Determinants of Banking System Stability:

A Macro-Prudential Analysis*

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Abstract

Over the past two decades, Germany experienced several periods of banking system instability rather than full-blown banking system crises. In this paper we introduce a continuous and forward-looking stability indicator for the banking system based on information on all financial institutions in Germany between 1995 and 2010. Explaining this measure by means of panel regression techniques, we identify significant macroprudential early warning indicators (such as asset price indicators, leading indicators for the business cycle and money market indicators) and spillovers. Whereas international spillover effects play a significant role across all banking sectors, regional spillover effects and the credit-to-GDP ratio are most important for cooperative banks and less relevant for commercial banks.

Keywords: Banking System Stability, Early Warning Indicators, Regional Spillover Effects, Panel Regression Techniques

JEL classification: C23, E44, G01, G21.

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* The views expressed herein are our own and do not necessarily reflect those of the Deutsche Bundesbank.

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Non-Technical Summary

Regular financial stability assessment and the identification of early warning indicators signaling coming risks to the banking system are major tasks of central banks and supervisory authorities. A safe and sound banking system ensures the optimal allocation of capital resources, and regulators therefore aim to prevent costly banking system crises and their associated adverse feedback effects on the real economy. This paper introduces a continuous and forward-looking stability indicator for the German banking system which is used to identify early warning indicators and spillover effects in both regional banking and international financial markets.

Over the past two decades, Germany experienced several periods of banking system instability rather than full-blown banking system crises. Instability could be observed across banking sectors as a consequence of reforms in banking legislation as well as national and international developments in financial markets. To describe the condition of the banking system, we develop an indicator compiling a basket of banks containing both major financial institutions and smaller banks. The indicator comprises three components: an institution's score (i.e., the standardized probability of default), a credit spread, and a stock market index for the banking sector. The probabilities of default are derived from the Bundesbank's hazard rate model for small banks; for large institutions, Moody's Bank Financial Strength Ratings (BFSR) are used. The empirical study is based on confidential supervisory reporting data provided by the Deutsche Bundesbank comprising up to 3,330 institutions over the period 1995 to 2010.

Stability determinants of the national banking system can be classified into macroeconomic, financial and structural variables. Applying panel regression techniques, we find that asset price indicators, leading indicators for the business cycle and money market indicators can be shown to be reliable early warning indicators. In addition, international spillover effects play a significant role for stability across all banking sectors, whereas regional spillover effects and the credit-to-GDP ratio mostly affect credit cooperatives but are less important for commercial banks. These findings indicate that the heterogeneous structure of the German three-pillar banking system (of which each banking sector is exposed to various shocks in a different way) might contribute to enhancing the stability of the banking system as a whole.

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I Introduction

Regular financial stability assessment and the identification of macroprudential leading indicators signaling coming risks to the banking system are of major importance for central banks and supervisory authorities. A safe and sound banking system ensures the optimal allocation of capital resources, and regulators therefore aim to prevent costly banking system crises and their associated adverse feedback effects on the real economy. This paper introduces a stability indicator for the German banking system which is used to identify macroprudential early warning indicators and spillover effects in both regional banking and international financial markets.

Over the last two decades, Germany experienced several periods of banking system instability rather than full-blown banking system crises. Around the burst of the dotcom bubble in 2000, especially German cooperative banks suffered from increased credit defaults. Furthermore, particularly Landesbanks had to realign business models and refinancing conditions in response to the abolition of state guarantees ("Gewährträgerhaftung" and "Anstaltslast" in German) in 2004/2005. Although savings banks and cooperative banks are still predominantly regionally centered, foreign lending of all banks (bonds included, in terms of balance sheet total) almost doubled from 14.3% to 27.2% between 1999 and 2010, reflecting the increasingly international nature of the German banking system. This corresponds to a high dependence on international developments that played a crucial role for banking system instability during the financial crisis in 2008/2009. Despite a slight recovery in 2010, major German banks, in particular, are still suffering from the uncertainty in financial markets caused by the sovereign debt crisis in 2010/2011.

The aim of this paper is to provide a tool for banking supervisors to monitor and assess banking system stability and its determinants. We address two research questions. First, due to the above mentioned periods of observed banking system instability instead of banking system crises we develop a continuous and forward-looking stability indicator for the German banking system. To this end, we use information on all financial institutions in Germany between 1995 and 2010, and we aggregate three important indicators to one stability measure: the institutions' individual standardized probabilities of default (PDs), a credit spread (i.e., the average bank risk premium) and a stock market index for the banking sector ("Prime Banks Performance Index"). Second, in line with the body of empirical literature on early warning indicators for banking system crises and -instability, we analyze the impact of macroprudential leading indicators for the German banking system. Our findings suggest that asset price indicators, leading indicators for the business cycle and money market indicators prove to be relevant early warning indicators. Furthermore, structural indicators such as international and regional spillover effects also have a significant impact on banking system stability in Germany.

The paper proceeds as follows. Section II gives an overview of existing measures of banking system stability and its determinants. Section III introduces the stability indicator for the German banking system and derives weights for its individual components. Section IV provides a discussion of macroprudential determinants of banking system stability, followed in Section V by a description of the data and the introduction of the empirical model. Results are discussed in Section VI, and Section VII concludes.

II Literature Review

Within the literature on financial stability analysis we focus on existing measures of banking system stability and its determinants based on theoretical and empirical consideration.

Although evidence on ordinal or continuous stability indicators for the banking system is less comprehensive, some important studies can be noticed. Bordo et al. (2001) develop and examine a discrete financial stress index including time series on business failures, banking conditions, the real interest rate and a quality spread describing the condition of the US financial sector.[1] Puddu (2008) constructs a real continuous indicator for the US banking system by aggregating balance sheet variables of the commercial banking sector and examines the impact of different weighting schemes on the replication ability of financial crisis events. Illing and Liu (2006) develop a financial stress index for the Canadian sector by variance-equal weighting several financial market indicators into one single index.[2] Its calculation for the US and euro-area financial market can be found in Borio and Drehmann (2009); it correctly signals future risks from 2007 onwards. Hanschel and Monnin (2005) both develop and examine a continuous stress index for the Swiss banking sector by equal-weighting market price, balance sheet, nonpublic and other structural data. With respect to highly industrial countries, e.g. Germany that did not suffer full-blown banking system crises in the past two decades but experienced periods of banking system instability, ordinal indicators allowing for more than two categories, or, at best, continuous stability indicators describing the condition of the banking system are needed to support banking supervisors in financial stability analysis and to provide empirical evidence on early warning indicators preceding periods of banking system instability.

As we are interested in a macroprudential analysis, theoretical literature and empirical evidence provides deep insight into the second core research question of our study, the

[1] The authors suggest that inflationary shocks between 1980 and 1997 are the most influential factor in the occurrence of financial distress.

[2] The financial stress index contains indicators from the banking sector, the foreign exchange market, debt markets and equity markets.

interaction between the financial and real sector, and helps us to derive subsequent explanatory variables and leading indicators as determinants for banking system stability. Among the first authors who theoretically proved an existing macro-financial linkage have been Bernanke et al. (1996), who initially formulated the financial accelerator mechanism. Lorenzoni (2008) shows that credit and investment booms associated with high asset prices can be inefficient as market participants do not internalize their impact on general market equilibrium. In his model, higher levels of ex ante credit, investment and asset prices may induce stronger reduction of market participants' net worth and in turn financial stability in case of a negative shock. Thereby, credit and investment booms precede financial system instability with a longer lead time than higher growth rates of asset prices, whereas exogenous real economic shocks contemporaneously accompany financial turmoil. We test the implications of this theoretical evidence in our empirical analysis. New strands of macro models directly address deficiencies inherent in previous models that became evident in the recent financial crisis of 2008/2009. These include the role of interbank markets, liquidity and political crisis management.[3] For example, Gertler and Kiyotaki (2010) explicitly take into account the role of financial intermediaries rather than addressing the financial friction itself. In their model, special attention is given to the interbank market within DSGE models as important driver of financial system stability.

