as a first order VAR. The implementation of the approach, however, does not constrain lag length.

14 Therefore, they do not appear as separate variables in the combined dynamic system. We aim to endogenize banks’ balance sheets in future research.
Table 3

The contribution of micro to the integrated VAR

<table>
<thead>
<tr>
<th>A-RMSE</th>
<th>All Banking groups</th>
<th>Distress category</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Com’cl Sav’s Coop’s</td>
<td>I II III IV</td>
</tr>
<tr>
<td>Macro only (VAR)</td>
<td>0.016 0.031 0.018</td>
<td>0.018 0.009 0.010</td>
</tr>
<tr>
<td>Micro and macro</td>
<td>0.011 0.016 0.007</td>
<td>0.013 0.002 0.008</td>
</tr>
<tr>
<td>Reduction (%)</td>
<td>31.00 48.75 61.05</td>
<td>26.70 81.43 18.59</td>
</tr>
</tbody>
</table>

Notes: A-RMSE: aggregate root mean-squared error.

of 31% underpins that the micro model also improves the description of the aggregate distress rate relative to a specification including macro only, i.e. a plain VAR. This substantial gain highlights the importance of accounting for both micro information and non-linearities, which help to capture the dynamics of the aggregate distress rate.

3.3.2. The structural form

Note the following about the structure of the combined micro–macro model (3). First, the model is a reduced form. 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 is measured 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 can identify the above combined micro–macro-system. A complete structural model, as in Eq. (4) below, describes the entire set of relations (both contemporaneous \((A, 4 \times 4)\) and lagged \((B, 4 \times 4)\)) between all variables in the system, and thus the response to each possible structural shock \(s_t\) \((4 \times 1)\).

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

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 Eq. (3) and, second, what we “know” happens after a monetary policy shock. Regarding the latter, we define a policy shock as one which initially has a positive effect on the interest rate, while neither increasing growth nor inflation \((R > 0, Y \leq 0, P \leq 0)\). This is a common set of restrictions in the macro literature (Peersman, 2005).

We identify monetary policy shocks using sign restrictions. Sign restrictions are used rather than a recursive identification scheme. There are, within the current setup, a number of reasons for doing so. First, this approach naturally extends into considering other types of structural shocks, such as demand and supply shocks (Peersman, 2005). Though beyond the scope of the current paper, identifying other shocks may be of particular interest in stress-testing exercises. Second, note that the restrictions we impose \((R\) rises, \(Y\) and \(P\) do not fall) nest the recursive (or
Choleski) response. In a recursive identification scheme the imposed instantaneous response is that $R$ rises, while $Y = 0$ and $P = 0$. In that sense, our identification is more general, relative to that of Jacobson et al. (2005). The approach differs in an important additional respect. The model of Jacobson et al. (2005) does not allow for any contemporaneous feedback from the financial side to the real economy. Our model can encompass such effects. The absence of a rigorous, widely accepted theory of financial stability makes it clear that such feedback effects should not be precluded a priori. The advantage of sign restrictions is that we can remain fully agnostic about the distress response to a monetary policy shock. A final virtue of the use of sign restrictions is related to the periodicity of the data. Our baseline model is annual in frequency. Many of the more traditional exclusion restrictions are only reasonable for higher frequencies.

3.4. Periodicity of distress

The data used to estimate the micro and macro models presented above have different frequencies. While the micro model is based on annual data, VARs are typically estimated on higher frequency data, quarterly in our case. The different periodicity is dealt with as follows. We estimate the reduced forms of the micro model (1) and the macro (2) model separately. Prior to combining the two models, we convert the VAR to its annual form. This makes the frequency equal for both models, enabling their combination. An alternative approach could combine the models at the quarterly frequency. However, because such approaches are very demanding in terms of the time series dimension of the data, we combine the models at the lower, annual frequency.

