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Interbank Lending and Distress: Observables, Unobservables, and Network Structure

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We provide empirical evidence on the relevance of systemic risk through the interbank lending channel. We adapt a spatial probit model that allows for correlated error terms in the cross-sectional variation that depend on the measured network connections of the banks. The latter are in our application observed interbank exposures among German bank holding companies during 2001 and 2006. The results clearly indicate significant spillover effects between banks' probabilities of distress and the financial profiles of connected peers. Better capitalized and managed connections reduce the banks own risk. Higher network centrality reduces the probability of distress, supporting the notion that more complete networks tend to be more stable. Finally, spatial autocorrelation is significant and negative. This last result may indicate too-many-to-fail mechanics such that bank distress is less likely if many peers already experienced distress.

Keywords: Spatial Autoregression, interbank connections, bank risk

JEL classification: E31, G21.

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1 Introduction

Do interbank markets help to stabilize the banking system by providing liquidity efficiently? Or do they pose a threat to financial stability by propagating shocks through the network, thereby increasing the risk that participating banks become distressed? This paper provides empirical evidence based on proprietary interbank and bank distress data paired with innovative econometric methods borrowed from spatial science. We observe bilateral lending and borrowing exposures of virtually all banks active in the German interbank market and estimate risk as the probability of distress (PD) of bank i at time t using a Bayesian spatial probit model. This method permits us to treat the matrix of interbank exposures as a source of contagion reflected by a so-called spatial autocorrelation parameter, and disentangle its effect on bank i's PD from that of the financial health of neighbours in the network and own network centrality.

Theoretical studies show that the contagion potential of interbank markets depends crucially on the structure of the network and that it is generally larger for incomplete networks (Allen and Gale, 2000)[1]. The model of Allen, Carletti, and Gale (2009) illustrates the fragility of these markets if banks do not have sufficient possibilities to hedge counterparty-specific and aggregate liquidity shocks, which may justify interventions by a central planner to avoid contagion of distress. Craig and von Peter (2010) show that the German banking market is characterized by two tiers, i.e. a few money centre banks which intermediate funds among many periphery banks. Therefore, contagion potential may exist and connections to distressed banks could also increase the risk of connected banks themselves. But Castiglionesi and Wagner (2013) show that bilateral interbank relations in the form of insurance can generate socially optimal outcomes in terms of liquidity provision if they occur through direct transfer rather than renumerated credit lines. In a tiered banking system like the German one, existing direct ties between periphery banks may serve exactly as such an efficient insurance mechanism. Therefore, it remains an empirical question whether interbank connectivity increases or mitigates the probability of distress of individual banks.

The empirical literature on interbank markets' contagion potential is growing rapidly. One strand of literature infers interbank exposures from payment

[1]Allen and Gale compare two canonical network structures: a "complete" network, in which all banks lend to and borrow from all other banks, and an "incomplete" network, in which each bank borrows from only one neighbor and lends to only one other neighbor.

system data by matching credited flows of funds with debited ones plus interest (see Furfine, 2000, 2002, 2003). Upper (2011) provides a comprehensive review of another strand of literature, which relies on simulated bilateral interbank exposures and possible risks of contagion. He concludes that simulation exercises are rather sensitive to the assumptions how contagion occurs. In addition, the method to distribute aggregate interbank positions of banks to bilateral exposures tends to overstate the potential for contagion as shown by a comparison between observed and imputed interbank market data in Mistrulli (2011).

The first contribution of this paper is to use interbank exposures that we observe for the entire German banking system from the large credit register of the central bank from 2000 until 2006 (Craig and von Peter, 2010). Evidence on this large and important banking system is so far only indirectly available based on aggregate interbank activity data (Upper and Worms, 2004).

The second contribution of this paper is the approach to explain the link between interbank market exposures and bank risk. Existing studies usually face two major challenges: unobservable bank distress and the inherent cross-sectional dependence of risk due to the connections of banks $i = 1, ..., N$ in the interbank network. For instance, Dinger and von Hagen (2009) assess the effect of aggregate net interbank loans in transition economies on bank risk as measured by loan-loss provisions, non-performing loans, and net charge-offs relative to equity. They carefully control for the possible endogeneity of net interbank assets and find that long-term net exposures in interbank markets reduce the risk of banks. However, the consideration of aggregate net interbank lending precludes any inference on possible effects of the network position of counterparties and thus the effect of their respective riskiness on the lending bank's stability. In this regard, Liedorp, Medema, Koetter, Koning, and van Lelyveld (2010) investigate the effect of connected banks' risk profiles for the Dutch banking system based on interbank exposures imputed from the large credit register of the Dutch Central Bank. They find hardly any relationship between risk-drivers of banks connected via interbank markets on individual bank risk.

A first problem in interpreting these results is the measurement of risk. Frequently used accounting-based measures are by definition backward looking and inevitably prone to endogeneity concerns. Market-based measures, in turn, are only available for a small fraction of banks, even in banking industries of developed economies. We use instead regulatory records of distressed states of banks. Distress is a situation where "an institution's existence will be endangered [. . .] without support measures" (Deutsche Bundesbank, 2007, p. 75). The probability of distress (PD) is thus exogenous to the bank because it is the regulator who defines distress events, often based on legal rules laid down in the banking act ("Kreditwesengesetz").[2]

The second problem is of a methodological nature. Exposures in the interbank network imply cross-sectional dependence among banks' risks borne out by their network connectivity. Akin to autocorrelation in a time-series setting, the PD of i, denoted as PD_i, is likely not independent of the PD of connected peers, PD_j for $j \neq i$. The basic approach in Liedorp et al. (2010) to specify risk determinants of all N banks except i, weighted by the exposure between the former and the latter to each other, is a first step to account for potential spill-overs (Anselin, 1988). We follow-up on this idea to treat the matrix of interbank exposures as a weight matrix very much in the vein of how geographic distances are treated in spatial econometrics. However, we advance by using recent spatial estimation methods that are needed to obtain unbiased parameters in the presence of spatial and serial correlation (Elhorst, 2008). Specifically, we adapt a Bayesian probit framework by Albert and Chib (1993) and Smith and LeSage (2004) to explain bank i's PD as a function of its own historic bank-specific characteristics X_{it-1} as well as all other banks' risk X_{jt-1}, $j \neq i$, that are weighted by connectivity. Connectivity is measured by the matrix of bilateral exposures of all N banks excluding the bank i itself, which we call $\overline{W}$. In addition, we allow the error terms to be dependent across banks conditional on their distance' from each other in interbank markets. This distance thus reflects directly each bank's position in the network. It is captured by a "spatial" autocorrelation term ρ. The latter gauges the dependence of PD's across banks due to the existence and intensity of interbank exposures and ensures the consistent estimation of remaining parameters.

