Abstract

Evidence on the interdependency between monetary policy and the state of the banking system is scarce. We suggest an integrated micro-macro approach with two core virtues. First, we measure the probability of bank distress directly at the bank level. 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 bank 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 relationship between monetary policy and bank distress. A monetary contraction increases the mean probability of distress. This effect disappears when neglecting micro effects, underlining the crucial importance of the former. Distress responses are economically most significant for weak distress events and at times when capitalization is low.

Keywords: Stress testing, bank distress, monetary policy
JEL: E42, E52, E58, G21, G28

Non-technical summary

Empirical evidence on the interdependency between monetary policy and distress in the banking system is virtually absent from the academic literature. On the one hand, information on the soundness of financial institutions is usually not publicly available. On the other hand, the theoretical implications of monetary policies on banking distress are largely unknown.

This paper provides evidence for the largest economy in the European Monetary Union: Germany. First, we calculate probabilities of bank distress at the microeconomic level. Distress is defined very broadly. It ranges from (many) weak incidences, such as disclosure of facts pursuant to the Banking Act, to (a few) absorbing events, such as restructuring mergers. Next to bank-specific covariates, probabilities of distress (PDs) are estimated with a hazard rate model augmented with macroeconomic covariates: output growth, inflation, and interest rates. Second, we specify a traditional vector autoregressive (VAR) model for those macroeconomic aggregates that also includes the aggregate PD of the banking system as an additional exogenous variable to estimate impulse response functions following a monetary shock. Third, we combine both layers by augmenting the VAR model with a fourth equation capturing the PD based on bank-level data. The combined model allows for feedback effects between the financial and monetary stance. Our main results are as follows.

A monetary contraction by one standard deviation leads to a significant, but small, increase in the aggregate PD. This result confirms the link between monetary policy and banking distress. The significant response of bank PDs to monetary policy vanishes when disregarding feedback effects. Consequently, the importance to allow for feedback effects of monetary policy changes at the bank level is crucial.

This result is due to a significant response of weak distress events. Instead, the PD of stronger distress events does not respond significantly to a monetary shock. This suggests that drastic distress, which implies the bank to cease as a going concern, is primarily driven by bank-specific traits rather than macroeconomic conditions or monetary policy.

Based on the integrated micro-macro model, we analyze the consequences of a monetary shock for two capitalization scenarios. We compare impulse responses assuming that the capitalization of the banking system is one standard deviation below the observed historical mean capitalization with impulse responses where capitalization is assumed to be one standard deviation higher then observed. This comparison shows that impulse responses are around six times larger in the 'low' capitalization scenario compared to the 'high' capitalization scenario. This corroborates also findings in the bank lending channel literature that emphasize that monetary transmission varies according to cross-sectional differences of financial intermediaries.

Nichttechnische Zusammenfassung

Der Zusammenhang zwischen Geldpolitik und der Stabilität individueller Banken ist weitgehend unerforscht. Dies liegt einerseits daran, dass die theoretischen Auswirkungen geldpolitischer Entscheidungen auf die Wahrscheinlichkeit einer 'Schieflage' bei Banken weitgehend im Dunkeln liegen. Außerdem sind Daten zur Stabilität einzelner Finanzdienstleister meist nicht öffentlich zugänglich.

Die vorliegende Studie untersucht diesen Zusammenhang für die größte Volkswirtschaft in der Europäischen Währungsunion: Deutschland. Zuerst schätzen wir mit Hilfe eines Risikomodells die Wahrscheinlichkeit einer 'Schieflage' von Banken (PDs). Dabei wird Schieflage sehr breit definiert. Dieses Maß beinhaltet nicht nur Marktaustritte, z.B. auf Grund von Restrukturierungsfusionen, sondern insbesondere auch schwächere Probleme, wie z.B Anzeigen nach §29(3) KWG, die auf eine Beeinträchtigung der Entwicklung oder Bestandsgefährdung hinweisen. PDs hängen neben bankspezifischen auch von makroökonomischen Größen ab: Wirtschaftswachstum, Inflation und Zinsen. Zunächst spezifizieren wir ein traditionelles Vektorautoregressives (VAR) Modell einschließlich der mittleren PD als erklärende Variable, um realwirtschaftliche Reaktionen in Folge eines geldpolitischen Schocks zu quantifizieren. Schließlich kombinieren wir die mikro- und makroökonomischen Komponenten in einem integriertem VAR Modell, welches eine PD Gleichung enthält. Hiermit ist es uns möglich, Rückkopplungseffekte zuzulassen und deren Bedeutung zu analysieren.

Unsere Ergebnisse bestätigen, dass eine geldpolitische Straffung von einer Standardabweichung einen signifikanten Anstieg der mittleren PD bewirkt, die selbst aber gering ist. Dieser Zusammenhang ist allerdings statistisch nur dann nachweisbar, wenn Rückkopplungseffekte explizit modelliert werden und unterstreichen daher deren große Bedeutung.

