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Abhandlungen

Early Warning Indicators for the German Banking System: A Macroprudential Analysis*

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Abstract

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 indicator 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 monetary indicators) and spillover effects. International spillovers play a significant role across all banking sectors, whereas regional spillovers and the credit-to-GDP ratio are more important for cooperative banks and less relevant for commercial banks.

Frühwarnindikatoren für das deutsche Bankensystem: Eine makroprudenzielle Analyse

Zusammenfassung

Frühwarnindikatoren für drohende Risiken im Bankensystem sollen einen wichtigen Beitrag für die regelmäßige Einschätzung der Stabilität des Banken-

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systems und die Identifizierung von systemischen Risiken liefern. Ein funktionierendes und stabiles Bankensystem ist für die Gewährleistung einer optimalen Kapitalallokation von grundlegender Bedeutung, so dass Regulatoren kostspielige Bankenkrisen und ihre damit verbundenen, negativen Feedbackeffekte auf die Realwirtschaft zu vermeiden versuchen. Die vorliegende Arbeit leistet einen Beitrag bezüglich der Entwicklung eines kontinuierlichen, zukunftsgerichteten Stabilitätsindikators für das deutsche Bankensystem, welcher zu der Identifizierung vorlaufender Frühwarnindikatoren sowie internationaler und regionaler Ansteckungseffekte im Bankensystem herangezogen wird.

Während der letzten zwei Jahrzehnte erfuhr Deutschland mehrere Perioden von Bankensysteminstabilität. Diese konnten über die Bankensektoren hinweg aufgrund von Gesetzesänderungen sowie (inter)nationalen Entwicklungen auf den Finanzmärkten beobachtet werden. Um die Stabilität im Bankensystem überwachen zu können, entwickeln wir einen Stabilitätsindikator, welcher Informationen sowohl von großen Finanzinstituten, als auch von kleineren Banken enthält. Der Indikator besteht aus drei Komponenten: Einem Bonitätsindikator (basierend auf der normierten Ausfallwahrscheinlichkeit eines Instituts), einem Credit Spread (d.h. der durchschnittlichen Risikoprämie verfügbarer Institute) und einem Aktienindex für den Bankensektor. Die Ausfallwahrscheinlichkeiten werden für kleinere Banken aus dem Bundesbank-Hazardratenmodell und für die großen Institute aus dem Moody's Bank Financial Strength Rating herangezogen. Die empirische Studie basiert auf einem von der Deutschen Bundesbank bereitgestellten, vertraulichen Datensatz und enthält bis zu 3,330 Institute über einen Zeitraum von 1995 bis 2010 auf jährlicher Basis.

Die Determinanten für Bankensystemstabilität können in makroökonomische, finanzielle und strukturelle Variablen klassifiziert werden. Unter Anwendung von Panelregressionstechniken können wir Vermögenspreisindizes, Frühindikatoren für den Konjunkturzyklus und Geldmarktindikatoren als robuste Frühwarnindikatoren identifizieren. Während internationale Ansteckungseffekte für alle Bankensektoren von Bedeutung sind, erweisen sich regionale Ansteckungseffekte und die nationale Kreditvergabe an den privaten Sektor im Verhältnis zum BIP als relevante Determinanten für Kreditgenossenschaften, sind aber weniger bedeutsam für Kreditbanken. Diese Ergebnisse weisen darauf hin, dass die heterogene Struktur des deutschen 3-Säulen-Systems (innerhalb dessen jeder Bankensektor durch verschiedene Schocks unterschiedlich beeinflusst wird) einen Beitrag zu der Stabilität des gesamten Bankensystems leisten kann.

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

JEL classification: C23, E44, G01, G21

I. Introduction

The stability and efficiency of a banking system ensures the optimal allocation of capital resources in an economy. Regulators therefore aim to prevent banking system crises and the associated adverse feedback

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effects on the real economy. Regularly assessing financial stability and identifying macroprudential leading indicators signaling emerging risks to the banking system is therefore of major importance for central banks and supervisory authorities. This paper introduces a stability indicator for the German banking system which is used to identify macroprudential early warning indicators and spillover effects in regional banking and international financial markets.

Over the last two decades, Germany has experienced several periods of banking system instability rather than full-blown banking system crises. After the dotcom bubble burst in 2000/2001, German cooperative banks especially suffered from increased loan defaults. Furthermore, Landesbanks in particular had to realign their business models and refinancing conditions in response to the abolition of state guarantees ("Gewährträgerhaftung" and "Anstaltslast" in German) in 2004/2005. Given increasing internationalization and consequently high dependence on international developments, the German banking system again suffered instability in 2008/2009 as a result of the financial crisis and the worldwide turmoil it provoked. In 2013, major German banks are still suffering from increased stress in financial markets that has been brought about by the European sovereign debt crisis. Therefore, the importance of our study remains high.

The aim of this paper is to provide new tools for banking supervisors to monitor and assess the stability of the German banking system and its determinants. We address two research questions. First, as periods of banking system instability have been observed rather than severe banking system crises, as described above, 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 aggregate three important indicators to create one stability measure: the institutions' individual standardized probabilities of default (PDs), an aggregate credit spread (i.e. the average bank risk premium) and a stock market index for the German banking sector ("Prime Banks Performance Index"). Second, in line with the body of empirical literature on early warning indicators for banking system crises and system instability, we analyze the impact of macroprudential leading indicators on the stability of the German banking system. Our findings suggest that asset price indicators, leading indicators for the business cycle, monetary indicators and spillover effects are relevant early warning indicators. International spillovers play a significant role

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across all banking sectors, whereas regional spillovers and the credit-to-GDP ratio are more important for cooperative banks and less relevant for commercial banks.