We find that connections with peers in the German interbank market influence the idiosyncratic risk of banks significantly through two channels. The first concerns the financial profile of banks weighted with their position in the interbank network. Aggregate sample results highlight that better capitalized peers that are managed efficiently and tend to write down losses on security and loan portfolios promptly enhance the stability of connected

[2] A number of studies on German banks use similar data to analyse, for example, moral hazard implications of bank bailouts (Dam and Koetter, 2012).

banks. Separate estimations by banking groups highlight however that significant differences exist across banking pillars regarding both the magnitude and the significance of specific aspects of CAMEL financial profiles. The second channel concerns autocorrelated errors in the cross-section of interbank exposures. For the aggregate sample this autocorrelation term is significantly negative, indicating that the probability of distress is lower if connected peers in the interbank market experienced distress. We interpret this result as a possible indication of too-many-to-fail mechanics at work since a frequent distress event are capital injections. These may be less likely if many institutions already had to be bailed out. However, this finding is tempered by the fact that the result is only driven by the group of small savings banks. Insurance schemes in the savings bank sector are regional and thus smaller as well as potentially quicker depleted compared to the to remaining banking sectors. However, given the unobservability of insurance fund capitalization this interpretation remains tentative.

The remainder of this paper is structured as follows. In Section 2, we introduce the econometric model. The data on bank distress, interbank exposures, and bank-specific controls is presented in Section 3. We discuss the results in Section 4 and conclude in Section 5.

2 Econometric model

We observe an exposure network neighborhood of a bank and utilize this information in two ways. The first one is direct, using the observed variables of banks within the neighborhood of the bank. The second way is indirect by imposing structure upon the unobservable error terms of the system of bank observations. With the first approach, we directly measure variables that affect a bank as well as the financial profiles of banks to which it is exposed to. The likelihood that a bank i is distressed at time t is described on the basis of a probit model. We use an $N \times N$ neighborhood matrix of exposures at time t, denoted as W_t, to weight the observed variables measuring other banks' health in the contemporaneous system, where W_t has entries equal to zero on the main diagonal. Thus, if X_{it} is a row vector of observed variables that include measures of the bank's health, we also include $W_t X_t$ in the probit equation that account for banks in bank i's "neighborhood", where $X_t = (X_1', X_2', \ldots, X_N')'$ is the $N \times K$ matrix of explanatory variables at time t. If only banks in the immediate exposure neighborhood are included in this set of variables, and Z_{jt} is a row vector measuring the relevant variables through which a neighboring bank could affect the failure probability of a bank, then the variables in a probit would also include $W_t Z_t$ where Z_t is a matrix of the stacked Z_{jt}. The format of the matrix Z_t is $N \times K$ reflecting that each bank has up to N neighbors, and each of these neighbors has K variables describing its financial profile. We also measured the second (and higher) order effects of the network of exposures recursively through the variables $W_t W_t Z_t$. As an example, banks which have distance 2 from a bank in the network affect neighbors of this bank which again influence the risk-characteristics of the bank under consideration.

This approach of modelling distress is captured by the probit estimating equation $\Pr(Failure_{it}) = \Phi(y_{it} - e_{it})$,where $\Phi(\bullet)$ is the cumulative of the standard normal distribution and

$$y_{it} = X_{it-1}\beta + W_{it-1}Z_{t-1}\gamma + e_{it}. \tag{1}$$

Note that we use the observations at time $t-1$ to explain bank distress at time t. Consequently, the matrix $W_{it-1}Z_{t-1}$ describes the impact of the direct neighbors of each bank. Equation (1) picks up the line which corresponds to the bank i. The error term, e_{it}, is assumed to be distributed as standard normal. Whereas we do not observe y_{it} itself, we do observe bank distress whenever $y_{it} > 0$.

Observation of W also enables us to measure network positions directly. This includes measures of the bank nodes with respect to their centrality within the weighted exposure network and the number of links that are reported by each node. Roughly speaking, a bank is considered to be central in the network if it has strong links to other banks which themselves have a central position. Consequently, the concept of centrality is a recursive one. The usage of weights in the definition implies that a bank becomes more central if the links to other banks having a high centrality are stronger, ie have a higher weight. There are a number of centrality measures available for use in a network. For this paper, we use the "Bonacich centrality" measure, which is an eigenvalue based centrality measure. We wish to distinguish the network centrality effects from the effects of the unobserved variables of close-by banks. Bonacich centrality is defined as the solution to

$$c_{it}(\alpha, \delta) = \sum_{j=1}^{N} (\alpha - \delta c_{jt}) W_{ijt}, \tag{2}$$

where c_{it} is the centrality measure for node i and W_t is the weighting matrix. The Bonacich centrality measure has a normalization parameter, α, and a free parameter, δ, that can vary between the reciprocal of the highest eigenvalue of W_t and its negative. The normalization parameter here is conventionally set so that the norm of all of the centrality parameters is equal to the square root of the size of the network. A higher value of Bonacich centrality indicates a bank that is more central in the network. The possible values of δ can be interpreted as the weight that is placed on the centrality of the bank's near neighbors. We report the coefficients on a centrality measure with δ set to a value of $.999\frac{1}{\lambda_1}$, where λ_1 is the highest eigenvalue of W_t, and because the Bonacich is undefined at this value, we chose a value arbitrarily close. Other values of δ were tried with little change in the results. When the measure δ gets close to $\frac{1}{\lambda_1}$ it becomes similar to other eigenvalue centrality measures such as the Page index. When δ is zero, then the Bonacich becomes a link measure of centrality which places a neutral weight on the centrality of close neighbors and is equivalent to a weighed measure of the direct links that the node is exposed to. The measure reported here places the largest weight on the centrality of a central node's near neighbors, a measure that we feel relates to the reality of the quality of information flows and possible contagion within the interbank system, where centrally placed nodes are more likely to transmit information to other centrally placed nodes.