Dieser Befund ist das Ergebnis eines signifikanten Anstiegs 'schwacher Probleme'. Dagegen reagiert die Wahrscheinlichkeit 'gravierender Probleme' nicht signifikant auf einen monetären Schock. Es ist anzunehmen, dass schwere Ereignisse, welche die Einstellung der Geschäftstätigkeit bedeuten, im Wesentlichen auf bankspezifische Faktoren und nicht auf makroökonomische bzw. geldpolitische Schocks zurückzuführen sind.

Auf der Basis des integrierten Mikro-Makro Modells untersuchen wir die Auswirkungen eines monetären Schocks für zwei Eigenkapitalszenarien. Wir vergleichen Impulsantworten unter der Annahme, dass das Bankensystem eine um eine Standardabweichung schwächere Eigenkapitalisierung aufweist mit den Impulsantworten unter der Annahme, dass das Bankensystem eine um eine Standardabweichung höhere Eigenkapitalisierung aufweist. Dieser Vergleich zeigt, dass Impulsantworten des 'schwachen' Szenarios etwa um das Sechsfache höher ausfallen als jene des 'hohen' Eigenkapitalisierungsszenarios. Dieses Ergebnis steht im Einklang mit der Literatur zum Bankkreditkanal, wonach die geldpolitische Transmission auch von Unterschieden zwischen den Finanzintermediären abhängt.

Contents

Monetary Policy and Bank Distress: An Integrated Micro-Macro Approach[1]

1 Introduction

This paper investigates interactions between banking sector distress 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 banking system soundness depend on each other. Specifically, we investigate how monetary policy affects banks' probabilities of distress and quantify the importance of feedback mechanisms between the real and financial sector.

The increasing interest in the relation between monetary policy and the soundness of the financial sector (Oosterloo et al., 2007) is presumably owed to a fairly successful record to control inflation, but increasing concerns regarding the latter (Borio, 2006). In addition, if the 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 bank distress is, however, still scarce. A number of scholars emphasize the important role of banks (De Bandt and Hartmann, 2000; Padoa-Schioppa, 2003; Schinasi and Fell, 2005). But while many studies analyze individual banks' probabilities of default,[2] Jacobson et al. (2005) highlight that only few studies employ microeconomic indicators, such as PDs of firms and/or banks, as a link to monetary policy and resulting PD responses. Related, Goodhart et al. (2004, 2006) emphasize the interdependence of microeconomic agents and macroeconomic performance. Thus, allowing for feedback mechanisms is essential (ECB, 2006).

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

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

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 on the basis of confidential Bundesbank bank data between 1995 and 2004. 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).

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 bank PDs. This model allows us to measure the interactions between monetary policy and bank distress more explicitly compared to previous studies. 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. Second, we disaggregate our measure of distress and according responses to monetary policy shocks with respect to different degrees of distress. 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 banking sector, but let the data determine their outcome. Fourth, we analyze the largest economy in Europe, namely Germany.

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 it's annual standard deviation. Hence, the effect is economically significant and confirms the interdependency between monetary policy and the state of the banking system. 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 PDs. Consequently, studies that neglect the integral role played by microeconomic agents may falsely fail to detect the interdependency between monetary policy and bank health. Third, distinguishing different degrees of distress and banking sectors yield heterogeneous responses. Moreover, the effects of monetary policy on banking distress are more severe when banks are poorly capitalized. To the extent that banking distress carries over to banks' lending behavior, this is in line with the bank lending channel literature.

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 distress level. We conclude in section 5.

2 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.[3] 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 because it provides a more exhaustive picture of stress borne by the banking system since it considers all types of risk. The German banking sector experienced substantial fluctuations in the occurrence of distressed events. The sample contains more than 1,100 events and the aggregate annual frequency of distress fluctuates approximately between 2 and 7% as shown in table 1.

Table 1: Annual distress frequency according to distress category

Year	**All**	**Distress categories**			
		I	*II*	*III*	*IV*
1995	1.9%	0.1%	0.4%	0.8%	0.6%
1996	2.5%	0.1%	0.4%	1.2%	0.7%
1997	3.4%	0.1%	0.7%	0.9%	1.7%
1998	4.7%	0.1%	1.4%	1.3%	1.9%
1999	5.6%	0.2%	2.4%	0.9%	2.1%
2000	5.0%	0.1%	2.2%	1.0%	1.7%
2001	6.9%	0.8%	3.1%	1.1%	1.9%
2002	7.0%	1.2%	3.3%	0.9%	1.6%
2003	6.6%	0.8%	3.4%	1.1%	1.3%
2004	4.1%	0.5%	2.5%	0.8%	0.3%
Obs	26,012	24,967	25,325	25,131	25,226

We observe differences across distress categories in our sample period. Therefore,

[3] See also Porath (2006), Kick and Koetter (2007), and Koetter et al. (2007).

we disentangle below responses of probabilities of distress to monetary shocks and depict next to the aggregate distress frequencies according splits in table 1, too.