Quarterly estimation of the macrocomponent of the model requires us to transform the annual distress measure to a quarterly series by employing an according indicator. The latter is constructed from three sub-databases of the annual distress catalogue of the Bundesbank, which indicate specific dates for individual measures (“Maßnahmen”), incidents (“Vorkommnisse”) and (distressed) mergers. While these subsets cover around 75% of all events specified in Eq. (1), the quarterly distress indicator is thus an approximation. Akin to Hoggarth et al. (2005), we use the former as a weighting scheme to distribute the annual distress series to quarters. Because there remains some periodicity, the quarterly series is smoothed via a four quarter moving average in a second step. The annual and quarterly raw data as well as the de-seasoned weighted annual series are shown in Fig. 1.

The series follow similar trends over time and thus provide only limited reason for concern regarding significant changes of their respective informational content. But naturally, any approach to distribute the annual distress series across quarters is inherently heuristic. The first reason for the suitability of this approach is in our case that the quarterly series used to construct the weighting scheme is closely related to the definition of distress according to regulatory authorities. Instead of using some correlated variable without a necessarily meaningful economic relation, the data we exploit forms the major share of raw data to generate the distress database of the Bundesbank. Hence, the information contained in these data should not contaminate our estimates of probabilities of distress. It might, however, add measurement error regarding the exact timing of events.

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15 For example, category III events contain capital injections, which could not be included in the quarterly series since data are only available annually.

16 For instance, a number of events are only recorded at the end of the year.

17 Different periodicity in macroeconomic studies is a frequently encountered problem. See Schumacher and Breitung (2006) for a discussion and a suggested remedy.
As a robustness check, we also execute an alternative approach to tackling the frequency mismatch and estimate the integrated model on a quarterly basis. Aware of the uncertainty about the exact timing of the distressed events, we estimate (1) where the left-hand side information now originates from the raw quarterly distress data. For the right-hand side variables, the balance sheet variables are assumed constant within a given year while the true quarterly macro-aggregates are incorporated. A similar approach is used in Jacobson et al. (2005).

According parameter estimates of the micro model are depicted in Table A.4 in the Appendix A. Additional measurement error in the quarterly model appears to be present as shown by a lower $R^2$ of around 8.2%. However, the discriminatory power deteriorates only slightly from an AUR value of 77 to 76. This indicates that the periodicity transformation does not change the informational content of the regressors for the PD measure substantially. Importantly, and in line with Jacobson et al. (2005), parameters of bank-specific covariates are hardly affected in terms of the direction of effects, their significance, and magnitude. This is comforting given the dominant contribution of bank-specific rather than macroeconomic effects in the hazard model. Macro parameters mimic this result with the exception of the estimate of the coefficient of the interest rate. Its change, however, does not necessarily imply that according responses simulated for the monetary shock are spurious. This, in turn, depends ultimately on the resulting responses of financial stability to monetary shocks, which we discuss in Section 4.3 below.

4. Results

We first analyze the effects of monetary policy shocks on financial distress in the combined micro–macro-system to indicate the average historical interrelation between monetary policy stance and the degree of financial stability. Subsequently, we present evidence on the importance of the micro–macro interdependence in this model, the robustness of results relative to an alternative
periodicity treatment, as well as detailed evidence according to different banking groups, types of distress, and capitalization states of the banking industry.

4.1. The aggregate response

Fig. 2 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. Therefore, a one standard deviation increase of the interest rate of around 0.1%, is compatible with, e.g., a two quarter increase of 20 basis points, or a one quarter increase of 40 basis points. On the macro side, this reduces GDP growth and inflation with 0.2% and 0.15%, respectively, during the first year. These magnitudes are comparable to other monetary VARs.

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 1 year. 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. A variance decomposition depicted in Table 3 confirms the quantitative significance of this response. Up to about one third of the variance of distress can be accounted for by monetary policy shocks. At the same time, the portion of variance explained of the macro variables is in line with extant macroeconomic research. Monetary shocks are not one of the main drivers of real fluctuations. On average, they explain about 10% of the forecast error variance of growth and inflation.

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18 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.

19 Smets and Wouters (1999) report for Germany virtually identical point estimates.
Table 4
Variance decomposition of the integrated model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Bounds</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lower</td>
</tr>
<tr>
<td>$Y$ (change in real GDP)</td>
<td>2%</td>
</tr>
<tr>
<td>$P$ (inflation)</td>
<td>2%</td>
</tr>
<tr>
<td>$R$ (interest rate (3 months))</td>
<td>1%</td>
</tr>
<tr>
<td>$D$ (distress frequency)</td>
<td>5%</td>
</tr>
</tbody>
</table>

The significant increase in the distress frequency is important since it shows that monetary policy affects the stability of the financial sector. In particular, it 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.