In addition to directly measured covariates of the exposed to banks, we also look at the effect of unobserved characteristics of such banks on the distress probability. The specification of the model is as in equation (1) except that a random bank-specific effects term is added. In this we closely follow the structure of Smith and LeSage (2004). We observe only whether y_{it} is greater than 0 or not (that is, we observe whether the bank is distressed or not) along with observable variables $X_{it}, W_{it}Z_t$, and $\overline{W}$, an average matrix of exposures which is explained below, in estimating the parameter vectors β, γ, and ρ. In other words,

$$y_{it} = X_{it-1}\beta + W_{it-1}Z_{t-1}\gamma + \theta_i + e_{it}, \tag{3}$$

where y_{it} is the dependent variable, i.e. the indicator of distress for bank i in period t, and the parameter θ_i is an observed random effect that is assumed constant across time. This random effect has its own structure, which is related to the matrix of exposures. In vector notation,

$$\theta = \rho\overline{W}\theta + u, \tag{4}$$

where the parameter ρ represents a first-order spatial autoregressive parameter, $\theta = (\theta_1, \theta_2, \ldots, \theta_N)'$ and u is a $N \times 1$ disturbance term, which is assumed to be normally distributed, $u \backsim \mathcal{N}(0, \sigma_u^2 I_N)$. Equation (4) identifies a random effect in the non-linear context where the dependent variable can take values of only 0 or 1. It should be noted that the equations (3) and (4) include two different weighting matrices, the time-varying matrix W_t and and the average matrix $\overline{W}$, which is constant. The matrices W_t are derived from the bilateral exposures which change over time.

The dynamic evolution of the bank holding companies presents an obvious challenge to the construction of the elements $\overline{w}_{ij}$ of the matrix $\overline{W}$. The reason is that the nodes i and j can change over time. We tried several aggregation schemes, all of which face several constraints.

First, because we measure bank distress with a limited dependent variable, we can not easily measure a residual e_{it}. This means that it is difficult in practice to identify a system where $\overline{W}$ is block diagonal where each block represents a separate time period and a separate network.

Second, the dynamics from the change in the nodes is largely due to mergers, exits, and to a lesser extent, entries of banks into the German market. A weighting matrix must take into account the fact that some of the weights only last as long as the exposed-to bank survives.

Our solution to this problem is to construct the matrix $\overline{W}$ in the following way: each entry w_{ij} represents the average exposure of bank i to bank j across time. The average is computed only taking into account those banks j to which bank i has a positive (i.e. a non-zero) exposure for at least some time within our sample period. Thus,

$$w_{ij} = \frac{\sum_{j \in sample} w_{ijt}}{\#years(j \in sample)}. \tag{5}$$

For those banks that did not survive the entire sample, the average exposure of bank i to this non-surviving bank j, w_{ij} is weighted only by those periods for which the bank was in existence. For example, if the bank j only survived for the initial three periods within our sample, then the average exposure is the sum of the exposures divided by three. The effect of this is to focus attention on regions of exposure which include unobserved characteristics of banks that exit as well as those that survive. After the w_{ij} are computed, they are normalized so that their sum over the exposures for node, i is one:

$$\overline{w}_{ij} = \frac{w_{ij}}{\sum_j w_{ij}}. \tag{6}$$

Given this structure, we estimate our parameters using the Bayesian methods proposed by Smith and LeSage (2004) for use in spatial settings because it has better small sample properties, appropriate to our problem. Alternatively we could have tried simple maximum likelihood methods although these can create difficult computational problems with convergence. In this model, we rewrite equation (4) so that the individual effect is expressed entirely in terms of the normal draw, u_{it}. If we define $B_\rho = I - \rho\overline{W}$ then $\theta = B_\rho^{-1}u$ so that the θ is drawn from a distribution conditioned on ρ and σ_u^2 as

$$\theta|\rho, \sigma_u^2 \backsim \mathcal{N}(0, \sigma_u^2(B_\rho' B_\rho)^{-1}).$$

Finally, following Smith and LeSage, we also assume that the error term for e_{it} is distributed as normal with a heteroskadastic variance, $v_i I$, and 0 cross covariances. Also following Smith and LeSage, we use the following diffuse priors for the parameters: β and γ have normal priors centered on 0 with variance of $10^{12}(I)$, σ^2 and each of the variances, v_i are given the conjugate inverse gamma priors Geweke (2003), and ρ is given a uniform prior that varies between $\frac{1}{\lambda_{\max}}$ and $\frac{1}{\lambda_{\min}}$, where the λ are the largest and smallest eigenvalues associated with weighting matrix $\overline{W}$. As mentioned above, we use these methods because of their good small sample properties and also because the likelihood functions can be difficult to compute under this structure. We compute the statistics about the posterior distributions using classic Bayesian Markov Chain Monte Carlo (MCMC) methods.

3 Institutional background and data

3.1 Bank distress

Distress events are systematically recorded by the German central bank, Deutsche Bundesbank, because they can jeopardize the existence of the bank as a going concern. Distress events reflect risk that is estimated regularly with a hazard rate model developed by Porath (2006) and reported annually in the financial stability report of the Bundesbank since 2004.

Six events that are, by and large, drawn from the German Banking Act (*"Kreditwesengesetz, KWG"*) constitute distress (see also Kick and Koetter, 2007). The first three are early indications of potential future problems: annual operating profit contractions in excess of 25 percent, losses of 25 percent of regulatory capital or above requiring a notification of the regulator according to §24(1) KWG, and general notifications by banks that the existence of the bank might be at risk in line with §29(3) KWG.

The next distress category are capital injections received by banks from sector-specific insurance funds. Note that it is neither the central bank nor the government that rescues banks directly in our sample. In Germany, the Federal Financial Supervisory Authority (*"Bundesanstalt für Finanzdienstleistungsaufsicht, BaFin"*) is responsible for prudential supervision. It conducts the ongoing supervision together with the Bundesbank. But ultimately the BaFin has the mandate to, for example, revoke banking charters. In addition, the auditors of the three banking sectors in Germany, commercial, savings, and co-operative banks, are closely involved to identify potential hazards to their member banks. It is often the insurance fund of e.g. savings and cooperative banks that decides on grounds of auditor reports that capital preservation measures are necessary to keep a member afloat.

As an alternative, these insurance funds may order a bank to engage in a restructuring merger, which constitutes the fifth event recorded by the Bundesbank as distress. Note that it is not the supervisory authorities, which arrange mergers or other resolution efforts. It is rather the insurance scheme of banks themselves aiming to resolve financial distress in this way. Prudential supervisors may require an extraordinary audit and demand the bank to present scheduled actions to heal its financial problems though. Finally, the BaFin can revoke charters by a moratorium if the bank fails to provide a convincing strategy, which did not happen during our sample period.

Table 1 shows the frequency distribution of distress over time. The data comprise bank holding companies from 2001 to 2006 from the three so-called 'pillars' in the German banking industry: private-owned commercial banks, government-owned savings banks, and mutually-owned cooperative banks.

On average, 3.8% of all these universal banks experienced a distress event. Distress occurred almost exclusively among smaller banks during this period.[3] Note that we observe distress at the level of single banking entities. In contrast, we observe interbank market exposures at the level of bank holding companies. Therefore, we show in Table 1 the evolution of observations for the latter entities, which are also the unit of analysis in this study. The number of bank holding companies is only slightly smaller compared to that of single entities, corroborating the well-known structure of the German banking market that is characterized by the presence of many local, relatively small

[3]Note that each banking pillar contains also large institutions, either the big banks in the commercial pillar or head institutions like Landesbanken and Central Cooperatives in the other two pillars.