The paper proceeds as follows. Section II gives an overview of the related literature. 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 an introduction of the empirical model. Section VI discusses results and robustness checks. Section VII concludes.

II. Related Literature

This section briefly discusses related studies on stability indicators for the banking and overall financial system as well as corresponding early warning indicators. A general review of the work on measures and leading indicators of financial stability can be found in *Bell/Pain* (2000), *Fell/Schinasi* (2005) or *Gadanecz/Jayaram* (2009).

Illing/Liu (2006) develop a financial stress index for the Canadian financial sector by variance-equal weighting several indicators from foreign exchange markets, debt markets, equity markets and the banking sector into one single index. *Borio/Drehmann* (2009a) calculate this index for the US and euro-area financial market; it correctly signals future risks from 2007 onwards. *Hanschel/Monnin* (2005) both develop and examine a continuous stress index for the Swiss banking sector by equal-weighting market price, balance sheet, non-public and other structural data. *Von Hagen/Ho* (2007) address shortcomings related to commonly applied definitions of a banking crisis.[1] Using those definitions might lead to a selection bias because the identification criteria include the occurrence of severe market reactions. Hence, the authors motivate their approach based on the currency crisis literature and derive a continuous index for money market tension based on a sample of both industrial

[1] *IMF* (1998a), *Demirgüc-Kunt/Detragiache* (1998). According to the latter, a crisis occurs if at least one of the following conditions holds: (i) The ratio of non-performing assets to total assets in the banking system exceeds 10 %, (ii) the cost of the rescue operation is at least 2 % of GDP, (iii) banking sector problems result in a large-scale nationalization of banks, (iv) extensive bank runs or emergency measures such as deposit freezes take place, prolonged bank holidays or generalized deposit guarantees are enacted by the government in response to the crisis, p. 91.

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and emerging market economies. Subsequently, a discrete banking crisis is identified for certain thresholds, i.e. the extreme tails of the index's distribution. Addressing the whole German and euro-area financial system, *van Roye* (2013) constructs a continuous Financial Market Stress Indicator by summarizing several variables for the banking sector, the securities and stock market as well as for the foreign exchange market in a dynamic factor model. In chapter III, we compare this measure to our banking system stability indicator.

For highly industrialized countries, e.g. Germany, that predominantly do not suffer from full-blown banking system crises, instead experiencing periods of banking system instability, ordinal indicators allowing for more than two categories, or, better still, continuous stability indicators describing the condition of the banking system are needed to support banking supervisors in financial stability analysis.[2] To the best of our knowledge, continuous stability indicators for the German banking system are still missing in the literature. The first contribution of our paper is therefore to fill this gap.

The recent financial crisis of 2008/2009 demonstrated that the microprudential perspective of bank stability analysis (e.g. supervisory models aimed at limiting the risk of the default of an individual financial institution) was not able to detect system-wide risks at the bank level. Therefore, the microprudential perspective needs to be enriched by a macroprudential perspective with the objective of limiting system-wide risks to financial stability.[3] Against this backdrop, our analysis focuses on the macroprudential perspective, i.e. developing a stability indicator for the whole banking system and subsequently identifying macroeconomic, financial and structural variables preceding banking system (in)stability with a lead in time.[4] Both the micro and the macroprudential perspective constitute a comprehensive supervisory framework for regular financial stability analysis.[5]

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[2] A binary indicator answers the question "Is there a crisis?" with "Yes" or "No". Thus, it cannot be used to draw detailed conclusions about the stability of a market. A further discussion of the advantages of a continuous indicator can be found in chapter III.

[3] *FSF* (2009), *Borio* (2003), *Clement* (2010).

[4] The *IMF* (1998b) states that a "macroprudential analysis is based on (…) macroeconomic information, and focuses on developments in important asset markets, other financial intermediaries, and macroeconomic developments and potential imbalances", p. 13.

[5] *Crockett* (2000).

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Macroeconomic models containing early warning indicators for banking system crises and instability provide deep insights into the mechanisms of interaction between the financial and the real sector. We do not present the underlying theoretical hypotheses for identifying suitable leading indicators in detail, but closely link our motivation to choose a certain set of macroprudential variables to the evidence provided by the following theoretical and empirical work. Among the first authors to prove a macro-financial linkage were *Bernanke* et al. (1996), who initially formulated the financial accelerator mechanism. *Lorenzoni* (2008) shows that credit and investment booms can be inefficient, as market participants do not internalize their impact on general market equilibrium.[6] According to this model, credit and investment booms precede financial instability with a longer lead time than increased growth rates of asset prices, whereas exogenous real economic shocks contemporaneously accompany financial turmoil. We test the implications of this theoretical evidence with regard to the set of relevant macroeconomic and financial variables as well as the suggested different leads in time in our empirical analysis. New strands of macroeconomic models directly address deficiencies inherent in previous models that became evident in the recent financial crisis in 2008/2009. These include the role of interbank markets, liquidity and political crisis management.[7] For example, *Gertler/Kiyotaki* (2010) explicitly take into account the role of financial intermediaries rather than addressing the financial friction itself. In their Dynamic Stochastic General Equilibrium models, special attention is paid to the interbank market as an important driver of financial stability. We include a suitable indicator representing the interbank market in our study and empirically test the authors' results for the German banking system.

Empirical studies on determinants of banking system crises and instability have a long history. Some studies capture periods of crisis for several countries with a binary variable and explain it using macroeconomic factors applying either logit/probit or signaling approaches. Other studies focus on a single country only and identify appropriate country-specific determinants of banking system stability. Important studies have been implemented by *Demirgüc-Kunt/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 prob-

[6] Similar theoretical work can be found e.g. in *Kiyotaki/Moore* (1997).