Given the institutional dichotomy between national supervisory authorities, usually central banks and/or other government agencies (Barth et al., 2001), 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.

While qualitatively in line with Jacobson et al. (2005), our result differs in terms of timing since it contradicts the immediate financial stability response reported for the Swedish economy. A potential explanation could relate to the fact that they measure financial stability as corporates’ probabilities of default. Thus, the result for the German sample might reflect that corporate distress relates to bank distress with some lag. An economic rational is that especially banks possess expertise to form expectations and insure against changes in monetary policy while corporates do not (to that degree of sophistication). Hence, a monetary contraction might have no significant instantaneous impact on bank PDs. This seems also reasonable from a more technical angle since the discriminating power of the hazard rate model is primarily determined by the micro variation across banks rather than macroeconomic effects. However, since the integrated model allows for continuous interaction between the real and the financial sector, bank PDs may respond later when solvency pressure on corporates is passed on to banks balance sheets, for example in terms of more non-performing loans and deteriorating profitability.

Alternatively, our approach to estimate an annual model may simply camouflage some of the intra-annual dynamics. The lack of a fully covered quarterly bank distress series and, more importantly, according bank-specific covariates prohibits in our view an ultimate answer to this question. However, we consider below the qualitative implications for the aggregate response based on the quarterly PD estimations assuming constant bank-specific covariates during the year and a quarterly VAR. Beforehand, we consider the importance to allow explicitly for the micro–macro interdependence.

4.2. The importance of accounting for micro and non-linearity aspects

Importantly, the identified trade-off between monetary and financial stability does not emerge in a traditional VAR. The absence of a significant change in financial stability is shown in Fig. 3. The impulse responses shown are those of a plain VAR on ($Y$, $P$, $R$, PD). In such an approach, the
aggregate frequency of distress is solely explained on the basis of macro data, without accounting for microeffects as is done in the integrated model.

The figure shows that, based on a standard VAR 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).

The importance of the microeffects 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 some banks’ financial accounts through its effect on their 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 (Drifill 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 deter-
minants 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. Is it the data?

In Section 3.4 we considered to what extent the microcomponent of the model is affected by the periodicity transformation of the bank failure series. Here, we test whether the identified trade-off between monetary and financial stability is driven by the transformation of our key variable to measure financial fragility: the PD. Following the approach laid out in Section 3 we use the quarterly hazard rate model depicted in Table A.4 in the Appendix A in conjunction with a quarterly VAR to simulate responses for a monetary shock. The according results in Fig. 4 demonstrate that the presence of a trade-off between monetary and financial stability persists.

The magnitude of PD response in an integrated model is strikingly similar to that reported for the annual model depicted in Fig. 2. Note that the response of distress is obscured in a plain quarterly VAR. This result is identical to the one obtained from the annual model and therefore corroborates two of our most important conclusions. First, the existence of a trade-off between monetary and financial stability and, second, the importance to consider the intricate relation between the micro and macrocomponent of the model explicitly. But we do find differences in terms of dynamics regarding the integrated model. In the quarterly model, responses show a significant instantaneous effect, which lasts for one period. The fact that the timing of the response is different is not too surprising, given the substantial uncertainty surrounding the exact (quarterly) timing of events in the raw data. In fact, it underpins our earlier cautioning with regards to the precise timing of events predicted by the model for this sample. However, it also demonstrates that the absence of
instantaneous financial stability responses to a tighter monetary stance documented by Jacobson et al. (2005) is not merely the result from differences in the methodological set-up pursued here.\footnote{For example, a lagged relation between macroeconomic conditions and bank distress in the microcomponent of the integrated model.}

Given the inherent uncertainty regarding the exact timing of distressed events paired with the lack of quarterly bank data, we caution to draw firmer inference on the exact dynamics of responses. Instead, we limit ourselves to conclude that both models consistently provide evidence in favor of a trade-off between the twin objective of central banks. Since the exact dynamics are subject to care, we focus next on differences in responses across banking groups, types of distress, and states of capitalization in the industry.