Empirical evidence of determinants of banking system crises and –instability has a long history. Whereas some studies capture periods of crisis for several countries with a binary variable and explain the latter with macroeconomic factors applying either logit/probit or signaling approaches, other studies focus on a single country and identify appropriate country-specific determinants of banking system stability. Important studies have been implemented by Demirgüc-Kunt and Detragiache (1998, 2005) who focus on leading indicators for banking crises. Applying a multivariate logit approach, the authors link a set of explanatory variables to the probability of occurrence of a binary crisis variable. Their results for both industrial and emerging market economies indicate that low real economic growth, high inflation and high real interest rates impact significantly on the probability of a banking crisis. In contrast, Hardy and Pazarbasioglu (1999) examine a sample that covers 50 predominantly emerging market economies between 1977 and 1997 and do not support overall evidence of macroeconomic factors preceding banking crises and rather support both country- and crisis specific determinants that can only be identified ex post. The authors conclude that national factors are relevant for banking instability, whereas

[3] A good overview on new strains of macro-financial models can be found in ECB (2010), Financial Stability Review, December.

international factors play a role in determining banking crises.[4] Borio and Lowe (2002) extend the signaling approach by applying so-called composite leading indicators which improve predictive power in their sample that contains both industrial and emerging market economies.[5] In addition, the authors focus on ex ante information only accounting for the policy maker's decision horizon, consider a small set of core variables and allow for the relevance of multiple horizons. Their results indicate that the common use of credit-to-GDP, gross fixed investment and asset prices (especially property prices) are among the best indicators in predicting banking crises. Their results have been confirmed by an in-sample and out-of-sample prediction of the recent financial crisis of 2008/2009 by Borio and Drehmann (2009), who also highlight the important role of property prices in predicting banking crises. At the country-specific level, Hanschel, Monnin (2005) confirm the leading indicators identified by Borio and Lowe (2002) to be likewise relevant determinants for the Swiss banking system. Misina and Tkacz (2008) forecast the indicator developed by Illing and Liu (2006) and find lending in combination with housing-sector asset price indicators to be the best predictors at the 1-2 year horizon for Canada. In line with the second strand of empirical studies, we address one of the most important industrial countries in the European Monetary Union: Germany.

Our contribution to the literature is threefold. First, we develop a continuous stability indicator which describes the state of banking system stability in Germany and suggest a new weighting procedure. Second, we derive potential macroeconomic leading indicators from the theoretical and empirical studies and test their ability to predict the condition of the German banking system. Third, we take into account experience from the financial crisis 2008/2009 and thus incorporate indicators for regional and international spillover effects as further determinants of banking system stability.

III Stability Indicator for the German Banking System

We develop a continuous and forward-looking stability indicator for the German banking system. This stability indicator is our proxy for national banking system stability, lower values indicating banking system instability. Based on a definition provided by Deutsche Bundesbank (2003) we understand banking system stability as "steady state in which the financial system efficiently performs its key economic functions, such as allocating resources and spreading risk as well as settling

[4] Here, the term "banking instability" is related to "banking sector difficulties" that do not result in a systemic crisis; see p. 10.

[5] According to the authors, composite indicators signal a crisis if the "coexistence" of two or three indicators passes a certain threshold. Indicators are calculated in deviation from their one-sided HP trend to approximate the idea of financial imbalances.

payments".[6] In other terms, we relate banking system stability to a sound banking system that primary constitutes of solvent financial institutions fulfilling above named functions. Deriving an appropriate indicator for this condition, we comprise suitable indicator components that constitute banking system stability in either direction. Following definitions by IMF (2003) and Segoviano et al. (2009) we suggest that banking system instability can arise either through idiosyncratic components related to poor banking practices adversely affecting an individual bank's solvency, from systematic components initiated by aggregate shocks entailing financial strains for the banking system or a combination of both.[7] Therefore, we select an institution's score (i.e. the standardized probability of default) as an idiosyncratic indicator component, whereas both a stock market index for the banking sector and a credit spread reflect systematic indicator components as they measure listed institution's risk-return ratio and an average bank risk premium, respectively.

As outlined in the literature review in the previous section, recent empirical studies develop stress indexes for the banking system by merging different relevant variables into a single measure. We proceed in line with this work and argue that our variables are more forward-looking and introduce a novel procedure for assigning weights to single indicator components.

1. *Deriving the Stability Indicator*

The German banking system is subdivided into a three-pillar structure of savings banks and Landesbanks, cooperative banks and their central institutions, as well as commercial banks.[8] The lattermost are privately organized and follow a profit seeking business model. The market share of private banks in terms of domestic business volume stood at 38.1% (end-2010). [9] Savings banks, on the other hand, are predominantly owned by the public sector and fulfill their public mandate of supporting the lower and middle classes as well as small and medium-sized enterprises as part of their business model, with a market share of 32.4% (end-2010). Finally, cooperative banks are owned by their members and support the idea of encouraging their associates by focusing on regionally located small and middle-income entrepreneurs. Their market share amounted to 12.1% (end-2010). While international activities and business in securities are rather important for private banks, savings deposits belong to the business concept of savings banks and cooperative banks.

[6] See Deutsche Bundesbank (2003), p. 8.
[7] See IMF (2003), p. 4 and Segoviano and Goodhart (2009), p. 6.
[8] In addition to universal banks, the German banking sector consists of specialized banks, the market share of which stood at 17.4% at the end of 2010. However, they are not relevant to our overall analysis and are thus excluded. Source: Deutsche Bundesbank.
[9] Business volume refers to domestic business according to the definition of the Deutsche Bundesbank's banking statistics without branches abroad.

The composite stability indicator is constructed by compiling a basket of banks containing both major financial institutions (i.e., big private banks, Landesbanks, central institutions of cooperative banks, and large special-purpose banks) and smaller banks (i.e., small private banks, savings banks, cooperative banks). The measure covers a total of between 3,330 institutions (in 1995) and 1,685 institutions (in 2010). According to our definition of banking system stability, the indicator comprises three components that well describe the current and expected condition of the German banking sector: The individual institutions' scores (i.e., standardized PDs), a credit spread (i.e., the average bank risk premium) and a stock market index for the banking sector ("Prime Banks Performance Index"). Whereas the bank-individual indicator reflects the idiosyncratic component, two latter two indicators are intended to capture the overall evolvement of banking system stability.

According to our definition of banking system stability, the main component of the stability indicator for the banking system is information on each individual bank's solvency in terms of its PD. For major banks we incorporate PDs which are derived from Moody's Bank Financial Strength Ratings (BFSR). As, however, ratings from the rating agencies are only available for major institutions, we use an additional bank rating model ("Bundesbank hazard rate model") to estimate PDs for small private, savings, and cooperative banks in the German banking system as well, which is described below.[10]

Following Porath (2004) as well as Kick and Koetter (2007), we specify a bank rating model that is based on the logistic link function which transforms a set of bank-specific covariates and a financial variable observed in year $t-1$ into the probability of default of that particular bank in year t. The right-hand side of the regression equation is based on the CAMELS taxonomy: Capital adequacy, Asset quality, Management, Earnings, Liquidity, and Sensitivity to market risk. In the model the banks' liquidity situation is proxied at an aggregate level by including the yield curve (which is described by the 10-year minus 1-year government bond rate).[11]

On the left-hand side of our logistic regression we use a unique data set of bank distress events collected by the Deutsche Bundesbank over the time period 1994 to 2006 which is only available for small banks. In contrast to previous studies (e.g., Porath (2004), Kick and Koetter (2007), etc.) this data set consists of a more detailed

[10] In the bank rating model institutions are regarded as "defaulted" if their existence is endangered within the one-year forecast horizon without support measures.

[11] Porath (2004) points out that banks' real liquidity risk cannot be measured adequately with the data available at the Deutsche Bundesbank. In particular for small cooperative and savings banks a high cash and interbank-loans to total assets ratio is rather an indicator for lacking business opportunities than for low liquidity risk.

distress definition and also covers a longer time period (up to 2006) for which distress data is available.[12]

The bank rating model is based on the following logistic link function, which is estimated by a panel population-averaged logit model.

$$P\left(y_{i,t}=1\right)=\frac{e^{\alpha+\beta X_{i,t-1}+\pi M_{t-1}}}{1+e^{\alpha+\beta X_{i,t-1}+\pi M_{t-1}}} \tag{1}$$

Here, $P(y_{i,t}=1)$ denotes the probability that bank i will be distressed in year t. It is estimated from a set of covariates $X_{i,t-1}$ observed for bank i in period $t-1$ to which a financial variable (the yield curve) M_{t-1} is added[13]; α, β and π are the parameters to be estimated. Based on the logistic link function, the bank rating model transforms this set of covariates into bank-specific default probabilities which are used (along with other stability indicators) in the further financial stability analysis.[14] As the composite stability indicator is used as dependent variable in empirical analysis, we exclude all factors from the logistic link function that might cause a biased panel regression set up. Regression statistics are reported in Appendix I.