Table 1: Observations and distress events over time and banking group

Year	**Commercials**		**Savings**		**Cooperatives**		**All**	
	N	*Distressed*	*N*	*Distressed*	*N*	*Distressed*	*N*	*Distressed*
2001	126	8	444	6	1,077	86	1,647	100
2002	125	14	450	6	1,090	72	1,665	92
2003	118	4	446	8	1,131	49	1,695	61
2004	116	3	447	9	1,150	46	1,713	58
2005	111	5	453	9	1,157	26	1,721	40
2006	113	7	454	7	1,151	24	1,718	38
Total	709	41	2,694	45	6,756	303	10,159	389

Notes: The table shows the frequency distribution of distress events aggregated to the bank holding company level. Distress events are defined according to Deutsche Bundesbank (2007). Distress comprises six events based on the German Banking Act (*"Kreditwesengesetz, KWG"*): annual operating profit contractions in excess of 25 percent, losses of 25 percent of regulatory capital or above requiring a notification of the regulator according to paragraph 24(1) KWG, general notifications by banks that the existence of the bank might be at risk in line with paragraph 29(3) KWG, capital injections from sector-specific insurance funds, restructuring mergers, and moratoria.

banks (see also IMF, 2011).

3.2 Interbank exposures to construct W_t and $\overline{W}$

To assemble the data on interbank exposures, we closely follow Craig and von Peter (2010). Bilateral interbank credit and liabilities w_{ij} between all banks $i = 1, ..., N$ are observed from the large credit register of the Bundesbank (*"Millionenkreditevidenz"*). Description of these data can be found in Craig and von Peter (2010). Exposures equal or larger than 1.5 million euro are observed for individual bank holding companies (*"Konzerne"*) and banks that are not in bank holding companies. Exposures of individual banks within bank holding companies are only reported for the entire bank holding company. The same data include definitions of the bank holding companies which change over time which also complicated the computation of $\overline{W}$ above. We report some summary statistics using the charts in Figure 1 and Figure 2 for the network of exposures matrix, $\overline{W}$. For the interpretation of these figures it is relevant to point out that the network described by $\overline{W}$ is more dense as the networks described by the individual matrices W_t. By definition the matrix $\overline{W}$ does not differentiate between links which exist throughout all years and those which disappear or enter in a certain year. Plotting the two figures we want to derive an intuition on how significantly some basic network

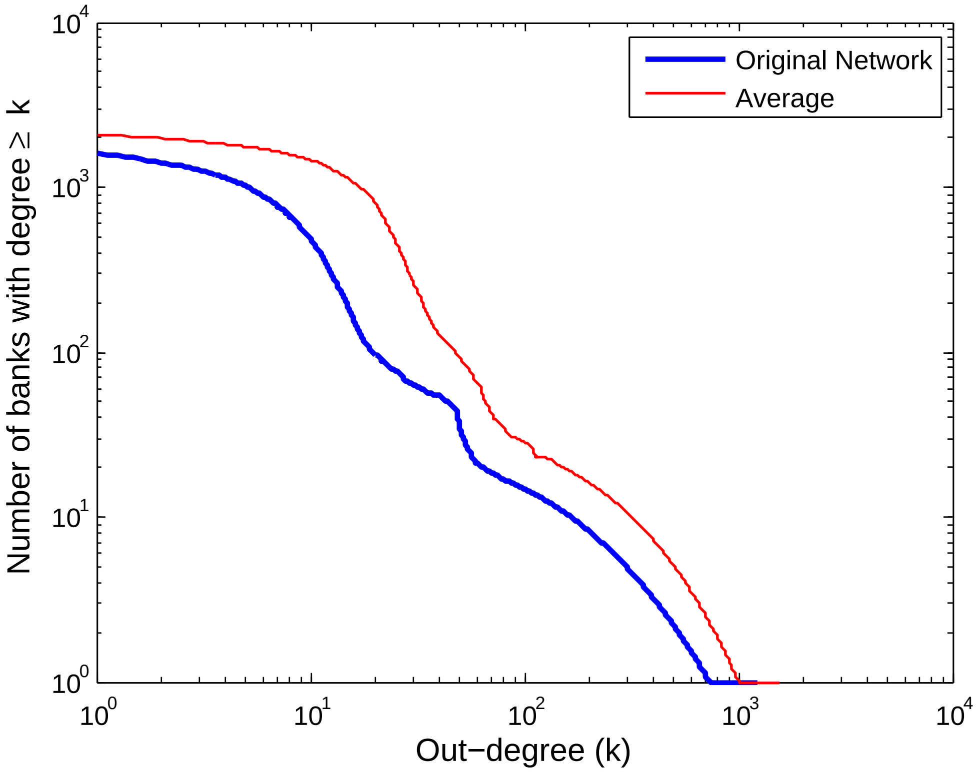

Figure 1: Histogram

parameters change through the usage of the constant matrix $\overline{W}$ instead of the time-varying matrix W_t.

Chart 1 is a histogram showing the number of banks whose out-degrees exceed a given number k. Here, ″out-degree″ refers to the number of links which exit each node. There are two lines in this chart, a blue one which refers to the average for the out-degrees for each individual matrix W_t. The red line refers to the out-degrees for the matrix $\overline{W}$.[4] Several things can be noted in this chart. First, there is a large amount of heterogeneity in the number of links of each of the nodes. Second, the matrix of exposures is quite sparse, having a density of less than 1% of all possible links. Third, the red line is close to the blue line and both lines move parallel which confirms that the construction of the matrix $\overline{W}$ from the individual matrices W_t preserves the basic network structure of each of the individual quarters. Besides this the impact of equations (5) and (6) is fairly proportional accross the network of banks.

[4]The endpoints of both lines are averaged with Pareto smoothing, so as to preserve the anonymity of the links for individual banks.