4.4. 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). These differences across banking groups also have implications for the transmission of monetary policy since bank lending reacts differently across these pillars as shown, for example, by Kakes and Sturm (2002) and Eickmeier et al. (2006). Financial stability responses are therefore likely to differ across banking sectors, too, and accordingly we also disaggregate our results. In Fig. 5, we present the impulse response functions of three types of local banks: commercial, savings and cooperative banks.\footnote{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.}

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.

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. Another reasoning relates to the public ownership of these banks. Explicit state guarantees might have partially insulated this banking group’s probabilities of distress to a large extent from interest rate movements if the former implied funding advantages during monetary tightening relative to competitors without such guarantees (Brunner et al., 2004).

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 own-
ers 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. 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.

4.5. Dissecting the evidence: types of distress

We also acknowledge the 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 Fig. 6. We plot how each of these categories respond to monetary policy shocks.

The figure shows that predominantly events of the relatively weak category II “warnings by the financial authority” respond significantly. This response closely resembles the aggregate response of Fig. 2. Thus, following a monetary restriction, about 0.40% 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 response of the automatic signals also significant, though substantially smaller. However, its response may underestimate the actual impact, because in the case of 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.22

These results suggest two implications. First, monetary policy shocks alone do not cause supervisors to prohibit certain bank activities, or worse, close the bank. This is not too surprising: the more severe corrective actions seem to be more closely related to structural deficiencies of a bank rather than an unexpected change in the monetary stance. Second, and related, a number

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22 Note that since these categories are the most severe, and the severest is always recorded, their non-response is not potentially underestimated.
of banks appear to have entered business activities that brought the bank to the verge of early indications of distress. While monetary shocks are unlikely to take a bank out of business 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. A monetary shock could then induce a fairly large portion of institutes to tumble over the rim and be put on the watchlist of financial stability guardians.

4.6. Banking sector capitalization and the resilience to shocks

It is reasonable to suspect that the relation between monetary policy and financial stability is subjected to initial conditions. Specifically, we analyze whether the effects of monetary policy shocks differ depending on the degree of banking sector capitalization. Our focus on capitalization is motivated, on the one hand, from a monetary policy perspective. The literature on the bank lending channel has emphasized the importance of banks’ financial health, and capitalization in particular, as an important driver in the transmission of monetary policy shocks (Kishan and Opieja, 2000). The importance of the bank lending channel in Germany is documented in, among others, Kakes and Sturm (2002). On the other hand, from a financial stability perspective, capital regulations have been at the center of banking regulations throughout our sample period. Moreover, capitalization is one of the most important determinants of bank distress in both our sample and other countries (Wheelock and Wilson, 2000; King et al., 2006).
To infer the effect of banking sector capitalization on the transmission of shocks, we simulate the system under two different initial conditions. The experiment contrasts the effect of a monetary policy shock at a time when the banking sector is poorly capitalized, with the effects of such a shock in a state where financial health (i.e. capitalization) is high. Capital is defined in terms of both our capitalization measures in the hazard model, equity and reserves. In Germany in particular, banks use mostly their reserves to adjust regulatory capital (Porath, 2006). The ‘low’ (‘high’) initial state is defined as one in which average banking sector capitalization is one standard deviation below (above) its mean. Fig. 7 compares the effect of a monetary policy shock on the probability of distress in both these states.

First note that irrespective of the state considered, distress increases significantly following the monetary policy impulse. This confirms the baseline qualitative conclusion on the existence of a trade-off. Second, quantitatively, the response in the highly capitalized scenario is much smaller relative to both the baseline model and the low-capital scenario. Monetary policy shocks have a very strong effect on banking sector distress when the latter’s financial health is poor. In particular, the effect is approximately six times as large in the poorly capitalized state relative to the well capitalized state.

From the monetary policy perspective, these findings confirm the importance of banks’ financial health in the transmission of monetary policy shocks. Potentially, higher bank distress might constrain their loan supply, either through increasing difficulties to obtain loanable funds or through restrictions imposed by the regulator. These different effects may influence the strength of the bank lending channel (Kashyap and Stein, 1995, 2000). For example, Kishan and Opiela (2000) report that poorly capitalized U.S. banks exhibit a significantly stronger loan contraction response to monetary shocks compared to large, well-capitalized banks. Note, however, that we do not model loan supply responses here explicitly and therefore caution to draw firmer inference regarding the bank lending channel.