With regard to the goodness of fit, it turns out that the discriminatory power of the panel logit model, measured by the Area Under the Receiver Operating Characteristics Curve (AUC), is excellent at 87.7%.[15] Coefficient estimates for the CAMEL vector and the yield curve are in line with both expectations and the findings in the literature. Moreover, most of the coefficients show significance at the 1% level. The regression statistics indicates that better capitalization and more bank reserves, as well as a higher profitability reduce the likelihood of bank distress. Lower bank distress can also be shown for a higher concentration in the banks' loan portfolios (measured by the Herfindahl-Hirschman Index of over 23 industry sectors) what means that specialized banks tend to be more stable than more diversified banks.[16]

In turn, a high reduction of bank reserves, a large share of customer loans (which can be assumed to be riskier than interbank loans), avoided write-offs on a bank's assets

[12] The definition of distress events comprises -among others- compulsory notifications of the German Banking Act or capital support measures. According to Porath (2004), "default is defined as any event that jeopardizes the bank's viability as a going concern", p.II. Hence, extending the analysis to 2010 implies forecasting the PDs based on the rating model up to 2006 which includes inevitable forecast uncertainty.

[13] The inclusion of the yield curve is intended to proxy the individual bank's liquidity and profitability position at an aggregate level.

[14] See De Graeve et al. (2008).

[15] In the context of bank rating models AUC values measure the ability of the model to discriminate between distress and non-distress events for a range of cut-off probabilities from zero to one. According to Hosmer and Lemshow (2000) values above 80% show an "excellent discrimination", and values above 90% an "outstanding discrimination" of the model. In comparison to regularly estimated Bundesbank Hazard Rate Models, an AUC between 80-90% varies in normal range.

[16] This result is in line with Behr et al. (2007) who find for the German banking market that specialized banks have a slightly higher return, as well as lower relative loan loss provisions and lower shares of non-performing loans, than diversified banks.

(also known as "hidden liabilities"), and a higher bank market concentration (measured as Herfindahl-Hirschman Index across bank branches per state) imply a higher PD. The management's ability to avoid the more risky fee-generating business in favor of the more stable interest business[17] is reflected by a (highly significant) positive coefficient for the share of fee income.[18] At the aggregate level, a more favorable yield curve increases the likelihood of bank distress. On the one hand, a widening spread between long-term and short-term risk-free rates allows banks to generate more profits through maturity transformation. On the other hand, however, such a trend in the banking industry creates incentives for excessive risk taking and moral hazard. Finally, when controlling for the major risk factors, we find that banking group dummies (savings banks, cooperative banks) are not significant in the bank rating model.

Turning to the other components of the stability indicator, the credit spread is calculated as the difference between the arithmetic means of returns on other bank debt securities outstanding and those on listed Federal securities with the same residual maturity.[19] The spread is understood as the average risk premium, which is higher the worse the banks' overall creditworthiness is and, thus, accurately reflects expected banking system instability by market participants and is included as the second component of the stability indicator. The third component of the indicator is the "Prime Banks Performance Index". This index contains the share prices of those banks that are listed in Germany. The growth rate of the index reflects market expectations regarding listed institutions' risk-return ratio and thus their current and expected profitability and development, indicating future (in)stability of the banking system.

In a second step constructing the stability indicator, the three components (bank-level PDs, credit spread, growth rate of the "Prime Banks Performance Index") are first $(0,1)$ - standardized, aggregated to form an institution-level metric,[20] and subsequently weighted with the respective institution's total assets.[21] The standardized PDs and the credit spread are entered reciprocally in order to ensure that all components of the indicator point in the same direction. The stability indicator can be reported for the entire banking system as well as for individual groups of institutions. Negative values indicate periods of instability; positive values denote periods of stability of the banking system.

[17] Concerning the riskiness of different income components De Jonghe (2007) points out that "Interest income is less risky than all other revenue streams." This finding is confirmed in a later study by Busch and Kick (2009).

[18] The share of fee income and also the RoE are highly correlated with the cost-income ratio used in many bank rating studies. Hence, the latter variable is removed from this regression.

[19] The credit spread with regard to other bank debt securities outstanding is calculable for about 200 German banks.

[20] The standardized indicators are entered into the calculation of the metric at their respective weight (see below).

[21] See e.g. Illing and Liu (2006), Puddu (2008) or Hanschel and Monnin (2005) for similar proceeding.

It should be noted that all three components of the indicator are regarded as forward-looking. Unlike other indicators of risk-bearing capacity, based on metrics and bank balance sheet data, this indicator therefore reflects the current and future development of the German banking system. The stability indicator measures contagion effects indirectly as for individual financial institutions, two banking-system wide components are added: First, if the PD for bank i in period t is low but, for example, the credit spread implies an increased bank risk premium, the stability indicator for that particular bank i is also higher in that period. Second, PDs for large institutions also comprise "contagion components" (i.e. they include the risk of spillover effects from the default of other major players in the banking market).[22] The basket indicator is much broader than standard market-based banking stability indicators (such as CDS spreads, or stock returns) and covers all institutions of the German banking system.[23] In particular, the basket indicator includes savings banks, cooperative banks, and small private banks; these institutions control a sizeable share of the German market and play a central role in the regional credit supply.

2. *Assigning Weights to Stability Indicator Components*

To evaluate possible weights allocated to the individual indicator components, we provide a novel weighting procedure. The literature provides no convincing methodology for assigning adequate weights to the components of a composite stability indicator for the German banking system. Even when theory suggests that a certain set of variables should be included, it still remains unclear how these components should be weighted. Techniques include the commonly applied variance-equal weight method, factor analysis or weighting schemes based on market shares of respective components. The latter two follow the idea that a main driver of financial instability can be identified. But, as Illing and Liu (2006) point out, the major difficulty lies in the lack of a benchmark against which adequate weights can be verified. However, the authors argue that their results remain qualitatively similar regardless of the method chosen. Similar, Hanschel and Monnin (2005) justify the variance-equal weight method as other methodologies would not yield meaningful results for the Swiss case. In our view this does not solve the initial problem of verifying the composite indicator's reliability.

Therefore, selecting a benchmark as target for the final choice on assigning weights should overcome above named shortcomings. We propose a unique methodology in accordance with the supervisory risk profile assessment which comprises an evaluation

[22] In particular, during the financial crisis it could be observed that the whole banking sector (and not only banks which were close-to-default) faced severe rating downgrades.
[23] As well as some special-purpose banks which, however, are excluded in empirical analysis.

of all of an institution's risks, its organization and internal control procedures and its risk-bearing capacity. The grading is done in four categories (A, B, C, D), where A means an excellent grading, while D denotes a "problem bank". The assessment is made by the Bundesbank at least once a year and passed on to BaFin for approval and any further regulatory decision-making.

Based on three components: (*i*) standardized PDs for an individual institution, (*ii*) the credit spread, and (*iii*) the stock market index, we calculate 36 composite stability indicators with weightings ranging from "10%-10%-80%" to "80%-10%-10%." Furthermore, we base the choice of the final stability indicator on the supervisory risk assessment.[24] As we are interested in a one-size-fits-all approach, weights are not allowed to vary by category of banks or size. We specify the following partial proportional odds model,

$$P\left(RP_{i,t} > j\right) = \frac{e^{\alpha_j + \beta_j SI_{i,t} + \eta_j X_{i,t} + \pi_j BG_i}}{1 + e^{\alpha_j + \beta_j SI_{i,t} + \eta_j X_{i,t} + \pi_j BG_i}} \qquad (2)$$

in which $SI_{i,t}$ is the respective composite stability indicator, X_{it} is a set of controls for the relevant qualitative risk factors (i.e., internal governance, internal capital adequacy assessment process (ICAAP), and other qualitative risk factors)[25] which are by definition not included in the stability indicator, but in the supervisory risk profile. BG_i are banking group dummies (savings banks and cooperative banks; private banks are the reference group), and α, β, η, and π are the parameters to be estimated.

For the final indicator selection we apply Wald tests with the hypothesis *"H0: Coefficients on the respective stability indicator for the worst supervisory risk profile categories C and D jointly zero"* in 36 regression models.[26] By assigning weights to the three indicator components, we aim to identify the stability indicator for the banking system with the maximum fit to the supervisory risk profile assessment. The Wald statistic shows a maximum for the following composite stability indicator: 70% standardized PDs (Moody's Bank Financial Strength Rating and bank rating model for small private, savings and cooperative banks), 20% credit spread and 10% "Prime Banks Performance Index". As variance-equal weighting does not significantly alter our results, we apply these weights to all further banking system stability analyses in this paper.[27]

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[24] See Deutsche Bundesbank and BaFin (2008). For a comprehensive discussion of the concept of supervisory risk profiles and the partial proportional odds model see also Kick and Pfingsten (2011).

[25] For each qualitative risk factor C and D grades are coded as individual variables where the categories A and B constitute the reference group.

[26] C and D indicate problematic and outstanding problem banks which represent a potential threat to the stability of the German banking system.

[27] However, we are currently examining in more detail the impact of the second and third best fit according to the supervisory risk profile assessment on our regression results.