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

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ability of a binary crisis variable occurring. Their results for both industrial and emerging market economies indicate that low real economic growth, high inflation and high real interest rates have a significant impact on the probability of a banking crisis.

By contrast, *Hardy/Pazarbasioglu* (1999) examine a sample that covers 50 predominantly emerging market economies between 1977 and 1997 and do not find overall evidence for macroeconomic factors preceding banking crises, but rather argue that both country and crisis-specific determinants that can only be identified ex post play a role. The authors conclude that national factors are relevant for banking instability, whereas international factors play a role in determining banking crises.[8] *Borio/Lowe* (2002) extend the signaling approach by applying so-called composite leading indicators, that improve the predictive power of their sample, which contains both industrial and emerging market economies.[9] The results indicate that the commonly used credit-to-GDP, gross fixed investment and asset prices (especially property prices) are among the best indicators in predicting banking system crises. At the country-specific level, *Hanschel/Monnin* (2005) confirm that the leading indicators identified by *Borio/Lowe* (2002) are also relevant determinants for the Swiss banking system. *Misina/Tkacz* (2008) forecast the indicator developed by *Illing/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 analyze the banking system of 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 for the German banking system and we propose a new weighting procedure for selected indicator components. To the best of our knowledge, this is the

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[8] Here, the term "banking instability" is related to "banking sector difficulties" that do not result in a systemic crisis; p. 10. Whereas the related literature presents studies that either examine banking or financial system (in)stability and/or crises, our study addresses the banking system as an important part of the overall financial system.

[9] According to the authors, composite indicators signal a crisis if the "coexistence" of two or three indicators passes a certain threshold. Indicators are calculated as deviation from their one-sided Hodrick Prescott trend to approximate the idea of financial imbalances. 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, p. 47.

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first attempt in the academic literature to develop a continuous stability indicator based on information on all German financial institutions. Second, we derive potential macroeconomic leading indicators from the existing theoretical and empirical studies and test their ability to predict the stability of the German banking system. Third, we take the experience of the financial crisis 2008/2009 into account and incorporate measures for regional and international spillover effects as additional early warning indicators. Although our results are directly relevant for policy makers and regulators, we likewise intend to address the academic audience by filling the gap in the literature on both banking system stability and early warning indicators for the country example of Germany.

III. Stability Indicator for the German Banking System

When building a composite indicator of financial stability, the choice of relevant indicator components is usually based on different sectors of the financial system (e.g. the banking sector, the equity market, the foreign exchange market). A comprehensive theoretical background for the selection of variables is missing in the literature. One reason for this is the imprecise nature of financial stability, which implies that corresponding definitions are still somewhat elusive.[10] Therefore, *von Hagen/Ho* (2007) relate their motivation to choose a certain set of indicator components to the currency crisis literature. By contrast, *Illing/Liu* (2006) select appropriate variables according to potential sources of banking stress.[11] The *ECB* (2007) points out that the structure of the financial system should be taken into account, e.g. a banking-based financial system needs to pay more attention to banking sector indicators. *Holló* et al. (2012) introduce an intermediate level of the financial system (markets, intermediaries, infrastructures) and aggregate various indicators for the separate building blocks into a composite index, which they call the Financial Stress Indicator.[12]

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[10] *Fell/Schinasi* (2005), *IMF* (1998a), *Demirgüc-Kunt/Detragiache* (1998).

[11] Selected variables cover the foreign exchange markets, debt markets, equity markets and the banking sector.

[12] The respective market segments for the intermediate level are: equity market, bond market, money market, foreign exchange market, derivatives market (markets); bank, insurance, other (intermediaries); payment systems, settlement system, clearing system (infrastructures).

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1. Deriving the Stability Indicator

We follow *Illing/Liu* (2006) and *Hanschel/Monnin* (2005) and motivate the selection of indicator components according to different sources of banking system instability. In so doing, we refer to commonly accepted characterizations in the literature. According to a definition provided by the *Deutsche Bundesbank* (2003) we interpret banking system stability as a "steady state in which the [banking] system efficiently performs its key economic functions, such as allocating resources and spreading risk as well as settling payments", p. 8. In other terms, we define banking system stability as a condition in which a sound banking system, which consists of solvent financial institutions, fulfils the functions outlined above. Against this background, we identify suitable indicator components that constitute banking system stability in either direction. Following definitions by *IMF* (2003) and *Segoviano/Goodhart* (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".[13]

Our stability indicator therefore consists of three single indicators: a bank's idiosyncratic probability of default, a credit spread and a stock market index for German banks. Unlike other indicators of risk-bearing capacity based on metrics and bank balance sheet data, the three components of the stability indicator are regarded as forward looking. They describe the current and the expected condition of the German banking system: The individual institution's probability of default reflects the future-oriented probability of a bank's demise, the credit spread points to potential credit risks in the banking system and the stock market index indicates market expectations regarding banks' current and anticipated profitability and development.

The three individual indicators that make up the stability indicator have – so far – not been used for German banking supervision by the Deutsche Bundesbank and the Federal Financial Supervisory Authority (Bundesanstalt für Finanzdienstleistungsaufsicht, BaFin). While the indicators themselves contain additional informational value, we rely on the combined knowledge and expertise of all banking supervisors within the

[13] *IMF* (2003), p. 4 and *Segoviano/Goodhart* (2009), p. 6.

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Deutsche Bundesbank and BaFin as a benchmark to derive the weighting of the indicators. The procedure used is described in chapter III.2.

The 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 overall measure covers a total of between 3,330 institutions (in 1995) and 1,685 institutions (in 2010). This stability indicator is our proxy for national banking system stability, lower values indicating higher banking system instability.