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 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.[4] 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, 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.

3 Methodology and auxiliary results

We first introduce the hazard rate model to estimate bank PDs. We use 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 similar to Jacobson et al. (2005). They 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 combine the reduced form micro and macro models in a way that differs from 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, an attractive feature given the absence of a (theoretical) consensus regarding financial sector interactions with the real economy.

[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.

3.1 A microeconomic measure of financial distress

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:

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

Here, PD_{it} denotes the probability that bank i will be distressed 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. 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 distress category are provided in table 5 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 included to establish the link with the macroeconomic VAR model. Moreover, the evolution of both bank-specific and macroeconomic covariates over time, depicted in figure 7 in the appendix, shows that no individual model component alone appear 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 equation (1) for the sample pooled across distress categories depicted in table 6.

This hazard rate model exhibits a good fit as witnessed by a pseudo-R^2 of approximately 11 percent. This is on the low side compared to Jacobson et al. (2005), who report aggregated (Laitila) pseudo-R^2s calculated for the full sample between 16 and 39%.[9] While these are in line with results reported in other corporate failure

[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 one 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).

[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 one 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.

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^2s to assess the adequacy of limited dependent 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 type 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 (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). It is thus more general and informative compared to type I and II errors or R^2.

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 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 distress group-specific logit models in the right-hand panels of table 6. 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 bank distress, we refrain from further inference and turn next to the macroeconomic component of the model.

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

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

	All	**Distress Category**			
		I	*II*	*III*	*IV*
A-RMSE					
Micro only	0.015	0.003	0.010	0.002	0.006
Micro and macro	0.011	0.002	0.008	0.002	0.003
Reduction (%)	28.45	43.12	14.41	27.92	40.44
AUR					
Micro only	0.77	0.83	0.72	0.85	0.78
Micro and macro	0.77	0.84	0.74	0.85	0.80
Gain (%)	1.04	1.09	2.30	0.00	1.62

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

[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 7 in the appendix.

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 in capturing the aggregate rate of distress over time. Macro variables reduce projection errors by at least 14 and up to 40 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.

This model comparison exercise implies, first, that the macro variables improve the estimation of the marginal effects of the hazard rate 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 bank distress. 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 distress 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 European Central Bank (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]

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 banking sector soundness, the probability of bank-distress (measured by the frequency of distressed events) is incorporated as an additional explanatory

[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 distress, we refrain from imposing them.

variable. The reduced form macro model thus has the following structure:[13]

$$Z_t = \begin{bmatrix} Y \\ P \\ R \end{bmatrix}_t = \Pi^{MM} \begin{bmatrix} Y \\ P \\ R \end{bmatrix}_{t-1} + \Pi^{MF} PD_{t-1} + u_t \tag{2}$$

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.

3.3 The integrated micro-macro model

The two models described in subsections 3.1 and 3.2 incorporate both macroeconomic as well as financial features. First, the VAR captures relations among the macro variables. In addition, it also includes the dependency of the macroeconomic aggregates on our measure of financial distress, or financial-macro feedback. The evolution of financial distress is itself captured in the micro model. As also shown by Jacobson et al. (2005), it is vital to take account of a number of features in estimating the determinants of the degree of distress. First, there is a role for macro covariates to explain distress risk over time and in the cross-section, in addition to the explanatory value of individual characteristics. The micro model therefore augments the traditional distress specification with macroeconomic variables. Second, the effects of the macro variables on distress may be ill-measured when micro-data are ignored. Therefore, we measure the impact of the macroeconomic variables on distress in a model that takes into account the micro-data explicitly. Third, the probability of distress is typically non-linearly related to its determinants. For example, reducing capitalization from 12 to 11% has different effects on the probability of distress compared to a situation in which it is reduced from 8 to 7%. Moreover, the inherent non-linearity in the logit equation (1) also allows the model to articulate concerns as, for example, the sensitivity of distress to macro-economic fluctuations may depend on the bank's buffer holdings of capital. In the following sections, we combine the two models into an integrated one. The properties of the individual models carry over to the integrated model. In order to provide a measure for the importance of these properties, Section 4.2, presents a model that disregards micro data and non-linearities. The latter model amounts to a standard four-variable VAR, in which the data generating process for distress is both linear and estimated on aggregate distress data.

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 equation (2) is a plain VAR augmented with the PD 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

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

generating process for the aggregate probability of distressed events originating from the micro model.

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

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.[14] 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 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 4.5.[15]

Considering the micro component in the integrated VAR improves the fit considerably as shown by the improvement of aggregate RMSE in table 3.

Table 3: The contribution of micro to the integrated VAR

	All	**Distress Category**			
		I	*II*	*III*	*IV*
A-RMSE					
Macro only (VAR)	0.016	0.009	0.010	0.005	0.005
Micro and macro	0.011	0.002	0.008	0.002	0.003
Reduction (%)	31.00	81.43	18.59	68.38	28.08

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

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 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,

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

[15] We illustrate this procedure with an example in appendix A.