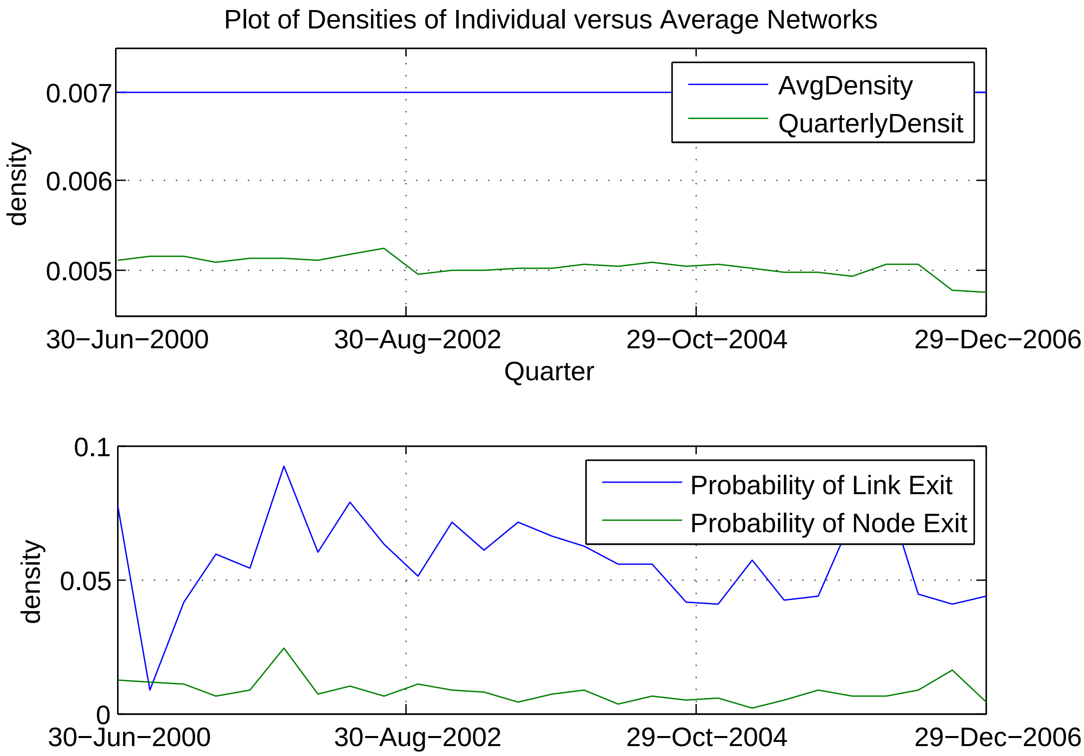

Figure 2: Densities and probabilities of link and node exits

Additional justification for our approach to model the distances between the banks using the matrix $\overline{W}$ is provided by the two charts in Figure 2. The first chart in this Figure describes the evolution of the average number of nodes across time for the matrices W_t and compares it with the density of the matrix $\overline{W}$. In addition the second chart shows the probabilities of a node exit or a link exit. Both probabilities are quite low over this time period. Consequently, the structure of network is fairly constant. As the density of $\overline{W}$ is only slightly higher as the average for the individual matrices W_t, the matrix $\overline{W}$ is a reasonable approximation of our network. Summarizing these observations we may state that choosing a fairly constant set of network weights, with some modification for those banks that exit the sample by disappearing as we have done above, may be a good approximation to the idea of the network neighborhood facing an individual node.

3.3 Controls

To control for bank-specific differences in risk taking, we follow the extensive bank hazard literature and specify a so-called CAMEL covariate vector X_{it-1},

Table 2: CAMEL covariates for sound and distressed banks

	Sound		*Distressed*		*All*	
Variable	Mean	Sd	Mean	Sd	Mean	Sd
Direct						
Equity over total assets	8.7	2.8	8.1	3.3	8.7	2.8
Depreciation and adjustments over equity	10.5	8.8	15.6	23.4	10.7	9.8
Administration expenses over total assets	2.3	4.5	2.7	3.0	2.3	4.4
Return on equity	4.7	6.5	0.1	18.0	4.5	7.4
Cash and overnight IB loans over total assets	7.3	5.2	8.4	5.3	7.4	5.3
Weighted						
Equity over total assets	8.8	6.2	8.5	4.2	8.7	6.2
Depreciation and adjustments over equity	13.4	10.3	13.2	8.1	13.4	10.3
Administration expenses over total assets	0.9	0.4	0.9	0.5	0.9	0.4
Return on equity	0.8	5.5	1.4	5.0	0.8	5.5
Cash and overnight IB loans over total assets	4.5	1.8	4.8	3.2	4.5	1.9

Notes: The table lists descriptive statistics across sound and distressed banks during 2001 until 2006. The total number of observations is 10,159 and the total number of banks is 1,821. All variables except log of total assets and centrality are expressed in percent.

which is lagged by one year to avoid endogeneity by construction (see, for example, and DeYoung (2003) and Wheelock and Wilson (2000)).[5] Table 2 describes the data for sound and distressed banks. We distinguish direct terms for the banks themselves as well as the spatial lags of CAMEL covariates, i.e. those of neighbors weighted by the interbank market exposure.

We measure capitalization as equity capital relative to risk-weighted assets. Larger equity buffers reduce bank risk by absorbing asset price shocks and by reducing the funding cost of the bank. To proxy for asset quality, we specify the ratio of depreciation and revaluations of securities and contributions to loan-loss provisions relative to book equity. A higher quality of both security and credit portfolios should reduce this share and we expect a positive effect on PDs. To proxy for managerial skill, we relate labor and other non-financial, operating expenses to total assets of the bank. Inefficiently operated intermediaries should exhibit higher cost-income ratios and be more prone to distress. We expect a positive coefficient. As a next covariate we specify the return on equity and expect a negative sign. The liquidity variable used for our regressions is defined as the total asset share of overnight net interbank assets. It is difficult to forecast its sign because it may indicate higher risk if these low-yield items reflect a lack of business opportunities. On the other hand a negative effect could arise if it represents

[5] **CAMEL** is an abbreviation for **C**apitalization, **A**sset quality, **M**anagerial skill, **E**arnings, **L**iquidity.

safety buffers against sudden shocks.

In addition to CAMEL covariates, we include the log of total assets to control for size differences to gauge potential (and implicit) too-big-to-fail guarantees of some very large intermediaries. To directly gauge the exposure of the bank to the complete network, we also use the Bonacich centrality for each bank as a centrality measure. It has been introduced in section 2 as a member of a larger family of centrality measures based around the eigenvalues of the network of exposure weights. Finally, we specify dummies for banking groups as well as federal states to control for regional macro effects.

The direct terms in the upper panel of Table 2 shows that distressed banks do not differ significantly along all dimensions captured by these control variables. Capitalization and profitability exhibit the largest (negative) differences compared to sound banks. But the dispersion of banking traits is rather large, indicating that univariate differences of banking traits are not sufficient to identify statistically significant differences.

Similar inference follows from a comparison of weighted CAMEL covariates in equation (1), i.e. the characteristics of those banks which are close in terms of exposure. Recall that for each bank i and each covariate an additional covariate has been introduced as a weighted average of the respective covariates of those banks which are close to i.