It is important to note that the institutional features of the German banking system affect the heterogeneity of the stability measure in a significant way. The German banking system is subdivided into a three-pillar structure of savings banks and Landesbanks, cooperative banks and their central institutions, and commercial banks.[14] Commercial banks are privately organized and follow a profit-seeking business model. Savings banks, on the other hand, are predominantly owned by the public sector and fulfill their public mandate, i.e. the supply of credit for people on lower and middle incomes and medium-sized businesses. Finally, cooperative banks are owned by their members and likewise focus on small and medium-sized entrepreneurs as well as retail clients in their respective regions.[15] While international activities and securities trading are fairly important for private banks, the business concept of savings banks and cooperative banks emphasizes savings deposits.

Subsequently, we characterize the formation of the selected three indicator components. We start by presenting the bank-specific (idiosyncratic) probability of default, focusing on a bank rating model for smaller banks. Afterwards we describe the credit spread and the stock market index in more detail.

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[14] In addition to universal banks, the German banking sector comprises specialized banks that do not belong to Germany's three-pillar banking system; such banks had a market share of 17.4 % at the end of 2010. Although the stability indicator also comprises special-purpose banks, they are dropped from the empirical analysis, as the number of these banks is small, their business strategy is completely different from universal banks, and their stability is closely linked to the creditworthiness of the sovereign. Source: Deutsche Bundesbank.

[15] The market share of private banks in terms of domestic business volume stood at 38.1 % (end-2010). Savings banks had a market share of 32.4 % (end-2010). The market share of cooperative banks amounted to 12.1 % (end-2010). Business volume refers to domestic business according to the definition of the Deutsche Bundesbank's banking statistics without branches abroad.

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a) The Idiosyncratic Probability of Default

The main component of the stability indicator for the banking system is information on each individual bank's solvency in terms of its probability of default (PD), which we understand as a primary factor in banking system stability according to the definition outlined above. For major banks, we incorporate PDs which are derived from Moody's Bank Financial Strength Ratings (BFSR). Those PDs explicitly take systemic risk into consideration, since major banks are an important source of, and are severely affected by, systemic risk. This is also highlighted by empirical observations, as large banks especially faced rating downgrades and applied for capital injections during the financial crisis in 2008/2009.

However, as 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.[16] The bank rating model is intended to capture microeconomic bank risk factors.[17] For small banks, the PDs thus do not cover systemic risk. This can also be explained using empirical evidence. The business model of small and medium-sized banks proved very robust during the 2008/2009 financial crisis, which is why their individual contribution to systemic risks in the banking system can be regarded as small.

Following *Porath* (2004) and *Kick/Koetter* (2007), we specify the bank rating model 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.[18] The logistic link function is estimated by a panel population-averaged logit model:

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

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

[17] By contrast, the stability indicator at the bank level is used to identify macroeconomic leading indicators in later empirical analysis. This is important to avoid any bias that might arise due to this two-step approach.

[18] *De Graeve* et al. (2008).

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Here, $P\left(y_{i,t} = 1\right)$ 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; α, β and π are the parameters to be estimated. 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 bank's liquidity situation is proxied by including the yield curve (which is described by the 10-year minus 1-year government bond rate).[19] 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/Koetter* (2007), this data set consists of a more detailed distress definition and also covers a longer time period for which distress data is available. The definition of distress events comprises – among others – compulsory notifications under the German Banking Act or capital support measures.[20] As the stability indicator at the bank level is used as dependent variable in the empirical analysis, we exclude all factors from the logistic link function that might cause a biased panel regression setup. 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 %.[21] Coefficient estimates for the CAMEL vector and the yield curve are in line

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

[20] According to *Porath* (2004), "default is defined as any event that jeopardizes the bank's viability as a going concern", p. II. Extending the analysis to 2010 means forecasting the PDs based on the rating model up to 2006, which includes inevitable forecast uncertainty. In addition, although the available time period does not include the recent financial crisis 2008/2009, it nevertheless covers significant stress events in the German banking market.

[21] 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 cutoff probabilities from zero to one. According to *Hosmer/Lemshow* (2000), values above 80 % suggest an "excellent discrimination", and values above 90 % an "outstanding discrimination" by the model, p. 162. In comparison to regularly estimated Bundesbank Hazard Rate Models, an AUC of between 80 and 90 % represents a normal range.

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with both expectations and the findings in the literature. Moreover, most of the coefficients show significance at the 1 % level. The regression statistics indicate that better capitalization, more bank reserves and a higher profitability reduce the likelihood of bank distress. Lower bank distress can also be shown for a higher concentration in the bank's' loan portfolios (measured by the Herfindahl-Hirschman Index (HHI) of over 23 industry sectors), which means that specialized banks tend to be more stable than more diversified banks. This is in line with earlier findings.[22] In turn, a large reduction of bank reserves, a high share of customer loans (which can be assumed to be riskier than interbank loans), avoided write-offs on a bank's assets (also known as "hidden liabilities"), and a higher bank market concentration (measured as HHI across bank branches per state) imply a higher PD. The management's ability to avoid the riskier fee-generating business in favor of the more stable interest business is reflected by a (highly significant) positive coefficient for the share of fee income.[23] Further, a steeper 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.

For each bank panel (small private banks, savings banks, cooperative banks and major banks), the idiosyncratic banks' PDs are separately converted to a standardized distribution by subtraction of the respective panel mean and division by the panel standard deviation.

b) The Credit Spread and the Stock Market Index

In addition to the standardized probability of default as a bank-idiosyncratic indicator, two aggregate indicators are included. The first component is a credit spread, which is understood as the average bank risk premium over some (approximately) risk free asset. The credit spread is higher the worse the banks' overall creditworthiness is and acts as a

[22] *Behr* et al. (2007).