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 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.[16] 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 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 this 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 widely accepted theoretical priors regarding the relation of financial distress and monetary policy underpins 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

[16]As a caveat, note that we do not model to what extent monetary policy might have been induced by stability shocks of the banking industry, for example as a reaction to turmoils recently observed in the wake of the sub-prime crisis in the U.S. financial system. This relates to the prevailing theoretical ambiguity as how to identify alternative shocks in general and we deem the issue out of the present paper's scope.

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 time series dimension of the data, we combine the models at the lower, annual frequency.

Quarterly estimation of the macro component 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 (*"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.[17] 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[18], 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 figure 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.[19] 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.

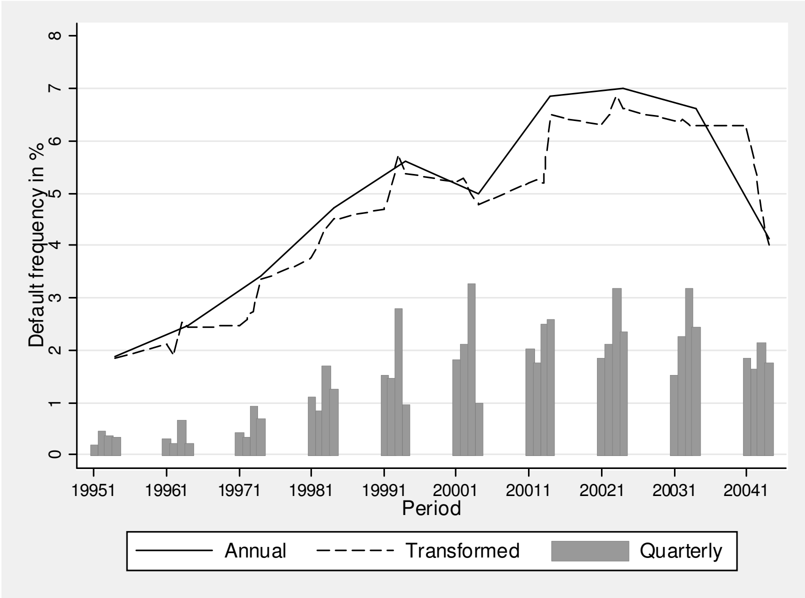
As a robustness check, we also execute an alternative approach to tackling the frequency mismatch and estimate the integrated model on a quarterly basis. Aware

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

[18] For instance, a number of events are only recorded at the end of the year.

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

Figure 1: Quarterly and annual distress frequencies



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 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 8 in the appendix. 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 bank distress to monetary shocks, which we discuss in section 4.3 below.

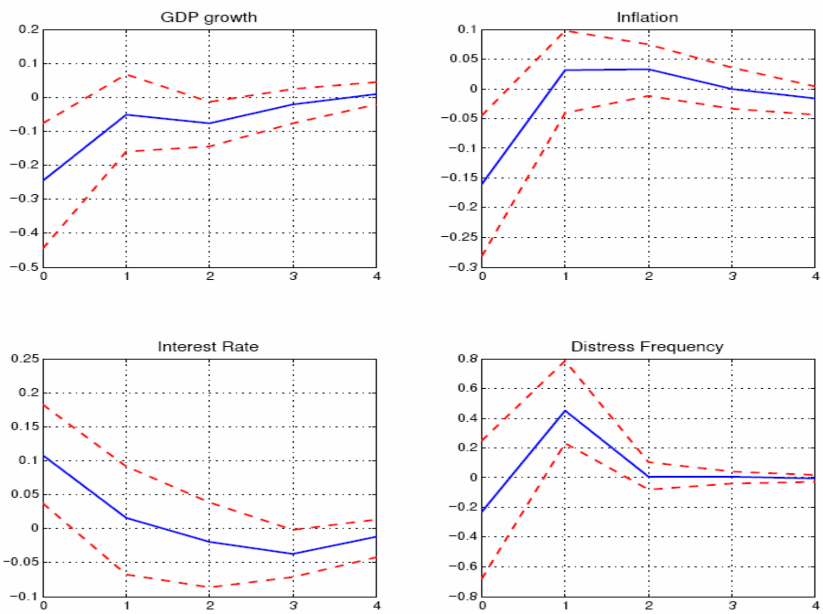
4 Results

We first analyze the effects of monetary policy shocks on financial distress in the combined micro-macro system. 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 types of distress and capitalization states of the banking industry.

4.1 The aggregate response

Figure 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.[20] 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.[21]

Figure 2: PD response to monetary shock with feedback



While the instantaneous response of the probability of distress is insignificant, our results indicate a significant deterioration of PDs in response to a monetary contraction after one 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 4 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

[20] 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.