Univariate differences between distressed and sound banks are often insignificant and thus corroborate a multivariate regression approach. In addition, the comparison of both panels shows also that neighboring banks exhibit rather different characteristics than distressed banks themselves. Thus, augmenting a conventional hazard rate model with spatial lags and spatial autocorrelation terms that gauge the connectivity among banks more directly seems warranted.

4 Results

4.1 Spatial lags and spatial autocorrelation

The first column in Table 3 shows the results from a simple probit model to predict bank distress with lagged covariates during the period 2000 until 2006. We specify throughout banking group and state dummies to control for regional macro developments but do not report the according coefficients to conserve space. The discriminatory power is good as reflected by a pseudo-R^2

of 11.8%.

Parameter estimates resemble to a large extent those obtained in previous German bank hazard studies. Better capitalized and more profitable banks, as measured by return on equity, are significantly less likely to exhibit distress. Larger banks are in turn more likely to experience a distress event. Note that the majority of distress events are capital injections from sector-specific insurance schemes. Therefore, the positive effect of size on the likelihood of distress is in line with the too-big-to-fail notion that larger banks are more likely to be rescued (O'Hara and Wayne, 1990). This result is consistent with evidence provided on the existence of moral hazard due to bank bailouts in Dam and Koetter (2012). Other banking traits, such as proxies for asset and managerial quality and liquidity do not correlate significantly with observed distress events.

The next pair of columns in Table 3 shows the results from a simple spatial lag model similar to that in Liedorp et al. (2010). The financial profile of neighboring banks in the interbank market contributes significantly to explaining bank distress as reflected by a slightly higher explanatory power of pseudo-R^2 of 12.3%. Previously mentioned risk-reducing direct effects of better capitalization and profitability and size are corroborated. In line with expectations, the specification of spatial lags implies also a significantly positive effect on risk if banks are managed less efficiently, as reflected by a positive coefficient regarding cost-income ratios.

Spatial lags themselves exhibit additional insights into the importance of connections through the interbank market on bank-specific distress probabilities. Ties to well-capitalized and efficiently managed peers reduce banks' probabilities of distress. These results indicate that individual bank stability exerts also a positive spillover effect on connected banks, thereby contributing to the systems overall resilience. Whereas profitability, liquidity, and size do not exhibit such statistically significant spillover effects, we also find connections to peers with poor asset quality. Larger write-downs on loans and securities relative to equity actually reduce probabilities of distress. A possible interpretation of this result is that links to banks that are prudent and conservative in their evaluation practice are beneficial for the risk of interbank trading partners. For example, Hoshi and Kashyap (2010) and Wheelock and Wilson (2000) argue that the timely realization of losses from revaluing assets is crucial to system stability. The significantly negative spatial lag coefficient on depreciation found in our sample may thus capture the beneficial effects on bank risk if write downs are done promptly.

The spatial lag model disregards, however, the lack of independence between connected banks in the interbank network. The final pair of columns in Table 3 therefore presents results from the Baysian probit model which permits for autocorrelated errors in the cross-section reflected by interbank exposures captured in $\overline{W}$. As such, this autocorrelation term therefore captures unobserved dependencies arising from links in the interbank network, whereas exposure-weigthed bank traits of connected peers represent observable potential for contagion through interbank markets.

The significant estimate of the autocorrelation term ρ supports the presence of correlated errors. The negative sign of ρ implies that bank distress is less likely if neighbors in the interbank network are in distress. Note, however, that the most frequent distress event are actually capital injections by pillar-specific insurance schemes. The result that distress events are less likely if close-by peers in the interbank market are in distress as well may therefore be due to two interpretations.

First, insurance schemes may want to subdue the moral hazard arising from rescuing banks by being hard-nosed on remaining banks in the scheme after having bailed out a peer. The negative estimate of ρ would then indicate that authorities are credible and able to overcome the commitment problem. Insurance participants act on the assumption (i.e. take risk) that they won't be rescued if in trouble despite past bailouts happening.

Alternatively, the negative effect of ρ may simply indicate that bailouts of neighboring banks already depleted insurance schemes such that the rescue of another bank is less likely. Ultimately, we cannot identify whether insurance schemes are unwilling or unable to inject capital because the capitalization of insurance schemes is unobserved. Note, however, that for example the regional insurance scheme architecture among savings banks is based on the idea that regionally close-by banks assist ailing peers, for instance by providing equity and/or by merging with the bank. Generally, regional savings contribute to a bailout the moment that a peer is in need, but they do not stock an insurance fund ex ante. Thus, it is not implausible that many bank rescues of peers reduce the likelihood of receiving another bailout for an individual bank that is last in line. In the vein of the too-many-too-fail notion described theoretically in Acharya and Yorulmazer (2007) and Brown and Dinç (2011), the Bayesian probit model may thus indicate the existence of a too-many-to-fail challenge. If too many banks have to be rescued, the likelihood for unassisted banks to receive support when in distress are lower. Further research on the identification of whether it is the unwillingness or the inability of bailout schemes to step in would be desirable.

Regarding direct effects and those of spatial lags, the Bayesian autocorrelation model corroborates earlier results. In fact, the specification of the autocorrelation term renders points estimates more precise and now yields significant effects for direct asset quality and liquidity proxies. The former are in line with expectations positive. Contrary to the beneficial results of neighbors realizing write-downs promptly, the risk of the bank facing such a loss increases. The latter direct liquidity effect, in turn, is negative. Larger liquidity buffers thus reduce the risk of banks, for instance by serving as a means to absorb sudden and unexpected shocks (see, for example, Bouwman and Berger, 2009).

4.2 Direct measures of network position

The Bayesian autocorrelation model is very suited to augment observed contagion effects from connected peers' financial traits with unobserved links through the interbank network. Another direct channel of potential contagion relates to an individual bank's position in the structure of the network. To this end, we specify in Table 4 the Bonacich measure of degree centrality described before.

The first column corroborates previous findings with regards to CAMEL covariates when neglecting both spatial lags and autocorrelated error terms. Better capitalized, more profitable, and smaller banks are less likely to experience distress.

The upshot in Table 4 is that banks, which are more central in the interbank network, are less likely to be distressed. Recall that the Bonacich measure of centrality gauges in particular the type of ties a bank maintains in the network. Simply speaking, the measure gives a larger weight to connections with banks that are themselves central in the network in terms of having many connections. One may thus think of this centrality measure to gauge the "gatekeeper" importance of a bank in the network. Exhibiting links to banks with many ties renders a Bonachich-central institution an important multiplier of shocks should it require assistance or exits e.g in the wake of a restructuring merger. In sum, the negative effect of centrality on bank risk as measured by the probability of distress suggests that centrality in the network contributes to individual bank stability. This result is in line with

Allen and Gale (2000), who emphasize a better resilience of financial systems towards common shocks that are characterized by complete networks.