From the financial stability perspective, the fact that resilience increases with banking sector capitalization is in line with the use of capital requirements. This is supportive of regulatory requirements imposed since the early nineties. However, even in the high capital state, we still find a significant response of banking sector distress. This also supports the recent debate about extending banking regulations beyond capital requirements. The persistent trade-off between price and financial stability paired with the potential relation to the bank-lending channel of monetary transmission highlights in our view once more the crucial need for close coordination between policy makers in charge of either component of the twin objective.

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 integrate a microeconomic hazard model for bank distress with a standard macroeconomic model. The advantage of the approach followed is that it incorporates micro information, allows for non-linearities and allows for general feedback effects between financial distress and the real economy. Our analysis is based on German bank and macro data between 1995 and 2004. Our main findings are as follows.

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 1 year. While we point out that inference regarding the exact timing of dynamics remains subject to care due to data limitations, the magnitude of this trade-off is robust to an alternative specification of the model in quarterly periodicity akin to Jacobson et al. (2005).

This significant disturbance of financial stability can not be identified if we employ a model that fails to account for microeconomic and non-linear 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.

The distinction of responses for different banking sectors exhibit heterogeneous dynamics, which may reflect respectively alternative business models. Publicly owned savings banks react less 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.

The disaggregation of the baseline result into 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 onto the financial regulator’s watchlists.

Finally, we find that the effect of monetary policy shocks on financial stability is substantially larger if bank capitalization is low. The resulting increase in distress is both statistically and economically significant and details a route through which the bank lending channel may generate real effects: an exacerbated PD response for poorly capitalized banks might imply higher re-financing costs of banks that lead to a more pronounced reduction of loan supply compared to well-capitalized banks. In that sense, our results are in line with Kishan and Opiela (2000) who also stress the importance of bank capitalization for monetary transmission.

The presence of a trade-off between monetary and financial stability has in our view another important policy implication. 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.

Acknowledgements

We thank seminar participants at the Riksbank, Deutsche Bundesbank, and the Financial Instability, Supervision and Central Banks conference organized by the Bank of Finland. Without implicating them, we thank Olivier de Bandt, Gunther Cole, Robert DeYoung, Robert Eisenbeis, Giorgio di Giorgio, Rocco Huang, Tor Jacobson, Jesper Lindé, Kasper Roszbach, Rudi Vander Vennet, as well as our discussant Pierre Siklos and an anonymous referee for most helpful comments. Michael Koetter acknowledges financial support from the Netherlands Organization for Scientific Research NWO. This paper is part of a research project sponsored by the foundation ‘Geld und Währung’. The paper represents the authors’ personal opinions and not necessarily those of the Deutsche Bundesbank. We are grateful to the Bundesbank for the provision of data. Any remaining errors are, of course, our own.
Appendix A