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

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proxy for the liability side of banks' balance sheets as potential source of banking system instability. It is calculated as the difference between the arithmetic means of returns on bank debt securities outstanding and those on listed German Federal securities of Germany under the assumption of the same residual maturity. Bank debt securities in our analysis refer to "other bank debt securities" outstanding and include all bank debt securities except mortgage bonds, civil bonds and specialist bank bonds. The listed Federal securities encompass all bonds, debenture stocks and treasury bills issued by the Federal government, its special assets and the privatization agency. Using Bundesbank statistics, the credit spread can be calculated for the years 1994–2011 and about 200 German banks.[24] The resulting aggregate credit spreads for each year are transformed into standardized coefficients by subtracting the time series mean and dividing by the time series standard deviation.

The second aggregate component is a stock market index for the German banking sector called "Prime Banks Performance Index".[25] This index contains the share price of banks that are listed in Germany. The growth rate of the index reflects market expectations regarding listed institutions' return on equity capital, thereby indicating their current and expected profitability and development. It is a proxy for the asset side of banks' balance sheets as potential source of banking system instability. Like the credit spread, the stock market index value for each year is standardized on a (0,1)-interval.

c) The Banking System Stability Indicator

The three indices are combined to constitute a single indicator available at the bank level. After the three components (bank-level PDs, aggregate credit spread, aggregate growth rate of the "Prime Banks Performance Index") are (0,1)-standardized, they are weighted (see III.2) to form an institution-level metric. The standardized PDs and the credit spreads enter reciprocally in order to ensure that all indicator components point in the same direction. The resulting institution-level stability indicator is also called basket indicator and will be used in our empirical analysis (see section III.3). The institution-level indicators are subsequently weighted with the respective institution's total assets to form a

[24] Deutsche Bundesbank, Statistical Supplements, Supplement 2 (Capital Market Statistics).

[25] Cp. ISIN DE0009660100.

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composite continuous indicator for banking system stability.[26] This also ensures that sizeable banks which are regarded as systemically important financial institution (SIFIs) weigh more in the overall index. In the following, we report some positive features of our banking system stability indicator.

A considerable advantage of our stability indicator is that it can be calculated for the entire banking system as well as for individual financial institutions. The composite stability indicator can thus be used as a macroprudential indicator. To see this, it should again be noted that the PD is the only component of the stability indicator which is computed at the individual bank level. For major banks, systemic risk is explicitly taken into account, while the impact of small banks on systemic risk is viewed as negligible. Furthermore, the (aggregate) credit spread and stock market index for German banks reflect credit risks and (un)certainty on banking markets, both representing macroprudential risks that affect all financial institutions.

Compared to other standard market-based banking stability indicators (e.g. CDS spread-based financial stability indicators or stock returns), the composite stability indicator is also much broader and, moreover, covers small and regional banks. This is of especial importance in Germany, since such banks control a sizeable share of the German market and are particularly important for small and medium-sized enterprises' financing. It should again be highlighted that the business model of such banks proved fairly robust during the recent crisis. This suggests that their contribution to systemic risk is fairly small. But taking a macroprudential perspective, systemic risk can also affect small regional banks. The basket stability indicator captures this interconnectedness between banks: 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. Further, 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).[27]

[26] See e.g. *Illing/Liu* (2006) or *Hanschel/Monnin* (2005) for similar proceedings. For graphical purpose, this composite indicator for the entire banking system is presented in section III.3.

[27] During the financial crisis in 2008/2009, for instance, specific banks (and not just those that were close-to-default) faced rating downgrades or required capital injections.

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As the proposed stability indicator for the banking system is continuous, it furthermore overcomes the drawbacks of a binary crisis variable. A binary indicator oversimplifies the real conditions on the banking market, since it only indicates the (non-)existence of a crisis. This leaves no room for a detailed analysis of current market stability (e.g. the magnitude or the severity of a crisis) and predictions about future market developments. As forecasts of the stability of the banking system are crucial for regulators, a continuous indicator can thus significantly improve the information foundation. Nevertheless, a continuous indicator involves some additional challenges. The different sectors of a financial system might be subject to interactions not reflected in corresponding indicator components. Furthermore, possible non-linearities in the transmission of shocks between sectors or those related to financial distress reflections complicate the measurement of financial stability, cf. *ECB* (2005). As regards the first argument, the stability indicator proposed in this paper avoids the above named issue as it focuses on the banking system alone. In terms of the second argument, our stability indicator assigns the same importance to changes in indicator values regardless of the initial value, i.e. an increase either from 49 to 50 or from –60 to –59 has the same implication for banking system stability. However, from a supervisor's perspective, more attention needs paying to periods of banking system instability.

2. *Assigning Weights to Stability Indicator Components*

To evaluate what weights to allocate to the individual indicator components, we provide a novel weighting procedure. The existing literature provides no convincing methodology for assigning adequate weights to the components of a composite stability indicator. Even when theory would suggest 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 the market share of the respective components. The last two follow the idea that a main driver of financial instability can be identified. But, as *Illing/Liu* (2006) point out, the major difficulty lies in the lack of a benchmark against which the adequacy of weights can be verified. However, the authors argue that their results remain qualitatively similar regardless of the method chosen. Similarly, *Hanschel/Monnin* (2005) justify the variance-equal weight method with the argument that other methodologies would not yield

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meaningful differing results for the Swiss case. In our view, this does not solve the initial problem of verifying the indicator's reliability.