[21] Smets and Wouters (1999) report for Germany virtually identical point estimates.

extant macroeconomic research. Monetary shocks are not one of the main drivers of real fluctuations. On average, they explain about ten percent of the forecast error variance of growth and inflation.

Table 4: Variance decomposition of the integrated model

Variable		**Bounds**	
		Lower	*Upper*
Y	Change in real GDP	2%	19%
P	Inflation	2%	17%
R	Interest rate (3 months)	1%	8%
D	Distress frequency	5%	35%

The significant increase in the distress frequency is important since it shows that monetary policy affects the soundness of the banking sector. While qualitatively in line with Jacobson et al. (2005), our result differs in terms of timing since it contradicts the immediate PD response reported for the Swedish economy. A potential explanation could relate to the fact that they measure corporate default probabilities. 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.

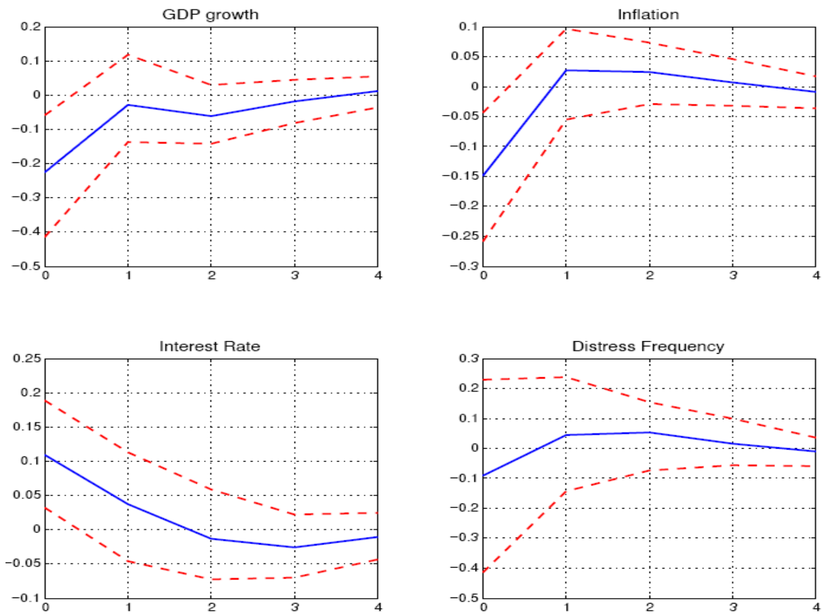
Alternatively, our approach to estimate an annual model may simply camouflage some of the intra-annual dynamics. The lack of a fully covered quarterly bank distress series and, more importantly, according bank-specific covariates prohibits in our view an ultimate answer to this question. However, we 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 micro aspects and non-linearities

Importantly, the identified interdependence between monetary policy and bank PDs does not emerge in a traditional VAR. The absence of a significant change in bank distress probabilities is shown in figure 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

Figure 3: PD response in a plain VAR



macro data, without accounting for micro-effects 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 PD response is in line with Jacobson et al. (2005), who also report no impact of a policy shock on firm distress 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).

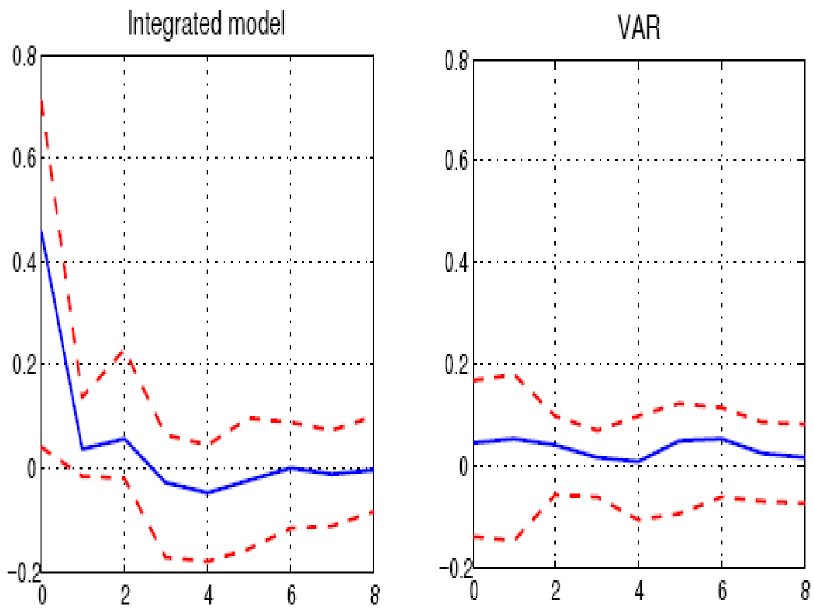
The importance of the micro effects is not only intuitively appealing, but also economically reasonable. While bank PDs may depend to some extent on macroeconomic conditions, too, most of the historical distress incidents are explained by bank-specific factors such as capitalization, profitability and 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 some banks' financial accounts through it's 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 (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 may render inference futile.