Two arguments limit the scope of our novel weighting procedure. First, as the supervisory risk profile assessment focus on idiosyncratic risk rather than systemic risk, this might bias our results towards a higher weight of the PD. Second, e.g. Krainer and Lopez (2008) show that stock and bond markets may yield further information not included in the current supervisory ratings which might also cause a similar bias towards higher weights associated with the idiosyncratic PDs. Related to the first issue, as the individual institution's score is our main component of the stability indicator according to our definition of banking system stability, we would have anyway assigned a higher weight to the idiosyncratic indicator component. Furthermore, information content in stock and bond markets at least constitutes 30% of the stability indicator. In sum, we believe that despite above named drawbacks we are able to present a useful benchmark approach on which appropriate weights can be derived and which should in any case be superior to e.g. variance-equal weighting that lacks any benchmark justification.

3. *Evolvement of the Stability Indicator*

We show the indicator in Appendix II. Over time, it was already on the decline in 2007 and entered negative territory in 2008. The expected recovery occurs in 2010 for most banking groups—Landesbanks excepted. For 2011, the indicator shows that the credit spread and the stock market index for the banking sector components contribute to a renewed deterioration of banking system stability. This trend largely reflects uncertainty surrounding the prospect of default (or debt rescheduling) in some euro-area peripheral countries. The uncertainty in the markets also affects the Landesbanks, for which Moody's BFSR deteriorated slightly further in 2011. At the current end, the small banks (savings banks, cooperative banks, and small private banks) are continuing to gain in stability, which is likely to be due both to their business model and their preparation for stricter capital rules (Basel III) from 2013 onwards. Although the evolution of the credit spread is for some periods quite similar to the time series pattern of the composite stability indicator, we argue our indicator to be a more comprehensive proxy for overall banking system stability. The latter is intended to indicate the overall condition of the banking system, whereas the bank-level stability indicators are used for empirical analysis. Overall, the stability indicator shows deterioration in 2011 compared to 2010; however, it is still well above its level in 2009, the low point of the financial and economic crisis.

IV Macroprudential Leading Indicators for Banking System Stability

Based on theoretical considerations and empirical evidence, we identify macroprudential leading indicators that may explain banking system stability at different lag operators and, as is usually done in the literature, classify them into macroeconomic, financial and structural variables, see Appendix III. Particular interest is devoted to country-specific variables that might help supervisors to identify imminent threats to the German banking system. In accordance with Fichtner et al. (2009), who argue that increased globalization has to be taken into account in empirical analysis by using extended composite leading indicators for the prediction of economic activity, we test both national and international adjusted leading indicators to control for increased internationalization of the German banking system.

1. Macroeconomic Variables

According to economic theory, higher asset and property price growth is associated with the boom phase in the business cycle that might imply a buildup of financial imbalances and has the potential to result in banking system instability.[28] For asset price indicators, it is important to distinguish between property and equity prices, as they reflect different transmission channels of exogenous shocks to the real economy.[29] Although real estate price indices did not reflect overheating in the German housing market indicating upcoming risk prior to the financial crisis of 2008/2009, Koetter and Poghosyan (2008) show that price-to-rent ratios may be important determinants for instability in the German banking system. In our empirical analysis we test the German real estate price index provided by Bulwien AG which is an indicator of asset price trends in national real estate markets. We also include asset price indicators for internationally important real estate markets as they played an important role in the financial crisis 2008/2009.

An important leading indicator for economic outlook in Germany is the ifo business cycle index. The indicator captures expectations of real economic development and indicates positive or negative shocks affecting the real economy. Expectations of economic upturn are contemporaneously expected to induce higher predicted banking system stability whereas, in the event of an expected economic downturn, future banking system stability should be negatively affected (e.g., via increasing defaults of borrowers). As e.g. Lorenzoni (2008) theoretically shows, high gross fixed investments are also expected to precede economic up/downturns reflecting real

[28] Borio and Drehmann (2009) refer to financial imbalances as "growing fragility of private sector balance sheets during benign economic conditions", BIS Quarterly Review, March 2009, p. 30.
[29] See Borio and Lowe (2002) for detailed argument. The authors argue that property prices have been more important in predicting banking crises than equity prices.

economic demand. Again, large positive growth rates are anticipated to signal market overheating with the potential of subsequent banking system instability.

2. *Financial Variables*

Turning to financial variables, we look at indicators for lending to the private sector, financial market indicators and monetary expansion. According to economic theory, lending booms may precede banking system instability as they imply increased risk-taking in the financial system that has the potential to result in financial turmoil if the economy is hit by a negative, adverse shock. Concerning equity market indices, we do not include indicators such as the DAX 30/Euro Stoxx 50 Index or the Euro Stoxx Banks as stock market indicator for the European banking sector since we are interested in drivers of banking system stability apart from the stability indicator's individual components.

With respect to financial market indicators, we take into account the role of the interbank market, which has become especially important during the financial crisis of 2008/2009, by testing the 3-month Libor as a possible leading indicator for future banking system stability. If financial market confidence is low, making banks wary of lending in the interbank market, the 3-month Libor is high and predicted instability in the banking system is expected to increase. With regard to monetary expansion, we look at M2-to-GDP indicating excessive liquidity in the financial market which possibly precedes a lending boom.[30]

3. *Structural Variables and Regional Spillover Effects*

As regards spillover effects between financial intermediaries, the literature has studied the effects of bank's failures on the equity returns of other banks and finds evidence for the existence of spillovers, which can largely be attributed to fundamentals rather than to irrational investor behavior; see e.g. Aharony and Swary (1983). In line with this finding, we include indicators for international and regional spillover effects.

First, we control for international spillover effects in the regression model. As we will describe in more detail in the next section, the dependence of the German banking system on international exposures steadily increased between 1995 and 2010. We take this structural change in national banks' balance sheet exposures into account as the observed period of predicted banking system instability in 2007/2008 can partly be explained by the revaluation of large foreign exposures. Although we are unable to calculate an indicator reflecting foreign lending and securities in terms of balance

[30] See von Hagen and Ho (2003) for a detailed discussion of M2 in preceding banking crises, pp. 9-10.

sheet total on banking group level at fair market value due to lack of adequate data we include the respective indicator based on book values in our analysis. Similar, Borio and Drehmann (2009) provide first evidence on the role of cross-border exposures in determining banking system crises.[31] In addition, we test the forward-looking Chicago Board Options Exchange Market Volatility Index as an indicator of international risk appetite and expected implied volatility of S&P 500 index options, with higher values indicating less expected banking system stability and vice versa to control for increased risk aversion and uncertainty of international financial market participants.[32]

Second, we analyze spillover effects in regional banking markets. For this purpose, we divide Germany into its respective area (county) levels l and measure the regional spillover effect for bank i by calculating the balance sheet total-weighted standardized PD of all financial institutions in l (except i), lagged by one period, which is included as an additional covariate in the regression model. That is, we test the explanatory effect of weighted standardized PDs of surrounding financial institutions on the stability indicator for bank i after one year.

V Empirical Analysis

1. Data and Descriptive Statistics

Our study analyzes banking system stability with respect to macroprudential determinants at institutional level, examining between 3,330 banks (in 1995) and 1,685 banks (in 2010) and including all German banks. During the 16-year period, the number of banks in the sample exceeds the number of effectively existing institutions in the German banking system caused by the technical treatment of mergers.[33] The stability indicator for the banking system—which is the dependent variable in our regression analysis—can be calculated for 37,151 bank-year observations, reflecting a panel of 70% cooperative banks (the vast majority), 22.5% savings banks and 7.5% commercial banks.[34] It adequately represents the existing distribution of financial institutions in the German three-pillar system. In the following, we highlight some

[31] In the context of their applied methodology, the authors construct an indicator that weighs signals issued by underlying macroprudential indicators in those countries to which the domestic banking sector is exposed. They confirm that signals resulting from cross-border exposures have especially been important for Germany and the Netherlands during the financial crisis of 2008/2009.

[32] See e.g. Bekaert et al. (2010) for a discussion of the VIX as a proxy for risk aversion and uncertainty in financial markets.

[33] At the time of the merger a new (third) bank is artificially constructed in the data set. This procedure is important in order not to distort the empirical results as, for example, a fixed effect is included in the regression model.

[34] The stability indicator also comprises special-purpose banks which do not belong to the German three-pillar banking system. As the number of these banks is small, and their business strategy is totally different from universal banks, special-purpose banks are dropped from the empirical analysis.

interesting developments of the leading indicators which enter the empirical model as regressors.