Selecting a benchmark against which to assess the final choice of assigned weights should overcome the shortcomings outlined above. In particular, we refer to the ability of Deutsche Bundesbank and BaFin banking supervisors to assess the stability of the German banking system; this is expected to be a good benchmark given their in-depth knowledge and expertise. We propose a unique methodology in accordance with the supervisory assessment of the risk profile, comprising an evaluation of all 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 bank in major trouble. 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. As a consequence, this grading reflects the joint knowledge of all supervisors involved in risk profiling rather than just relying on a single supervisor's assessment. For detailed information on the supervisory risk profile assessment, see *Kick/Pfingsten* (2011).

Based on (*i*) standardized PDs for an individual institution, (*ii*) the credit spread, and (*iii*) the stock market index, we calculate 36 basket stability indicators with weights ranging from "10 %–10 %–80 %" to "80 %–10 %–10 %." Furthermore, we base the choice of the final stability indicator on the supervisory risk profile assessment.[28] As we are interested in a one-size-fits-all approach, weights are not allowed to vary by bank category or size. We specify the following partial proportional odds model,

$$P\left(RP_{i,t} > j \right) = \frac{e^{\alpha j + \beta j SI_{i,t} + \eta j X_{i,t} + \pi j BG_i}}{1 + e^{\alpha j + \beta j SI_{i,t} + \eta j X_{i,t} + \pi j BG_i}} \tag{2}$$

where $P(RP_{i,t} > j)$ denotes the probability that the grading by the supervisory risk profile assessment is greater than j. $SI_{i,t}$ is the respective basket 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)[29] which are

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

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

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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 are jointly zero" in 36 regression models.[30] 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 the best fit for the following basket 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". In a robustness check, we examine the impact of other weights on our regression results. The second and third best fit according to the supervisory risk profile assessment point to weights that are similar in magnitude, with 70–10–20 and 80–10–10 weights for the standardized PDs, credit spread and "Prime Banks Performance Index", respectively. As these weights do not significantly alter the statistical and economic significance of estimated standardized beta coefficients, but lead to a decline in the within-R-squared for the third best fit, we apply the first-best weights to all further banking system stability analyses in this paper.

Two arguments limit the scope of our novel weighting procedure. First, as the supervisory risk profile assessment focuses on idiosyncratic risk rather than systemic risk, this might bias our results towards a higher weight for the PD. Second, e.g. *Krainer/Lopez* (2008) show that stock and bond markets may yield further information that is not included in the current supervisory ratings which might cause a similar bias towards higher weights associated with the idiosyncratic PDs. In terms of the first issue, as we consider the individual institution's probability of default to be the main component of the stability indicator according to our definition of banking system stability, it may be justified to assign a higher weight to the idiosyncratic indicator component. Furthermore, the information content in stock and bond markets constitutes at least 30 % of the stability indicator. In sum, we believe that despite the above named

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

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drawbacks, we are able to present a useful benchmark approach from 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. As will be shown in the following chapter, the stability indicator using the proposed weighting scheme is able to identify and predict (in)stability on the banking market appropriately.

3. *Evolvement of the Stability Indicator*

We show the composite financial stability indicator for the entire banking system in the chart below. It decreased from 1997 onwards and turned slightly negative in 2002, representing the aftermath of the bursting of the dotcom bubble. During that time, cooperative banks especially suffered from increased loan defaults. The composite stability indicator subsequently showed an upward trend until 2006, but was on the decline in 2007 – ahead of the financial crisis – and entered negative territory in 2008. A recovery occurred in 2010 for most banking groups – excluding Landesbanks. For 2011, the aggregate stability components show that the credit spread and the stock market index for the banking sector contributed to a renewed deterioration of banking system stability. Elevated stress in financial markets still affected Landesbanks, for which Moody's BFSRs 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.[31] Overall, the stability indicator shows a deterioration in 2011 compared to 2010; however, it is still well above its level for 2009, the low point of the financial and economic crisis.

In the following, we compare our stability indicator to other continuous measures of banking system stability and the widely used International Monetary Fund banking crisis database.[32] According to the latter, Germany has been experiencing a banking crisis since 2008, which be-

[31] 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 that our indicator is a more comprehensive measure of overall banking system stability, as it is also available at the institutional level.

[32] *Laeven/Valencia* (2012). In that database, a systemic banking crisis occurs if two conditions are met: First, significant bank runs, losses in the banking system and/or bank liquidations are observed and contribute to significant financial distress. Second, significant policy interventions are needed in response to observed losses in the banking system, p. 4.

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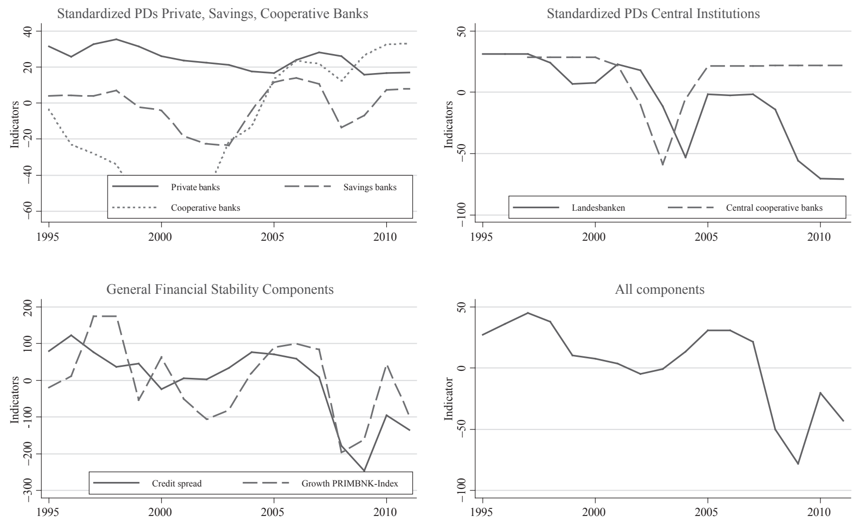

Figure 1: Stability Indicators for the German Banking System. Own Calculations

came systemic in 2009. While our stability indicator is likewise negative from 2008 onwards, we can draw a differentiated picture as – except for Landesbanks – most banking groups experienced a recovery in 2010. Although the aggregate components point to renewed banking system instability and some large private banks exhibited increased financial stress in 2011, the business models of credit cooperatives and savings banks proved robust during the subsequent European sovereign debt crisis.