Augmenting the model with spatial lags in the second pair of columns shows that network centrality remains to exert a risk-reducing effect for the bank itself. The effects of both direct and connected bank traits are very close to those reported in Table 3. The negative direct effect of centrality on risk is mitigated when banks are connected to other central players in the industry. Weighted centrality measures of neighbors exhibit a positive coefficient, albeit only at a substantially smaller magnitude compared to the direct effect of degree centrality on bank risk. Intuitively, distress of a peer which fulfils an important gatekeeper function in the interbank network aggravates a bank's own riskiness. As such, this result would therefore highlight a potentially important observable channel of contagion through interbank networks.

However, the specification of the Bayesian autoregressive model in column 3 of Table 4 puts this result into perspective. There, the centrality measure of neighbors turns insignificant. Hence, the results clearly indicate a risk-reducing effect of individual bank risk whereas any spillover effects from connections to peers in the interbank market are either captured by selected spatial lags, as before capitalization, profitability, and managerial skill, or the autocorrelation term. The latter becomes negative after explicitly accounting for the position of banks themselves in the network as well as the network position of their peers through Bonacich centrality. In contrast the negative autocorrelation term is bigger in magnitude compared to the model without centrality measure. Therefore, this robustness check supports the too-many-to-rescue notion mentioned in the previous subsection. It also emphasizes the importance of unobservables to capture the entire spectrum of potential contagion channels through interbank markets.

4.3 Banking pillars

The German banking system is, however, subject to legal and de facto separation into the three pillars. It is also characterized by large size differences and vastly different business models, for example international full-service providers versus regional retail banks. The market structure implies that pillar specific head institutions in the savings and cooperative banking sectors frequently act as clearing houses for their local banks and conduct numerous wholesale and investment banking operations on their behalf.

Since head institutions are primarily of relevance for the savings and, to a lesser extent, the cooperative banking sector, we also estimate the Bayesian spatial lag model with autocorrelation and explicit measures of centrality for separate banking groups. The first column in Table 5 groups all large, (inter)nationally active banks like the big four, Landesbanken, and central cooperatives as well as regional commercial banks together. The remaining two pairs of columns pertain to local savings and co-operative banks, respectively.

A comparison of direct terms in the first panel corroborates a number of aggregate results, such as the risk-reducing effects of higher profitability. While the directions of most other effects are in line with prior results for the full sample, group-specific estimations also highlight a number of differences regarding the significance of factors across banking pillars.

First, capitalization reduces risk for commercials and cooperative banks but is not statistically significant for savings banks. Second, risk among large banks from any pillar does not respond significantly to size differences within this group. Among regional cooperative and savings banks, in turn, larger players are more likely to experience distress. Third, liquidity held among large banks from any pillar reduces risk, thus apparently acting as an effective buffer against unexpected shocks. Larger liquidity shares among savings banks, in turn, enhances risk, which indicates inefficient levels of low-yield cash and net-interbank positions. Cooperative banks, at last, do not respond significantly to this liquidity proxy. Higher centrality reduces the risk of distress significantly only for the group of large banks and regional cooperative banks, but not for savings banks.

Consider next the results for interbank exposure-weighted CAMEL covariates of peers. These emphasize also important differences across pillars. For the first group only connections to peers with poor managerial skill as measured by cost-income ratios or peers that are relatively small increase risk. The aggregate result of lower risk in response to connections with better capitalized and higher asset quality peers is driven by cooperative banks, as shown in column 2. Poorly managed peers increase cooperative bank risk. The beneficial effects of prompt depreciation in the overall sample is also due to the most numerous group of small cooperative banks. Also connections to banks that hold more liquidity buffers enhance the stability of small cooperative banks. Among savings banks, in turn, it is only the size of connections that matter for a savings banks own risk.

A final important upshot of Table 5 is that the negative autocorrelation is solely driven by the (large) group of cooperative banks. This result supports the notion of too-many-to-rescue issues in a pillar with many regionally active banks that may not bear enough rescue capacity due to too depleted support funds if the frequency of distress that requires bailouts becomes too high.

5 Conclusion

We adapt spatial econometric techniques to test more explicitly for possible spillover effects of bank risk among participants in the German interbank network between 2001 and 2006. To this end we combine observed interbank loans from the large exposure database of the Bundesbank with official distress events as a measure of bank risk.

The comparison of plain probit models with a model augmented by interbank-exposure weighted financial traits of peers as well as Bayesian autocorrelation models provides clear evidence of spillover effects of neighbors in the interbank market on individual bank risk.

One observed channel concerns weighted financial characteristic of connected peers. These indicate that neighbors which are better managed, are well capitalized, and conduct write-downs promptly enhance system resilience. Separate regressions for different banking groups highlight that these effects are largely driven by the most numerous group of small cooperatives. For large banks only the size and the management quality of peers have significant risk-reducing effects. And regional savings banks' risk is only affected by the size of connected banks.

In addition, we also gauge spillovers from unobservable dependence in the cross-sectional dimension of interbank market exposures in terms of significant autocorrelation in the Bayesian probit model. This autocorrelation term is negative, which indicates that distress is less likely if a bank is connected in the interbank market. The most frequent distress event are bailouts. One possible interpretation is therefore that banks are less likely rescued if many peers already had to be bailed out. We do not observe the state of insurance scheme funding. Therefore, we cannot identify whether such a mechanism is due to depleted funds or reflecting attempts of authorities to be credibly hard-nosed so as to avoid moral hazard as a result of bank bailouts. Either way, the German banking system appears to exhibit a too-many-to-rescue pattern between 2001 and 2006. As with direct effects, the significance of the autocorrelation term is driven by the group of regional cooperative banks.

Finally, the structure of the interbank network and a bank's position therein has a significant effect on bank distress as well. Generally, a higher centrality of a bank itself reduces its likelihood to be officially classified as distressed. The centrality of neighbors in the interbank network is insignificant after accounting for dependence in the cross-section of interbank exposures in the Bayesian autocorrelation model. This effect is also significant for separate banking group samples, except regional savings.