With regard to our set of macroeconomic variables, the national commercial real estate variable is suited to indicate increased real estate prices prior to two observed periods of predicted banking system instability in Germany in 2002/2003 and 2008/2009. The ifo index contemporaneously well captures exogenous shocks to the real economy. Within our observation period, several shocks can be identified, e.g. exogenous shocks in 2001 and 2008 were accompanied by significant adverse effects. Also, periods of higher expected banking system stability have been accompanied by an increasing ifo index, especially during the period of economic upturn between 2004 and 2007.

Among our set of financial variables, we expect the 3-month Libor to be statistically relevant in explaining the stability indicator for the banking system. The index precedes observed periods of predicted banking system instability in 2002/2003 and 2008/2009 by a sharp reversal of its growth rate. Interestingly, in contrast to e.g. the US financial sector and other euro-area countries that experienced huge national private credit-to-GDP ratios prior to the financial crisis 2008/2009, Germany did not experience any major expansionary phase between 1995 and 2010. The indicator even declined prior to the financial crisis of 2008/2009 and thus did not issue any signals for future banking system instability. According to economic theory, this evolvement over time suggests the national private credit-to-GDP ratio or real domestic credit growth to be less important in preceding anticipated national banking system instability, although these variables repeatedly proved to be among the best-performing indicators in predicting banking system crises and -instability in industrial and emerging market economies.[35]

Instead, we observe increased dependence of the national banking system on international exposures between 1999 and 2010.[36] Foreign lending and securities doubled in terms of balance sheet total from 14.3% in 1999 to 28.5% in 2009 with a slight decline to 27.2% in 2010. During that time, holdings of foreign stocks and bonds nearly tripled from 3.4% in 1999 to 8.3% in 2009. Especially commercial banks and Landesbanks invested heavily in international markets and securities. The latter can be explained in part by the abolition of state guarantees (“Gewährträgerhaftung” and “Anstaltslast” in German) in 2004/2005, forcing affected banks to find new investment opportunities according to altered business models and refinancing conditions that partly replaced public sector with business investments. This crowding out reveals clear structural changes in the composition of banks’ balance sheet exposures and will be considered in the empirical analysis by including the VIX index,

[35] See the literature review for corresponding empirical studies.

[36] See Appendix IV.

indicating to increased international risk aversion of financial market participants, e.g. in 2001/2002 and 2007 to 2009.

Descriptive statistics of original time series are available in Appendix V.

2. *Panel Regression Model*

In the empirical analysis, we explain the stability indicator for the banking system across Germany's three-pillar structure and over a total of 37,151 bank-year observations, which allows us to take into account unobserved time-invariant individual heterogeneity. The data-generating process of the stability indicator is dynamic as the indicator $y_{i,t}$ follows an AR(1) process. Using lag operators to identify determinants of future banking system stability may imply predetermined or endogenous explanatory variables. Thus, we consider an autoregressive distributed lag (1, p, q) model in panel version of the following form:[37]

$$y_{i,t} = \alpha y_{i,t-1} + \sum_{j=1}^{J} \beta_j X_{j,t-p} + \sum_{k=1}^{K} \beta_k Z_{i,k,t-q} + \mu_i + \nu_{i,t},\ t = 2,..,T \quad (3)$$

The dependent variable is the stability indicator for the banking system at the institutional level i at time t and is denoted by $y_{i,t}$, and its lagged value is denoted accordingly. As we are not interested in the evolution of the explanatory variables over time but in their most significant lagged values, $X_{j,t-p}$ and $Z_{i,k,t-q}$ contain only lag $t-p$ respective $t-q$ of the explanatory variables. The lags are thus allowed to differ across explanatory variables. Hereby, $X_{j,t-p}$ denote macroprudential variables and $Z_{i,k,t-q}$ denote bank-specific control variables. The coefficients β_j and β_k describe the effect of $X_{j,t-p}$ and $Z_{i,k,t-q}$ on $y_{i,t}$ and are constant across entities and time. The fixed effect is described by μ_i and the idiosyncratic error term by ν_{it}. Whereas the bank specific control variables capture the cross-sectional (bank-level) variation in the risk indicator, our focus is on the time series variation explained by macroprudential leading indicators. As such these are intended to explain the aggregate (average) risk level in the banking system. As we use bank-level data to carry out the empirical analysis, the boost in observations will lead to much lower standard errors. We therefore concentrate on the economic rather than on the statistical significance of our results.[38]

When using dynamic panel data models, two problems which lead to inconsistent OLS estimation usually arise. The first is associated with the "Nickell Bias" or "Dynamic Panel Bias" as the regressor $y_{i,t-1}$ is correlated with the error term μ_i which is, by

[37] See Wooldridge (2010) for a detailed discussion of ARDL (1, p, q) models in panel version.

[38] We might also relate our macroprudential indicators to bank-specific variables. However, as this proceeding does not relate to our core research question, we leave it to future research.

definition, independent of time in the regression model.[39] The second problem appears when removing the individual heterogeneity term μ_i by first differencing the estimation equation.[40]

To control for the above named problems, a two-step Arellano-Bond (1991) difference GMM estimation procedure is appropriate. However, as instrumenting is technically difficult in the Arellano-Bond model due to highly unbalanced panel data, we also apply a standard fixed-effects model including the lagged dependent variable as an additional regressor. Again, we have to ensure reliable OLS estimates. The first problem of "dynamic panel bias" is addressed by within-transformation of the estimation equation; the second problem of endogeneity remains as the lagged dependent variable is not instrumented in our fixed-effects model. We argue that our estimation results are, however, asymptotically valid for two reasons. First, the coefficient α approximately equals 0.36 in both the Arellano-Bond and fixed-effects estimations which is quite robust and suggests the bias to be small.[41] Second, as Mehrhoff (2009) finds, the "Nickell Bias" decreases with increasing T and decreasing α; it should be in an acceptable range as T is at least 16 and α is low. We therefore rely on the results from the fixed effects model specification.

We start our empirical analysis for all banks without any other regressor except the control variable as a benchmark model.[42] Successively, we include additional explanatory variables with respect to our classification scheme of macroeconomic, financial and structural indicators and test theoretical evidence on separate lag operators of explanatory variables.[43] To achieve interpretable results, growth rates of explanatory variables are specified in the estimation equation except for the bank specific control variables. The choice of an optimal model is based on a separately calculated AIC criterion.

We find evidence that our data is correlated along two dimensions. The observations of macroprudential indicators are correlated within year as they all capture effects of economic up(down)swings. In addition, observations of macroprudential indicators are correlated along the panel identifier as they are identical for each bank i in year t. To control for standard errors that are not identical and independently distributed (i.i.d.)

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[39] See Nickell (1981).

[40] This leads to an endogeneity problem by definition because $(y_{i,t-1} - y_{i,t-2})$ is correlated with $(\nu_{it} - \nu_{i,t-1})$. Instrumental variables can be applied and lead to consistent estimates if corresponding assumptions are fulfilled.

[41] Regression results for the Arellano Bond model are available upon request.

[42] We also tested other control variables, e.g. the value of total assets itself and (core) deposits in terms of total assets, the latter reflecting different business models, but found no significant improvement.

[43] In line with e.g. Hanschel and Monnin (2005) or Borio and Drehmann (2009) we consider four and more lags to constitute an irrelevant long time horizon in preceding banking system stability or – crises. As the business cycle is usually characterized by a time horizon of four years, it suggests the appliance of more than four lags to be inappropriate. In a robustness check, we also identify the individual optimal lag structure of our set of macroprudential indicators based on AIC criterion by including them separately into our benchmark model. As this proceeding leads to identical lag structures, we only report the same lag choice for different model specifications.

and subject to problems of heteroskedastic and autocorrelated patterns in idiosyncratic error terms, we apply clustered standard errors following Cameron et al. (2006). Most of the serial correlation in idiosyncratic error terms is eliminated by first differencing of logarithmic explanatory variables except for the control variables and avoids biased t-statistics and confidence intervals due to non-stationary explanatory variables. The assumption of strict exogeneity with $cov(\varepsilon_{it}, x_{it}) = 0$ is ensured.

Estimation results can be found in tables (1) – (3) in Appendix VIa - VIb. Whereas the first model (1) reports an international estimation specification, the second model (2) refers to a national model. The overall model specification is given in column (3).

VI Results

Our main results reveal that macroprudential early warning indicators commonly used to predict banking system crises and –instability in both developing and developed countries are not necessarily useful leading indicators for Germany. We present our findings not only for the whole banking system, but also for different banking sectors. Regarding our set of macroeconomic, financial and structural explanatory variables, we identify indicators that prove explanatory power and a constant optimal lag structure among various specifications according to AIC criterion. These indicators will be subsequently presented in detail. As argued in the previous section, there is no serious “dynamic panel bias” problem in our data, and our findings are robust throughout different regression techniques. Therefore, we report and discuss results derived from a fixed-effects regression model (instead of the Arellano-Bond model, which is hard to estimate because of unbalanced panel data).