With respect to methodology, *von Hagen/Ho* (2007) use the currency crisis literature to identify banking crises. Using a sample of both industrial and emerging market economies, a crisis is defined for extreme tails of the index's distribution. However, the authors' focus on severe tensions on the money market does not capture all possible sources of banking system instability, e.g. stress related to idiosyncratic problems at state-owned banks.[33] By contrast, our indicator includes information on all financial institutions in Germany. The literature still lacks continuous stability indicators for the German banking system. We therefore refer to the Financial Market Stress Indicator (FMSI) developed by *van Roye*

[33] *von Hagen/Ho* (2007), p. 1039.

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(2013) for the whole German financial system. Within our observation period, the FMSI indicated elevated stress levels around the Russian and Asian Crisis in 1997/1998 and after the dotcom bubble burst in 2000/2001. It shows its strongest increase during the financial crisis 2008/2009 and remains elevated, albeit at a lower level, during the subsequent European sovereign debt crisis. By comparison, our stability indicator does not point to a similar increase in banking system instability around the Russian and Asian crisis, as the indicator was on the decline from 1997 onwards. The difference might be due to the fact that increased stress was more prevalent in the capital markets than in the banking system. In contrast to the FMSI, our stability indicator is able to capture the fact that increased instability was mainly experienced by Landesbanks and central cooperative banks, which had to realign their business models and refinancing conditions in response to the abolition of state guarantees ("Gewährträgerhaftung" and "Anstaltslast" in German) in 2004/2005. The later periods of banking system instability, e.g. during the financial crisis of 2008/2009 and the subsequent European sovereign debt crisis, are captured by our stability indicator in a very similar way.

It can thus be concluded that our stability indicator yields a comprehensive picture of the current state and the development of German banking system stability. Building on the stability indicator as dependent variable and macroprudential leading indicators as regressors, the indicator can be used to detect banking system crises or increasing instability in advance. The relevant procedure is depicted in the following chapter IV.

IV. Macroprudential Leading Indicators for the German Banking System

Based on theoretical considerations and empirical evidence, we select macroprudential leading indicators that may explain banking system stability at different lag operators. In the next step, we follow the conventions by classifying them into macroeconomic, financial and structural variables, see Appendix II. Particular interest is devoted to country-specific variables that 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 leading indicators for the prediction of economic activity, we test both national and international adjust-

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ed leading indicators to control for increased internationalization of the German banking system, cf. IV.3.

1. *Macroeconomic Variables*

According to economic theory, higher asset and property price growth is associated with boom phases in the business cycle that might imply a buildup of financial imbalances and has the potential to result in banking system instability.[34] 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.[35] 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/Poghosyan* (2008) show that price-to-rent ratios may be important determinants for instability in the German banking system. 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 at the one to four year horizon, according to theoretical expectations. We also include asset price indicators for internationally important real estate markets, as they played an important role in the financial crisis of 2008/2009.

An important leading indicator for the economic outlook in Germany is the ifo business cycle index provided by the Ifo Institute for Economic Research. The indicator captures expectations of real economic development and indicates positive or negative shocks affecting the real economy. Expectations of an economic upturn are expected contemporaneously 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). Within our observation period, several negative shocks can be identified (e.g. in 2001/2002 and 2008) that were accompanied by significant adverse effects. We therefore include the ifo index both contemporaneously and with a lag of one period into our analysis. *Lorenzoni* (2008) theoretically shows that high gross fixed investments reflecting real economic demand are expected to precede potential banking system insta-

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[34] *Borio/Drehmann* (2009b) refer to financial imbalances as "growing fragility of private sector balance sheets during benign economic conditions", p. 30.

[35] See *Borio/Lowe* (2002) for detailed argument. The authors argue that property prices have been more important in predicting banking crises than equity prices.

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bility with a longer lead time than real economic shocks or asset prices. Thus, gross fixed investments will be incorporated at two to four lags.

2. Financial Variables

Turning to financial variables, we look at indicators for lending to the private sector, financial market indicators and monetary indicators. According to economic theory, lending booms may precede banking system instability, as they imply increased risk-taking in the financial system, which potentially results in financial turmoil if the economy is hit by a negative, adverse shock. We therefore include the national private credit-to-GDP ratio at two to four lags in our analysis.[36] 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 a 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 of future banking system instability. This is an important observation as this variable has traditionally proved one of the best-performing indicators in predicting banking system crises and instability in industrial and emerging market economies.

With respect to financial market indicators, we take into account the role of the interbank market, which became especially important during the financial crisis of 2008/2009. To separate the effects of distress on the interbank market and monetary policy, we include the 3-month Libor over 3-month Bubill (German treasury discount papers), which is similar to a Treasury Bill Eurodollar Difference Spread. We also include the 3-month Bubill separately to account for key ECB interest rate cycles. We expect loose monetary policy and an increased Libor spread to precede banking system instability: 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 also look at M2-to-GDP, indicating excessive liquidity in the financial market which possibly pre-

[36] As regards 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 indicators for the European banking sector since we are interested in drivers of banking system stability that are separate from the related stability indicator's individual components.