Table A.1
Mean CAMEL covariates per banking group and distress category

<table>
<thead>
<tr>
<th>Variable</th>
<th>All</th>
<th>Com’cl</th>
<th>Sav’s</th>
<th>Coop’s</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equity ratio, $c_1$</td>
<td>8.45</td>
<td>14.67</td>
<td>7.64</td>
<td>8.20</td>
<td>9.98</td>
<td>7.77</td>
<td>7.54</td>
<td>8.22</td>
</tr>
<tr>
<td>Total reserves, $c_2$</td>
<td>0.93</td>
<td>0.21</td>
<td>1.39</td>
<td>0.86</td>
<td>0.48</td>
<td>0.72</td>
<td>0.36</td>
<td>0.44</td>
</tr>
<tr>
<td>Customer loans, $a_1$</td>
<td>11.13</td>
<td>13.12</td>
<td>11.13</td>
<td>11.03</td>
<td>13.58</td>
<td>12.98</td>
<td>15.38</td>
<td>13.83</td>
</tr>
<tr>
<td>Off-balance sheet, $a_2$</td>
<td>3.14</td>
<td>6.49</td>
<td>2.78</td>
<td>2.96</td>
<td>3.00</td>
<td>3.07</td>
<td>3.96</td>
<td>3.62</td>
</tr>
<tr>
<td>RoE, $e_1$</td>
<td>14.80</td>
<td>7.68</td>
<td>19.08</td>
<td>14.18</td>
<td>1.08</td>
<td>7.30</td>
<td>1.46</td>
<td>2.99</td>
</tr>
<tr>
<td>Liquidity, $l_1$</td>
<td>6.70</td>
<td>11.35</td>
<td>4.43</td>
<td>7.04</td>
<td>8.71</td>
<td>7.69</td>
<td>7.92</td>
<td>7.63</td>
</tr>
<tr>
<td>Change in real GDP, $m_1$</td>
<td>1.70</td>
<td>1.67</td>
<td>1.66</td>
<td>1.72</td>
<td>1.56</td>
<td>1.56</td>
<td>1.73</td>
<td>1.79</td>
</tr>
<tr>
<td>Inflation, $m_2$</td>
<td>0.92</td>
<td>0.95</td>
<td>0.91</td>
<td>0.92</td>
<td>0.82</td>
<td>0.68</td>
<td>0.89</td>
<td>0.65</td>
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<tr>
<td>Interest (3 months), $m_3$</td>
<td>3.79</td>
<td>3.80</td>
<td>3.77</td>
<td>3.80</td>
<td>3.84</td>
<td>3.59</td>
<td>3.78</td>
<td>3.69</td>
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<tr>
<td>Observations</td>
<td>26012</td>
<td>1509</td>
<td>5569</td>
<td>18736</td>
<td>88</td>
<td>446</td>
<td>252</td>
<td>347</td>
</tr>
</tbody>
</table>

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.

Fig. A.1. Evolution of bank-specific, distress, and macroeconomic covariates.
Table A.2
Logit model parameters per banking groups and distress categories