4.3 Is it the data?

In section 3.4 we considered to what extent the micro component of the model is affected by the periodicity transformation of the bank failure series. Here, we test whether the identified relation between monetary policy and bank PDs is driven by the frequency transformation of the latter. Following the approach laid out in section 3 we use a quarterly hazard rate model together with a quarterly VAR to simulate responses for a monetary shock.

The according results in figure 4 by and large confirm the results obtained previously from an annual VAR. The magnitude of PD response in an integrated model is strikingly similar to that reported for the annual model depicted in figure 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.

Figure 4: Distress responses from a quarterly integrated model and a plain VAR

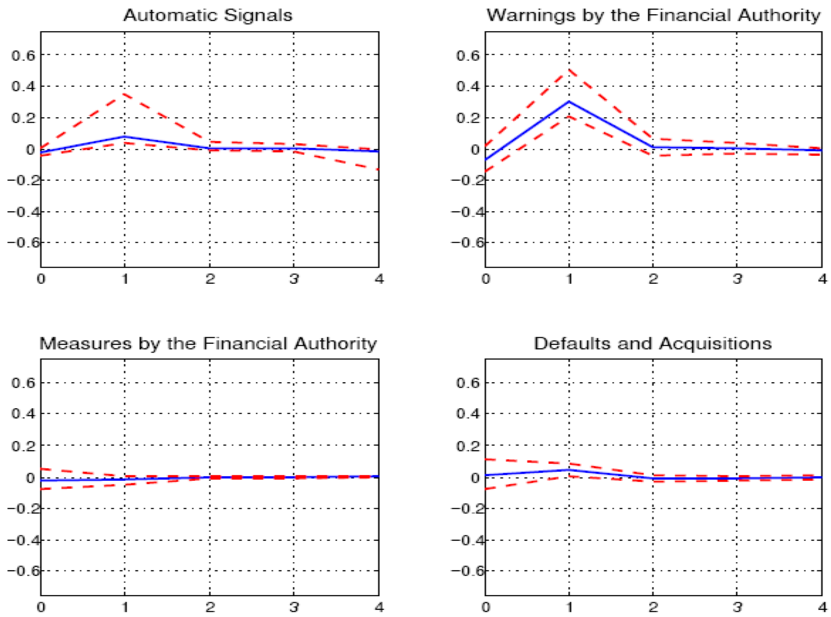


This corroborates our earlier identification of a significant relation between monetary policy and bank PDs and the importance to consider both the micro and macro component of the model explicitly. But we do find differences in terms of dynamics regarding the integrated model. In the quarterly model, 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 PD 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.[22]

4.4 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 figure 5. We plot how each of these categories respond to monetary policy shocks.

Figure 5: Distress responses across types of distress



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 figure 2. 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.

[22]For example, a lagged relation between macroeconomic conditions and bank distress in the micro component of the integrated model.

The response of the automatic signals is also significant, though substantially smaller. However, it's 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.[23]

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 closer related to structural deficiencies of a bank rather than a 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. 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 supervisors.

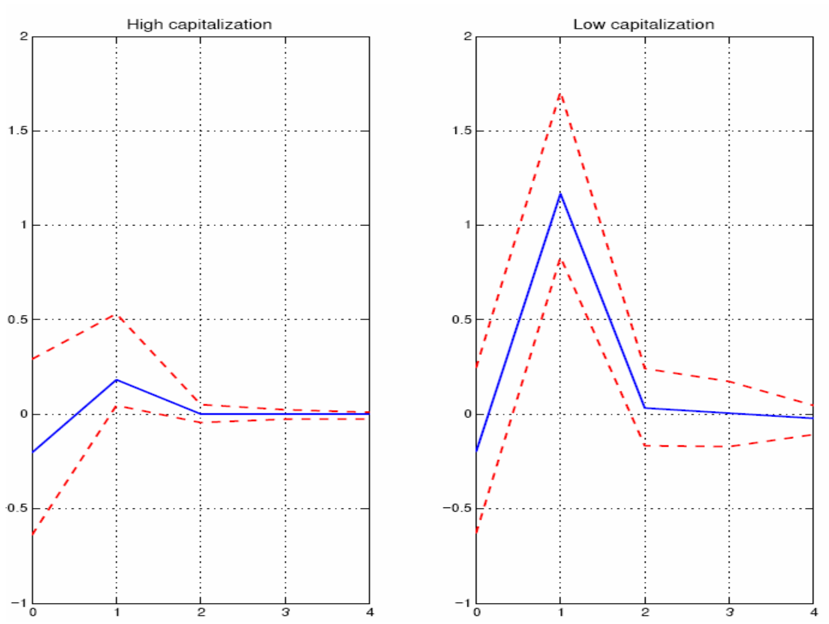
4.5 Banking sector capitalization and the resilience to shocks

It is reasonable to suspect that the relation between monetary policy and bank PD's is subjected to initial conditions. Specifically, we analyze wether 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 Opiela, 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 supervisory 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. Figure 6 compares the effect of a monetary policy shock on the probability of distress in both these states.