Table 3: Baseline – interbank-exposure weights and Bayesian autocorrelation model

Variables	Simple probit $\boldsymbol{\beta_i}$	Exposure weighted $\boldsymbol{\beta_i}$	Bayesian AR $\boldsymbol{\beta_i}$
Direct			
Constant	-10.032	-10.039	7.543 ***
	(0.950)	(0.955)	(0.002)
Equity over total assets	-0.007 **	-0.008 ***	-0.088 ***
	(0.024)	(0.009)	(0.000)
Depreciation and adjustments over equity	0.002	0.002	0.011 *
	(0.298)	(0.206)	(0.067)
Administration expenses over total assets	0.004	0.006 *	-0.048 ***
	(0.200)	(0.074)	(0.000)
Return on equity	-0.033 ***	-0.033 ***	-0.032 ***
	(0.000)	(0.000)	(0.008)
Cash and overnight IB loans over total assets	0.004	0.004	-0.025 *
	(0.307)	(0.360)	(0.058)
ln total assets	0.167 ***	0.164 ***	-1.017 ***
	(0.000)	(0.000)	(0.000)
Variables for the neighbors (weighted)			
Capitalization		-0.024 **	-0.094 ***
		(0.023)	(0.000)
Depreciation and adjustments over equity		-0.006 *	-0.025 ***
		(0.042)	(0.000)
Administration expenses over total assets		0.129 **	0.346 **
		(0.022)	(0.015)
Return on equity		0.008	0.004
		(0.122)	(0.361)
Cash and overnight IB loans over total assets		0.014	-0.005
		(0.284)	(0.402)
ln total assets		0.001	0.002
		(0.522)	(0.285)
ρ			-0.063 ***
			(0.000)
Log likelihood	-1455.714	-1446.796	
(pseudo) R2	0.118	0.123	

Notes: The table lists limited dependent variable regression results explaining the occurrence of a distressed event among German banks during 2001 until 2006. The total number of observations is 10,159 and the total number of banks is 1,821. All variables except log of total assets and centrality are expressed in percent. ρ is the autocorrelation term as in equation (4). Standard errors are in brackets. Fixed effects for states ("Bundesländer") and banking sectors (commercial, savings, and cooperative) are included but not reported. *,**, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Baseline results augmented with Bonacich centrality measure

Variables	Simple probit β_i	Exposure weighted β_i	Bayesian AR β_i
Direct			
Constant	-10.052	-10.013	12.314 *
	(0.955)	(0.955)	(0.063)
Equity over total assets	-0.007 **	-0.009 ***	-0.052 ***
	(0.022)	(0.007)	(0.000)
Depreciation and adjustments over equity	0.002	0.002	0.013 ***
	(0.346)	(0.190)	(0.006)
Administration expenses over total assets	0.004	0.007 **	-0.056 ***
	(0.192)	(0.029)	(0.000)
Return on equity	-0.033 ***	-0.033 ***	-0.025 *
	(0.000)	(0.000)	(0.063)
Cash and overnight IB loans over total assets	0.005	0.004	-0.013
	(0.285)	(0.375)	(0.193)
ln total assets	0.174 ***	0.178 ***	-0.909 ***
	(0.000)	(0.000)	(0.000)
Centrality measure	-0.032 *	-0.036 **	-0.030
	(0.047)	(0.028)	(0.299)
Variables for the neighbors (weighted)			
Equity over total assets		-0.019 *	-0.074 ***
		(0.067)	(0.000)
Depreciation and adjustments over equity		-0.007 **	-0.030 ***
		(0.020)	(0.000)
Administration expenses over total assets		0.129 **	0.477 **
		(0.019)	(0.028)
Return on equity		0.001	-0.005
		(0.797)	(0.348)
Cash and overnight IB loans over total assets		0.017	-0.009
		(0.177)	(0.322)
ln total assets		-0.009 ***	-0.012 *
		(0.001)	(0.054)
Centrality measure		0.011 ***	0.014 *
		(0.000)	(0.050)
ρ			-0.104 ***
			(0.000)
Log likelihood	-1453.552	-1437.114	
(pseudo) R2	0.119	0.129	

Notes: The table lists limited dependent variable regression results explaining the occurrence of a distressed event among German banks during 2001 until 2006. The total number of observations is 10,159 and the total number of banks is 1,821. All variables except log of total assets and centrality are expressed in percent. ρ is the autocorrelation term as in equation (4). Standard errors are in brackets. Fixed effects for states ("Bundesländer") and banking sectors (commercial, savings, and cooperative) are included but not reported. *,**, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Separate estimation per banking group

Variables	Larger banks $\boldsymbol{\beta_i}$	Small cooperatives $\boldsymbol{\beta_i}$	Small savings $\boldsymbol{\beta_i}$
Direct			
Constant	-9.708 ***	-7.754 ***	-16.605 *
	(0.005)	(0.000)	(0.074)
Equity over total assets	-0.014 ***	-0.417 ***	-0.428
	(0.000)	(0.000)	(0.162)
Depreciation and adjustments over equity	0.015	0.001	0.004
	(0.151)	(0.520)	(0.463)
Administration expenses over total assets	0.058 ***	0.010	0.009
	(0.000)	(0.238)	(0.426)
Return on equity	-0.031 **	-0.060 ***	-0.131 ***
	(0.018)	(0.000)	(0.000)
Cash and overnight IB loans over total assets	-0.070 ***	-0.001	0.217 ***
	(0.000)	(0.475)	(0.000)
ln total assets	0.054	0.471 ***	0.400 *
	(0.557)	(0.000)	(0.050)
Centrality measure	-0.110	-3.217 ***	1.639 ***
	(0.221)	(0.000)	(0.000)
Variables for the neighbors (weighted)			
Capitalization	-0.086	-0.124 ***	-0.135
	(0.155)	(0.009)	(0.247)
Depreciation and adjustments over equity	0.052	-0.022 ***	0.013
	(0.143)	(0.000)	(0.387)
Administration expenses over total assets	0.697 *	0.424 *	1.506 *
	(0.045)	(0.059)	(0.063)
Return on equity	0.080	-0.001	-0.016
	(0.125)	(0.436)	(0.307)
Cash and overnight IB loans over total assets	0.029	-0.067	-0.061
	(0.213)	(0.121)	(0.335)
ln total assets	-0.033	-0.012 *	-0.026
	(0.175)	(0.087)	(0.113)
Centrality measure	0.034	0.018 ***	-0.022
	(0.228)	(0.006)	(0.255)
ρ	0.000	-0.725 ***	-0.262
	(0.992)	(0.000)	(0.205)
Observations	792	6744	2623

Notes: The table lists limited dependent variable regression results explaining the occurrence of a distressed event among German banks during 2001 until 2006. The total number of observations is 10,159 and the total number of banks is 1,821. All variables except log of total assets and centrality are expressed in percent. ρ is the autocorrelation term as in equation (4). Standard errors are in brackets. Fixed effects for states ("Bundesländer") and banking sectors (commercial, savings, and cooperative) are included but not reported. *,**, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

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