Overall, the explanatory power of several estimated fixed-effects models for all banks is good, as the within-R-squared varies around 30% except for commercial banks for whom the within-R-squared is somewhat increased. The estimated coefficient of the dynamic term is significant and robust among several specifications, and is close to the estimated coefficients of the Arellano-Bond GMM regression model.

1. *Macroprudential Indicators*

Among our set of macroeconomic variables, we begin with asset price indicators, of which the national commercial real estate price index shows explanatory power in preceding the banking system stability indicator with a lag of one period. The sign of the estimated standardized beta coefficient is negative and robust among various specifications and explains about 15% of the standard deviation of y. Higher growth rates of the commercial real estate price index thus indicate a boom phase in the business cycle and imply less banking system stability in the subsequent period. We conclude that property prices are relevant predictors for banking system stability, reflecting their importance in the transmission channel of capital costs, as has been shown in studies examining banking system crises in panels of developed countries, e.g. by Borio and Drehmann (2009).

Concerning leading indicators for economic outlook and the business cycle, the ifo index is significant and robust among various estimation specifications. Due to its positive sign, a positive growth rate of the ifo index indicates positive economic expectations and contemporaneously leads to more banking system stability. Again, the estimated beta coefficient explains about 15% of the standard deviation of y. Although theoretical evidence suggests gross fixed investments to be a promising leading indicator of the economic outlook and driver of banking system stability, the indicator proved to have little explanatory power. Likewise, Hanschel and Monnin (2005) do not find investments to be a robust leading indicator of the stability of the Swiss banking sector but instead European real GDP, which shows the country to be less nationally dependent and more internationally open.

As for the set of financial indicators, the 3-month Libor is robust among several estimation equations in preceding the stability indicator for the banking system by two lags according to AIC criterion, explaining about 16% of the standard deviation of y. Due to its negative sign, as higher interbank interest rates are associated with less confidence in the interbank market and lending that gets more expensive, large positive growth rates of the 3-month Libor translate to a deterioration of banks' refinancing conditions and lead to less anticipated banking system stability in the two subsequent periods, which supports the importance of the interbank market in determining stability in the banking system. However, due to its robust and constant lag structure among several estimation equations, higher growth rates of the 3-month Libor do not explain coincident instability in the banking system. Instead, the variable rather reflects the business cycle of key ECB interest rates.[44] With respect to monetary expansion, the ratio of M2 to national real GDP shows less explanatory power and is not robust among various estimation specifications. We conclude that monetary policy rather affects national banking system stability via the transmission channel of key ECB interest rates than via the money supply given by M2.

The most prominent leading indicators of banking system crises and banking system instability in the existing literature are the credit-to-GDP ratio and the credit growth variable. Our results, however, do not confirm an overall outstanding explanatory power of these indicators for Germany. We find, however, evidence for the relevance of the national private credit-to-GDP ratio at the banking sector level, which will be

[44] We are currently working on a better separation between the effects of monetary policy and distress on the interbank market by including the ECB key interest rate and the 3-month Libor over 3-month Bubill similar to the TED-Spread in empirical analysis. We expect loose monetary policy and an increased Libor spread to precede banking system instability.

discussed below. This is important, as it reveals evidence that the indicators might be among the best predictors of banking system crises and -instability in various panels of emerging and industrial countries[45], but they do not prove similar explanatory power for the whole German banking system.

Turning to the set of structural variables, we first discuss the relevance of international and regional spillover effects. For the identification of a macroprudential indicator which explains international spillover effects, we find that the VIX index based on S&P stock market index options (reflecting implied volatility in financial markets) significantly captures international risk aversion of financial market participants and explains about 8% of the standard deviation of y. The inclusion of the variable improves explanatory power of the overall model from about 26% to 30% which is stated, not reported. It precedes the stability indicator for the banking system with a lag of one period. This implies that a higher growth rate of the VIX index induces less banking system stability one period later, as increased fluctuations in financial markets, which have adverse impacts on national banking system stability, are expected. According to the overall model, this variable accurately reflects international spillover effects and seems to have a higher impact on banking system stability than regional effects, as estimated standardized beta coefficients are notably higher. However, our indicator of counterparty exposures in terms of balance sheet total at the banking group level turned out to be insignificant in the empirical analysis. We do believe that this owes to difficulties in constructing the variable using exposures at book-market values only instead of market-based prices which is due to lack of adequate data. The construction of indicators which adequately reflect cross-country exposures has undoubtedly become important against the background of the 2008/2009 financial crisis and is left to future research.[46]

2. *Analyses by Banking Sector*

With respect to regression models for separate banking sectors, we find that the overall explanatory power reflected by within-R-squared remains approximately in the same interval as for the overall model, except for the rising explanatory power of the estimated models for commercial banks because the estimated standardized beta coefficients of the lagged dependent variable are significantly higher. This implies that commercial banks seem to be less driven by macroprudential indicators, depending more on their lagged stability indicator. This finding is supported by the fact that commercial banks are highly complex and intertwined with international financial

[45] See, for example, Borio and Lowe (2002), Borio and Drehmann (2009).

[46] The approach by Borio/Drehmann (2009) offers a first step in the right direction but should, in the future, also include exposures to a foreign country rather than exclusively focus on lending by institutions located in a given country. See footnote 20 on p. 42.

markets due to their business models; other supervisory tools that examine, for example, liquidity or contagion effects should therefore complement the monitoring of real economic and financial developments. All other leading indicators remain predominantly robust and significant with approximately the same estimated beta coefficient among various specifications, supporting their fundamental relevance across all banking sectors.

Interestingly, whereas the private credit-to-GDP ratio indicates explanatory power throughout various specifications for all banks, the variable becomes strongly significant for cooperative banks, but remains insignificant for commercial banks. The results are mixed for savings banks. We conclude that national private credit-to-GDP is a relevant predictor for regionally focused banks in determining banking system stability, but it is less important for internationally oriented banks. This suggests that nuanced indicators are relevant for the financial analysis of the German banking system. International asset price indicators indeed show some explanatory power for commercial banks with a lag of one period but are not robust among several specifications.[47]

3. *International and Regional Spillover Effects*

Turning to international and regional effects across banking sectors, we observe heterogeneous determinants of banking system stability that require us to take a different view in our analysis of the stability of the German banking system. Banking sector specific early warning models turn out to be relevant. In the empirical analysis of commercial banks, regional effects become irrelevant in determining stability in the German system. Instead, the 3-month Libor and VIX capture international effects accurately throughout various estimation equations. As commercial banks obtain funding on international financial markets and are internationally oriented, institutions are therefore highly dependent on international developments, whereas regional factors only play a minor role.

However, regional spillover effects become a significant determinant for banking system stability in particular for small cooperative banks, whereas results for savings banks are ambiguous. We employ a regional spillover variable in the regression model in order to measure the effect of the one-year lagged asset-weighted standardized PD calculated for financial institutions of region l on institution i located in the same area level and thus the impact of banking distress in surrounding financial institutions on institution i. As the estimated standardized beta coefficient is significant with positive sign, increased banking distress in surrounding financial institutions transmit to increased banking distress for bank i one subsequent period. Under the assumption

[47] Estimation results are available upon request.

that the –in most model specification insignificant– control variable regional per-capita GDP growth is an appropriate proxy for regional real economic stress, we are able to rule out that the real economy, e.g. insolvency of local companies, is in effect driving regional banking stability and this finally limits the channel for regional banking stress to the regional spillover effects we observe.

Cooperative banks and savings banks predominantly obtain funding through their central institutions and are thus less dependent on international financial markets and at least predominantly regionally focused. However, the VIX index is statistically significant across both banking sectors, reflecting the fact that credit cooperatives and savings banks likewise start participating in international financial markets. These heterogeneous determinants of banking system stability hint at a diversification effect of the German three-pillar banking system (of which each banking sector is exposed to various shocks in a different way) which might enhance overall national banking system stability.

In summary, we conclude that our empirical results give rise to banking sector specific early warning models which allow for heterogeneous determinants of the stability of the German banking system. Whereas the commercial real estate price index, the ifo index, the 3-month Libor and the VIX seem to be useful macroprudential leading indicators in all models, regional effects and the credit-to-GDP ratio play a significant role for cooperative banks, but are less important for commercial banks.