<table>
<thead>
<tr>
<th>Variable</th>
<th>All</th>
<th>Com’l</th>
<th>Sav’s</th>
<th>Coop’s</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equity ratio</td>
<td>−0.0787*** (0.0173)</td>
<td>0.0174 (0.0119)</td>
<td>−0.1949** (0.0983)</td>
<td>−0.1320*** (0.0247)</td>
<td>0.0130 (0.0234)</td>
<td>−0.1346*** (0.0274)</td>
<td>−0.1536*** (0.0367)</td>
<td>−0.0608** (0.0266)</td>
</tr>
<tr>
<td>Total reserves</td>
<td>−0.7558*** (0.0859)</td>
<td>−0.6941* (0.4134)</td>
<td>−0.8506*** (0.2007)</td>
<td>−0.6644*** (0.1067)</td>
<td>(0.2734)</td>
<td>−0.2981*** (0.0756)</td>
<td>−1.5298*** (0.4497)</td>
<td>−1.2238*** (0.1549)</td>
</tr>
<tr>
<td>Customer loans</td>
<td>0.0224*** (0.0028)</td>
<td>0.0053 (0.0070)</td>
<td>0.0465*** (0.0130)</td>
<td>0.0203*** (0.0036)</td>
<td>0.0166* (0.0086)</td>
<td>0.0210*** (0.0046)</td>
<td>0.0292*** (0.0054)</td>
<td>0.0193*** (0.0048)</td>
</tr>
<tr>
<td>Off-balance sheet</td>
<td>−0.0038 (0.0095)</td>
<td>−0.0247 (0.0205)</td>
<td>0.0192 (0.0737)</td>
<td>−0.0010 (0.0136)</td>
<td>−0.0727* (0.0389)</td>
<td>−0.0361** (0.0184)</td>
<td>0.0181 (0.0164)</td>
<td>0.0124 (0.0131)</td>
</tr>
<tr>
<td>Size</td>
<td>−0.0547*** (0.0212)</td>
<td>0.0117 (0.0916)</td>
<td>−0.1688 (0.1408)</td>
<td>0.1595*** (0.0343)</td>
<td>0.1462** (0.0622)</td>
<td>−0.0558* (0.0325)</td>
<td>−0.0614 (0.0378)</td>
<td>−0.1516*** (0.0404)</td>
</tr>
<tr>
<td>RoE</td>
<td>−0.0411*** (0.0022)</td>
<td>−0.0108** (0.0054)</td>
<td>−0.0598*** (0.0091)</td>
<td>−0.0443*** (0.0030)</td>
<td>−0.0354*** (0.0047)</td>
<td>−0.0327*** (0.0026)</td>
<td>(0.0037)</td>
<td>−0.0377*** (0.0029)</td>
</tr>
<tr>
<td>Liquidity</td>
<td>0.0286*** (0.0052)</td>
<td>−0.0005 (0.0085)</td>
<td>0.1110*** (0.0382)</td>
<td>0.0380*** (0.0080)</td>
<td>0.0161 (0.0124)</td>
<td>0.0363*** (0.0074)</td>
<td>0.0327*** (0.0092)</td>
<td>0.0156* (0.0095)</td>
</tr>
<tr>
<td>Change in real GDP</td>
<td>−0.2988*** (0.0800)</td>
<td>−0.0016 (0.3148)</td>
<td>−0.3749 (0.3436)</td>
<td>−0.2584*** (0.0865)</td>
<td>−1.4865*** (0.2825)</td>
<td>−0.5429*** (0.1219)</td>
<td>0.0953 (0.1679)</td>
<td>−0.0295 (0.1447)</td>
</tr>
<tr>
<td>Inflation</td>
<td>−0.5222*** (0.0731)</td>
<td>−0.4397 (0.2735)</td>
<td>−0.7368** (0.2859)</td>
<td>−0.4378*** (0.0806)</td>
<td>−1.4000*** (0.2565)</td>
<td>−0.7782*** (0.1112)</td>
<td>−0.0323 (0.1591)</td>
<td>−0.4512*** (0.1259)</td>
</tr>
<tr>
<td>Interest (3 months)</td>
<td>0.2117** (0.1035)</td>
<td>0.2068 (0.3801)</td>
<td>0.3133 (0.4522)</td>
<td>0.1491 (0.1109)</td>
<td>1.9196*** (0.4018)</td>
<td>0.3566*** (0.1624)</td>
<td>−0.2239 (0.2157)</td>
<td>−0.0538 (0.1797)</td>
</tr>
<tr>
<td>Constant</td>
<td>−0.7354 (0.5122)</td>
<td>−3.7112* (2.1470)</td>
<td>1.1132 (3.1157)</td>
<td>−4.2133*** (0.7673)</td>
<td>−11.3544*** (1.6585)</td>
<td>−4.457* (7.953)</td>
<td>−0.8691 (0.9941)</td>
<td>0.5311 (0.9161)</td>
</tr>
<tr>
<td>Observations</td>
<td>26012</td>
<td>1509</td>
<td>5569</td>
<td>18736</td>
<td>24967</td>
<td>25325</td>
<td>25131</td>
<td>25226</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.1133</td>
<td>0.0405</td>
<td>0.2031</td>
<td>0.1206</td>
<td>0.1218</td>
<td>0.068</td>
<td>0.1515</td>
<td>0.1199</td>
</tr>
<tr>
<td>AUR*</td>
<td>0.7741</td>
<td>0.6641</td>
<td>0.8443</td>
<td>0.7796</td>
<td>0.8354</td>
<td>0.7395</td>
<td>0.8501</td>
<td>0.7963</td>
</tr>
</tbody>
</table>

Notes: Robust standard errors in parentheses; ***, **, * denote significant at the 1%, 5%, 10% level, respectively. For variable descriptions see Table A.1.