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

Figure 6: Distress responses for different capitalization states



First note that irrespective of the state considered, distress increases significantly following the monetary policy impulse. 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 without modeling it more explicitly.

5 Conclusion

We provide in this study empirical evidence on the relation between monetary policy and bank distress. Our approach rests on an integrated micro-macro model and we aim at two main contributions. First, we measure the soundness of banks 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 bank and macro data for all universal banks operating in Germany between 1995 and 2004. Our main findings are as follows.

We provide empirical evidence on the relation between monetary policy and the financial soundness of banks. A tightening of monetary policy by one standard deviation increases the average probability of bank distress by 0.44% after one 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 effect is robust to an alternative specification of the model in quarterly periodicity akin to Jacobson et al. (2005).

This significant effect 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 the financial soundness of banks is confirmed.

Our results suggest a significant relation between monetary policy and weak forms of bank distress, but no evidence of monetary policy igniting outright bank failures. 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 likelihood of weaker distress events, which are the most frequent ones in this sample, increase the most.

Finally, we find that the effect of monetary policy shocks on bank PDs is substantially larger if 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.

A number of limitations of this study outline the scope for future research. First, we do not investigate here possible contagion effects among banks. Alternative methods, such as extreme value theory, might encompass and focus on this aspect. Second, we do neither investigate responses to bank distress shocks nor further shocks that are of importance to policy makers, for example oil price or fiscal policy shocks, too. Theoretical work on the identification of such scenarios would be insightful. Third, we treat the vector of bank-specific hazard determinants as exogenous. Future work might aim to endogenize these micro components since asset quality, capitalization, or bank profitability are most likely also related to macroeconomic developments. Finally, endeavors towards a measure of financial distress encompassing other agents, institutions, and financial markets beyond the banking industry is necessary as to capture the stability of the entire financial system in future research.

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Appendix A: Reduced form of the integrated model

The reduced form combines the VAR and the micro equation. The system is estimated equation by equation. In principle, one may apply SUR corrections in the reduced form, yet these are negligible. The VAR is (assuming one lag for ease of exposition):

$$\begin{aligned}
Y_t &= a_{11}Y_{t-1} + a_{12}P_{t-1} + a_{13}R_{t-1} + a_{14}PD_{t-1} + e_1 \\
P_t &= a_{21}Y_{t-1} + a_{22}P_{t-1} + a_{23}R_{t-1} + a_{24}PD_{t-1} + e_2 \\
R_t &= a_{31}Y_{t-1} + a_{32}P_{t-1} + a_{33}R_{t-1} + a_{34}PD_{t-1} + e_3
\end{aligned}$$

The data generating process for the distress rate implied by the micro model (1) is:

$$PD_t = a_{41}Y_{t-1} + a_{42}P_{t-1} + a_{43}R_{t-1} + e_4$$

where the coefficients $a_{4.}$ are the marginal effects of (1) and balance sheet characteristics (X) are assumed constant. That is, for the case of Y:

$$a_{41} = \left[\frac{\delta PD_t}{\delta Y_{t-1}}\right]_X = \frac{e^{\beta X + \pi Z_{t-1}}}{(1 + e^{\beta X + \pi Z_{t-1}})^2}\pi_Y = p(1-p)\pi_Y$$

where π_Y is the estimated coefficient for Y in the micro equation (1), reported in Table 6, $Z = (Y, P, R)$, and

$$p = \frac{e^{\beta X + \pi Z_{t-1}}}{1 + e^{\beta X + \pi Z_{t-1}}}$$

Analogous definitions apply for marginal effects of the interest rate (R) and inflation (P). The reduced form (3) consists of these first four equations. In computing impulse responses, the reduced form is transformed similar as when going from VAR to SVAR. The difference, however, is that the coefficients $a_{4.}$ are non-linear and adapt each period depending on the macroeconomic state. In the exercise of Section 4.6, we condition on different levels of X

Appendix B: Tables and figures

Table 5: Mean CAMEL covariates per distress category

Variable		**All**	**Distress category**			
			I	*II*	*III*	*IV*
Equity ratio	c_1	8.45	9.98	7.77	7.54	8.22
Total reserves	c_2	0.93	0.48	0.72	0.36	0.44
Customer loans	a_1	11.13	13.58	12.98	15.38	13.83
Off-balance sheet	a_2	3.14	3.00	3.07	3.96	3.62
Size	a_3	19.22	19.63	19.20	19.24	19.03
RoE	e_1	14.80	1.08	7.30	1.46	2.99
Liquidity	l_1	6.70	8.71	7.69	7.92	7.63
Change in real GDP	m_1	1.70	1.56	1.56	1.73	1.79
Inflation	m_2	0.92	0.82	0.68	0.89	0.65
Interest (3 months)	m_3	3.79	3.84	3.59	3.78	3.69
Observations		26,012	88	446	252	347