VII Concluding Remarks

Over the past two decades, Germany experienced several periods of banking system instability rather than full-blown banking system crises. We therefore introduce a continuous and forward-looking stability indicator for the German banking system which is used to identify macroprudential early warning indicators and international and regional spillover effects. The indicator comprises not only major systemically relevant institutions, but also small private, savings, and cooperative banks, which are in particular relevant for regional credit supply. Therefore, the stability indicator is meant to provide a macroprudential analysis tool for banking supervisors and policy makers.

The indicator comprises three components: an institution’s probability of default, a credit spread, and a stock market index for the banking sector. The probabilities of default (PDs) are derived from the Bundesbank’s hazard rate model for small banks; for large institutions, Moody’s Bank Financial Strength Ratings are used. We apply the supervisory risk profile assessment as a benchmark for assigning weights to indicator components.

The empirical study is based on confidential supervisory reporting data provided by the Deutsche Bundesbank which consists of up to 3,330 institutions over the period 1995 to 2010. We apply panel regression techniques and find that asset price indicators, leading indicators for the business cycle and money market indicators can be shown to be reliable early warning indicators. This stresses the necessity of monitoring macroprudential indicators in banking supervision and supports regulators developing regulatory requirements incorporating the business cycle. In addition, international spillover effects play a significant role for banking system stability across all banking sectors, whereas regional spillover effects and the national credit-to-GDP ratio mostly affect credit cooperatives, but are less important for commercial banks. These findings imply heterogeneous determinants of banking system stability that hint at a diversification effect of the German three-pillar banking system of which each banking sector is exposed to various shocks in a different way. This might enhance the stability of the banking system as a whole.

Beyond the scope of this paper, further research is needed to develop indicators that adequately map increased cross-border exposures of financial institutions that became especially important during the recent financial crisis of 2008/2009.

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Appendix

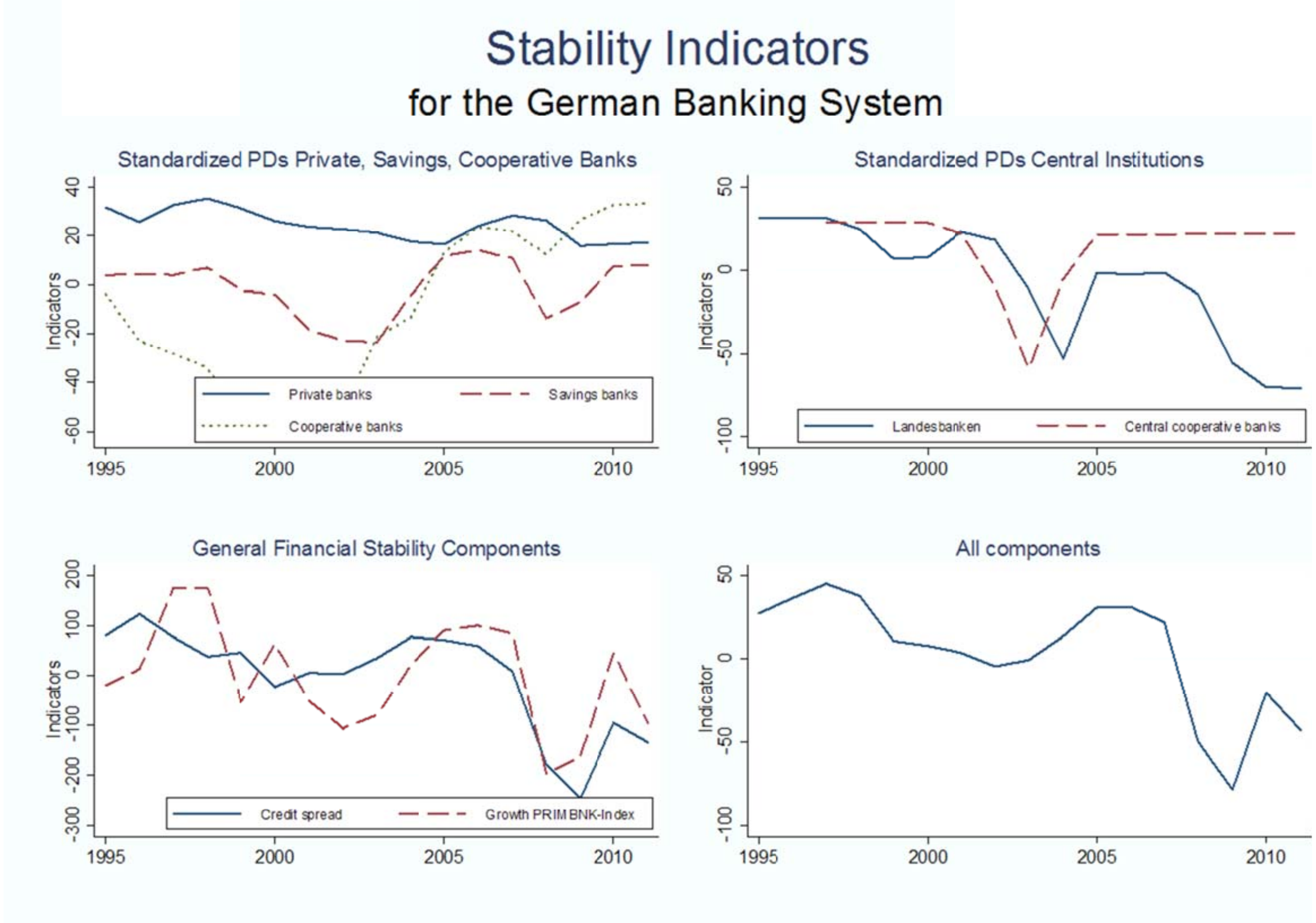
Appendix I: Regression Statistics "Bundesbank Hazard Rate Model" for Savings, Cooperative, and Small Private Banks.

This table shows regression statistics from a bank rating model that is based on the logistic link function which transforms a set of bank-specific covariates and a macroeconomic variable observed in year t-1 into the probability of default (PD) of a bank in year t. The right-hand side of the regression equation is based on the CAMELS taxonomy. On the left-hand side of our logistic regression we use a unique data set of bank distress events collected by the Deutsche Bundesbank over the time period 1994 to 2006 which is only available for small banks. Along with PDs from Moody's Bank Financial Strength Ratings, the PDs from this rating model constitute the main component of the financial stability indicator.

Variable	
Tier 1 capital ratio	-0.04691***
	[-3.039]
Total bank reserves	-1.69905***
	[-13.410]
Reserves reduction	0.54120***
	[6.487]
Share of customer loans	0.00815**
	[2.265]
Sector HHI	-0.00845**
	[-2.272]
Hidden liabilities	0.62935***
	[6.977]
Share of fee income	0.02784***
	[3.518]
RoE	-0.05372***
	[-15.729]
Branches HHI	0.00069***
	[4.102]
Yield curve	0.11602**
	[2.288]
Dummy savings banks	-0.30262
	[-1.332]
Dummy cooperative banks	0.06767
	[0.426]
Constant	-2.46671***
	[-6.383]
Observations	29,991
Number of banks	4,682
AUC	0.877

Tier 1 ratio = Tier 1 capital to risk-weighted assets. **Total bank reserves** = Total bank reserves (according to sections 340f and 340g of the German Commercial Code) to total assets. **Reserves reduction** = Dummy takes one if total bank reserves are used. **Share of customer loans** = Customer loans to total assets. **Sector HHI** = Herfindahl-Hirschman Index over 23 industry sectors (i.e., larger values indicate higher concentration in the loan portfolio). **Hidden liabilities** = Dummy indicates avoided write-offs on the bank's assets. **Share of fee income** = Fee income to total income. **ROE** = Operating results to equity. **Branches HHI** = Herfindahl-Hirschman Index over bank branches per state (i.e., larger values indicate higher branch concentration in the respective "Bundesland" banking market). **Yield curve** = Interest rate on 10-year minus 1-year German government bond. **Dummy savings banks** = Dummy takes one for savings banks. **Dummy cooperative banks** = Dummy takes one for cooperative banks. All ratios in percent; t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Appendix II: Stability Indicators for the German Banking System.



Appendix III. Set of Explanatory Variables, Variable Code and Data Source.

	Type	Variable	Code	Source
Macroeconomic Variables	**Asset Price Indicators**	National real estate price index (commercial)	*REALEST_PRICE*	Bulwien AG
	Leading indicators for business cycle	ifo business cycle expectation	*IFO_INDEX*	Ifo-Institute
		Gross fixed investments	*GR_FIXED_INV*	German Federal Statistical Office
Financial Variables	**Lending**	National private credit to GDP	*CRED_TO_GDP*	Deutsche Bundesbank
	Money Market	Libor (3-month)	*LIBOR_3M*	British Bankers' Association
		M2-to-GDP	*M2_TO_GDP*	Deutsche Bundesbank
Structural Variables	**Regional Spillovers**	Asset-weighted probability of default for institutions in the same county, excluding the respective bank	*COUNTY_PD*	Deutsche Bundesbank
		Regional GDP (percentage change)	*COUNTY_GDP*	German Federal Statistical Office
	Counterparty Exposures	International exposures in terms of balance sheet total (at banking group level)	*INT_EXP*	Deutsche Bundesbank
	Risk aversion	Indicator for risk appetite	*VIX_INDEX*	Chicago Board Options Exchange
	Bank size	Logarithm of GDP-deflated total assets	*Ln_ASSETS*	Deutsche Bundesbank

Source: Various. Note: We also included further indicators (e.g. real GDP) at national and European level that turned out not to be significant and are available upon request.