* Area under the Receiver Operating Characteristics curve (Hosmer and Lemshow, 2000).
<table>
<thead>
<tr>
<th>Variable</th>
<th>All</th>
<th>Banking groups</th>
<th>Distress categories</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Com’cl</td>
<td>Sav’s</td>
<td>Coop’s</td>
</tr>
<tr>
<td>Equity ratio</td>
<td>0.0751*** (0.0171)</td>
<td>(0.0117)</td>
<td>(0.1005)</td>
</tr>
<tr>
<td>Total reserves</td>
<td>0.6885*** (0.0827)</td>
<td>(0.7207* (0.4907)</td>
<td>(0.7636*** (0.1903)</td>
</tr>
<tr>
<td>Customer loans</td>
<td>0.0188*** (0.0028)</td>
<td>(0.0059 (0.0072)</td>
<td>(0.0306** (0.0125)</td>
</tr>
<tr>
<td>Off-balance sheet</td>
<td>0.0108 (0.0101)</td>
<td>(0.0294 (0.0205)</td>
<td>(0.0149 (0.0733)</td>
</tr>
<tr>
<td>Size</td>
<td>0.0315 (0.0206)</td>
<td>(0.016 (0.0916)</td>
<td>(0.167 (0.1363)</td>
</tr>
<tr>
<td>RoE</td>
<td>0.043*** (0.0022)</td>
<td>(0.008 (0.0051)</td>
<td>(0.0621*** (0.009)</td>
</tr>
<tr>
<td>Liquidity</td>
<td>0.0287*** (0.0052)</td>
<td>(0.0008 (0.0085)</td>
<td>(0.102*** (0.0398)</td>
</tr>
<tr>
<td>Constant</td>
<td>1.3072** (0.5122)</td>
<td>(3.3692 (2.147)</td>
<td>(1.5279 (3.1157)</td>
</tr>
<tr>
<td>Observations</td>
<td>26,012</td>
<td>1,509</td>
<td>5,569</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.766</td>
<td>0.623</td>
<td>0.839</td>
</tr>
</tbody>
</table>

| Notes: Robust standard errors in parentheses;***,**,* denote significant at the 1%, 5%, 10% level, respectively. For variable descriptions see Table A.1. |
| AUR<sup>a</sup> | 0.103 | 0.024 | 0.188 | 0.113 | 0.095 | 0.051 | 0.149 | 0.106 |

<sup>a</sup> Area under the Receiver Operating Characteristics curve (Hosmer and Lemshow, 2000).
### Table A.4
Quarterly and annual hazard parameters compared

<table>
<thead>
<tr>
<th>Variable</th>
<th>Quarterly</th>
<th>Annual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equity ratio</td>
<td>-0.096*** (0.0159)</td>
<td>-0.0787*** (0.0173)</td>
</tr>
<tr>
<td>Total reserves</td>
<td>-0.631*** (0.072)</td>
<td>-0.7558*** (0.0859)</td>
</tr>
<tr>
<td>Customer loans</td>
<td>-0.008*** (0.003)</td>
<td>0.0224*** (0.0028)</td>
</tr>
<tr>
<td>Off-balance sheet</td>
<td>0.031*** (0.0102)</td>
<td>-0.0038 (0.0095)</td>
</tr>
<tr>
<td>Size</td>
<td>-0.049*** (0.017)</td>
<td>-0.0547*** (0.0212)</td>
</tr>
<tr>
<td>RoE</td>
<td>0.031*** (0.001)</td>
<td>-0.0411*** (0.0022)</td>
</tr>
<tr>
<td>Liquidity</td>
<td>0.034*** (0.004)</td>
<td>0.0286*** (0.0052)</td>
</tr>
<tr>
<td>Change in real GDP</td>
<td>-0.603*** (0.046)</td>
<td>-0.2988*** (0.0800)</td>
</tr>
<tr>
<td>Inflation</td>
<td>-0.279*** (0.119)</td>
<td>-0.5222*** (0.0731)</td>
</tr>
<tr>
<td>Interest (3 months)</td>
<td>-0.284*** (0.037)</td>
<td>0.2117*** (0.1035)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.691</td>
<td>-0.7354 (0.5122)</td>
</tr>
</tbody>
</table>

Observations: 111656, 26012
R-squared: 0.082, 0.1133
AUR*: 0.7559, 0.7741

Quarterly logit model of bank distress. Bank-specific covariates are lagged by four quarters as in Jacobson et al. (2005). Coefficients for macroeconomic covariates denote cumulative effects. Notes: Robust standard errors in parentheses; ***, **, * denote significant at the 1%, 5%, 10% level, respectively. For variable descriptions see Table A.1. * Area under the Receiver Operating Characteristics curve (Hosmer and Lemeshow, 2000).

### References