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

Figure 7: Evolution of bank-specific, distress, and macroeconomic covariates

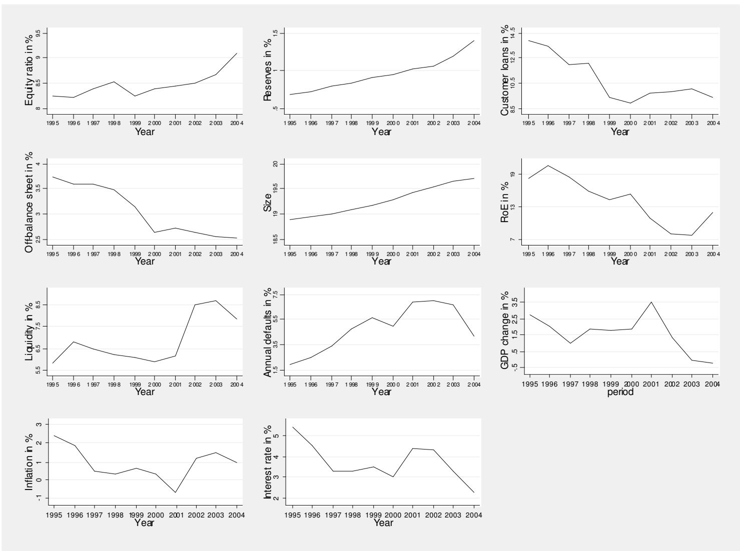

Table 6: Logit model parameters per distress categories

Variable	All	Distress categories I	II	III	IV
Equity ratio	-0.0787***	0.0130	-0.1346***	-0.1536***	-0.0608**
Total reserves	-0.7558***	-0.9732***	-0.2981***	-1.5298***	-1.2238***
Customer loans	0.0224***	0.0166*	0.0210***	0.0292***	0.0193***
Off-balance sheet	-0.0038	-0.0727*	-0.0361**	0.0181	0.0124
Size	-0.0547***	0.1462**	-0.0558*	-0.0614	-0.1516***
RoE	-0.0411***	-0.0354***	-0.0327***	-0.0377***	-0.0377***
Liquidity	0.0286***	0.0161	0.0363***	0.0327***	0.0156*
Change in real GDP	-0.2988***	-1.4865***	-0.5429***	0.0953	-0.0295
Inflation	-0.5222***	-1.4000***	-0.7782***	-0.0323	-0.4512***
Interest (3 months)	0.2117**	1.9196***	0.3566**	-0.2239	-0.0538
Constant	-0.7354	-11.3544***	-1.4457*	-0.8691	0.5311
Observations	26012	24967	25325	25131	25226
R-squared	0.1133	0.1218	0.068	0.1515	0.1199
AUR[1)]	0.7741	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 5. [1)]Area under the Receiver Operating Characteristics curve (Hosmer and Lemshow, 2000).

Table 7: Logit model neglecting macroeconomic covariates

Variable	All	Distress categories I	II	III	IV
Equity ratio	-0.0751***	0.0107	-0.128***	-0.1497***	-0.0562**
Total reserves	-0.6885***	-0.8495***	-0.2148***	-1.4978***	-1.1476***
Customer loans	0.0188***	0.0144	0.0158***	0.0274***	0.0156***
Off-balance sheet	-0.0108	-0.0935**	-0.0476**	0.0153	0.0065
Size	-0.0315	0.191***	-0.0206	-0.052	-0.1309***
RoE	-0.043***	-0.0387***	-0.0354***	-0.0382***	-0.0387***
Liquidity	0.0287***	0.0224**	0.0382***	0.0313***	0.012
Constant	-1.3072**	-8.5205***	-2.3024***	-1.764*	-0.4521
Observations	26,012	24,967	25,325	25,131	25,226
R-squared	0.103	0.095	0.051	0.149	0.106
AUR	0.766	0.826	0.723	0.850	0.784

Notes: see Table 6.

Table 8: Quarterly and annual hazard parameters compared

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.

	Quarterly	**Annual**
Equity ratio	-0.096***	-0.0787***
Total reserves	-0.631***	-0.7558***
Customer loans	0.008***	0.0224***
Off-balance sheet	-0.031***	-0.0038
Size	-0.049***	-0.0547***
RoE	-0.031***	-0.0411***
Liquidity	0.034***	0.0286***
Change in real GDP	-0.603***	-0.2988***
Inflation	-0.279**	-0.5222***
Interest (3 months)	-0.284***	0.2117**
Constant	-0.691	-0.7354
Observations	111,656	26,012
R-squared	0.082	0.1133
AUR[1)]	0.7559	0.7741

Notes: Notes: see Table 6.