Appendix IV. Selected Balance Sheet Items in € Billion, All Banks.

	1999	**2004**	**2007**	**2009**	**2010**
Stocks and bonds from foreign issuers	195.9	382.5	675.0	639.0	592.1
In % of balance sheet total	3.41	5.74	9.09	8.27	7.75
Foreign lending (bonds included)	823.2	1519.0	2245.3	2199.9	2074.2
In % of balance sheet total	14.34	22.79	30.22	28.48	27.15
Of which					
Lending to foreign banks (bonds and money market securities included)	427.1	889.4	1379.0	1332.4	1255.2
In % of balance sheet total	7.44	13.35	18.56	17.25	16.43
Lending to foreign non-banks (bonds included)	396.1	629.5	866.3	867.5	819.0
In % of balance sheet total	6.90	9.45	11.66	11.23	10.72
Deposits and borrowing from foreign banks	483.6	603.3	745.5	696.1	749.8
In % of balance sheet total	8.42	9.05	10.03	9.01	9.82
Deposits and borrowing from foreign non-banks	284.4	311.2	318.3	254.9	254.6
In % of balance sheet total	4.95	4.67	4.28	3.3	3.3

Source: Deutsche Bundesbank.

Appendix V: Descriptive Statistics.

Variable	Mean	Std. Dev.	Skewness	Kurtosis	Min.	Max.
Ln_ASSETS (in billion EUR)	19.35	1.51	0.34	3.63	7.61	26.01
COUNTY_GDP (% change)	1.27	3.60	0.27	6.38	-23.06	32.39
REALEST_PRICE (COMMERCIAL) (1990 = 100)	101.60	7.82	1.04	2.75	93.55	118.70
IFO_INDEX (2005 = 100)	99.97	4.35	-0.03	1.99	92.99	107.90
GR_FIXED_INV (in billion EUR)	93.12	5.62	0.56	2.22	85.14	105.10
CRED_TO_GDP (in %)	1.48	0.21	-0.86	2.19	1.06	1.68
LIBOR_3M (in %)	3.97	1.91	-0.51	1.92	0.343	6.53
M2_TO_GDP (in %)	0.62	0.07	0.53	2.72	0.510	0.78
VIX_INDEX (index)	20.27	6.20	0.38	2.04	12.42	32.69

Note: Original time series. Various sources; see appendix III.

Appendix VIa: Empirical Results for Fixed Effects Estimation, All Banks & Commercial Banks.

This table shows regression statistics from a standard fixed-effects model with clustered standard errors. On the left-hand side of our estimation equation we use a composite banking stability indicator at institutional level over the time period 1995 to 2010. The Indicator is based on the institutions' individual standardized probabilities of default, a credit spread (i.e., the average bank risk premium) and a stock market index for the banking sector ("Prime Banks Performance Index"). The right-hand side of the regression equation is based on various macroprudential variables included with different lags.

	All Banks			Commercial Banks		
BASKET_SI	(1)	(2)	(3)	(1)	(2)	(3)
L1.BASKET_SI	0.362*** [10.026]	0.365*** [10.667]	0.364*** [10.639]	0.488*** [17.379]	0.494*** [15.424]	0.474*** [18.111]
Control Variable						
Ln_ASSETS	-0.264*** [-3.291]	-0.345*** [-5.678]	-0.339*** [-6.828]	-0.071 [-1.32]	-0.070 [-1.299]	-0.052 [-1.06]
Regional Variables						
L1.COUNTY_PD	0.031*** [2.576]	0.017* [1.728]	0.018** [2.144]	0.010 [0.562]	0.009 [0.568]	0.010 [0.529]
COUNTY_GDP	-0.007 [-0.895]	0.007 [0.562]	0.006 [0.565]	0.016 [0.786]	0.027 [0.813]	0.007 [0.384]
Macro Variables						
L1.REALEST_PRICE	-0.134*** [-4.568]	-0.135*** [-5.71]	-0.137*** [-5.347]	-0.124*** [-5.199]	-0.091*** [-4.89]	-0.132*** [-5.705]
L0.IFO_INDEX	0.146*** [8.955]	0.205*** [10.859]	0.199*** [6.957]	0.166*** [10.201]	0.189*** [8.779]	0.149*** [4.733]
L2.GR_FIXED_INV		0.037 [1.323]	0.034 [1.074]		-0.005 [-0.169]	0.011 [0.274]
L1.CRED_TO_GDP		-0.102*** [-3.291]	-0.096** [-2.257]		-0.003 [-0.113]	0.041 [1.141]
Financial Variable						
L2.LIBOR_3M	-0.114*** [-3.09]	-0.193*** [-9.34]	-0.184*** [-2.968]	-0.144*** [-3.09]	-0.196*** [-7.489]	-0.115** [-2.326]
International Variable						
L1.VIX_INDEX	-0.074** [-2.457]		-0.009 [-0.21]	-0.065 [-1.526]		-0.099** [-2.144]
Observations	32,116	32,116	32,116	2,375	2,375	2,375
Number of times	16	16	16	16	16	16
F-statistic	302.4	186.0	492.0	114.9	132.0	115.0
Within-R2	0.304	0.308	0.308	0.479	0.476	0.481

Appendix VIb: Empirical Results for Fixed Effects Estimation, Cooperative Banks & Savings Banks.

This table shows regression statistics from a standard fixed-effects model with clustered standard errors. On the left-hand side of our estimation equation we use a composite banking stability indicator at institutional level over the time period 1995 to 2010. The Indicator is based on the institutions' individual standardized probabilities of default, a credit spread (i.e., the average bank risk premium) and a stock market index for the banking sector ("Prime Banks Performance Index"). The right-hand side of the regression equation is based on various macroprudential variables included with different lags.

	Credit Cooperatives			Savings Banks		
BASKET_SI	(1)	(2)	(3)	(1)	(2)	(3)
L1.BASKET_SI	0.344*** [7.1]	0.337*** [7.733]	0.339*** [7.955]	0.360*** [7.902]	0.365*** [8]	0.357*** [7.98]
Control Variable						
Ln_ASSETS	-0.537*** [-3.09]	-0.742*** [-4.727]	-0.797*** [-6.492]	-0.479*** [-2.652]	-0.510*** [-2.612]	-0.486*** [-2.652]
Regional Variables						
L1.COUNTY_PD	0.042*** [3.09]	0.024** [2.241]	0.029*** [5.143]	0.016 [1.198]	0.011 [0.863]	0.014 [1.359]
COUNTY_GDP	-0.014 [-1.193]	0.003 [0.315]	0.007 [0.817]	0.004 [0.292]	0.013 [0.722]	0.004 [0.298]
Macro Variables						
L1.REALEST_PRICE	-0.119*** [-2.612]	-0.126*** [-3.09]	-0.099*** [-2.612]	-0.109*** [-3.09]	-0.099*** [-3.09]	-0.113*** [-3.291]
L0.IFO_INDEX	0.150*** [6.856]	0.220*** [8.179]	0.204*** [5.698]	0.157*** [9.049]	0.186*** [10.83]	0.170*** [5.245]
L2.GR_FIXED_INV		0.041 [1.083]	-0.009 [-0.213]		0.014 [0.676]	0.017 [0.53]
L1.CRED_TO_GDP		-0.150*** [-3.291]	-0.139** [-2.457]		-0.036* [-1.69]	-0.012 [-0.337]
Financial Variable						
L2.LIBOR_3M	-0.103*** [-2.697]	-0.185*** [-9.039]	-0.184*** [-4.541]	-0.150*** [-6.477]	-0.197*** [-9.01]	-0.155*** [-3.291]
International Variable						
L1.VIX_INDEX	-0.077** [-2.274]		0.017 [0.469]	-0.048** [-2.543]		-0.043 [-1.19]
Observations	22,224	22,224	22,224	7,373	7,373	7,373
Number of times	16	16	16	16	16	16
F-statistic	183.6	101.6	184.0	557.0	507.3	270.9
Within-R2	0.290	0.304	0.303	0.301	0.300	0.301