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cedes a lending boom.[37] Whereas empirical evidence suggests that an increased TED spread leads either coincidentally or with a short lead time to banking system instability, other monetary indicators are considered at the one to two year horizon.

3. *Structural Variables and Regional Spillover Effects*

Looking at spillover effects, we first control for international spillover effects in the regression model. The dependence of the German banking system on international exposures increased steadily between 1999 and 2010. Foreign lending and securities as a percentage of total balance sheet assets doubled from 14.3 % in 1999 to 28.5 % in 2009, with a slight decline to 27.2 % in 2010 for all banks. During that time, percentage holdings of foreign stocks and bonds nearly tripled from 3.4 % in 1999 to 8.3 % in 2009. Commercial banks and Landesbanks increasingly invested in international markets and securities.[38] For Landesbanks, this 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 based on altered business models and refinancing conditions. In some instances, this resulted in a shift from public sector investments to business investments. The crowding-out led to clear structural changes in the composition of banks' balance sheet exposures towards a greater dependence on international developments. We account for this in the empirical analysis by including the VIX index. The VIX index is a forward-looking indicator based on S&P stock market index options. It serves as a proxy for international risk aversion and expected implied volatility in international financial markets, with higher values indicating less expected banking system stability and vice versa.[39] As the period of predicted banking system instability observed in 2008/2009 can partly be explained by the revaluation of large foreign exposures, we also take the structural change in national

[37] See *von Hagen/Ho* (2007) for a detailed discussion of M2 in the run-up to banking crises, pp. 9–10.

[38] See Appendix III. For commercial banks (Landesbanks), foreign lending and securities as a percentage of the balance sheet total increased from 23.8 % (17.8 %) in 1999 to 36.5 % (40.4 %) in 2009. For credit cooperatives (savings banks), foreign lending and securities as a percentage of the balance sheet total stood at 1.6 % (1.8 %) in 1999 and 8.2 % (4.0 %) in 2010. Source: Deutsche Bundesbank.

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

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banks' balance sheet exposures into account. This is done by including in our analysis an indicator reflecting foreign lending and securities in terms of balance sheet total based on book values, which, for financial institutions, should be a suitable proxy. Similarly, *Borio/Drehmann* (2009b) provide first evidence on the role of cross-border exposures in determining banking system crises.[40] Based on evidence from the financial crisis of 2008/2009, we include both coincident and one period lagged indicator values in our study.

Second, we analyze spillover effects between financial intermediaries. The literature has studied the effects of one bank's failure 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, e.g. *Aharony/Swary* (1983). In addition to the TED spread, 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. In other words, we test the explanatory effect of weighted standardized PDs of the surrounding financial institutions on the stability indicator for bank i after one year.

It is important to note that the choice of explanatory variables is also motivated by forward-looking macroprudential indicators, since our stability indicator is regarded as future-oriented. For example, the ifo index captures expectations of real economic development, and the VIX index reflects expected implied volatility in international financial markets.

V. Empirical Analysis

1. Data

Our study analyzes banking system stability with respect to macroprudential determinants at the institutional level, examining between 3,330 banks (in 1995) and 1,685 banks (in 2010) and including all German

[40] 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 were especially important for Germany and the Netherlands during the financial crisis of 2008/2009.

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banks. We have recourse to the database Bankaufsichtliches Informationssystem (BAKIS) provided by the Deutsche Bundesbank, which is used in regular banking supervision. During the 16-year period, the number of banks in the sample exceeds the number of institutions actually existing in the German banking system because of the technical treatment of mergers.[41] 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. It adequately represents the existing distribution of financial institutions in Germany's three-pillar system. See Appendix IV for descriptive statistics of the original and rescaled time series.

2. *Panel Regression Model*

In the empirical analysis, we explain the stability indicator for the banking system across Germany's three-pillar structure, 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:[42]

$$y_{i,t} = \alpha y_{i,t-1} + \beta Z_{i,t-p} + \sum_{j=1}^{J} \gamma_j X_{j,t-q} + \mu_i + \nu_{i,t}\,. \tag{3}$$

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 only in their most significant lagged values, $Z_{i,t-p}$ and $X_{j,t-q}$ contain only lag $t-p$ respectively $t-q$ of the explanatory variables. The lags are thus allowed to differ across explanatory variables. $Z_{i,t-p}$ denotes a bank-specific control vari-

[41] 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.

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

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able and $X_{j,t-q}$ denotes macroprudential variables. The coefficients β and γ_j describe the effect of $Z_{i,t-p}$ and $X_{j,t-q}$ 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}. The bank specific control variable captures the cross-sectional (bank-level) variation in the risk indicator over time. However, our focus is on the time series variation of the indicator for each bank explained by macroprudential leading indicators. These are intended to explain the aggregate (average) risk level in the banking system. Since we use bank-level data to carry out the empirical analysis, the greater number of observations will lead to much lower standard errors. We therefore concentrate on the economic rather than on the statistical significance of our results.[43]

The use of dynamic panel data models usually gives rise to two problems, which lead to inconsistent OLS estimation. 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 definition, independent of time in the regression model.[44] The second problem appears when removing the individual heterogeneity term μ_i by first differencing the estimation equation.[45]

To control for the above named problems, a two-step *Arellano/Bond* (1991) difference Generalized Method of Moments (GMM) estimation procedure would be preferable. However, as instrumenting is technically difficult in the *Arellano/Bond* model with highly unbalanced panel data (which is the case for our dataset), we apply a standard fixed-effects model including the lagged dependent variable as an additional regressor. If we use this procedure, 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 is approximately estimated at 0.36 in both the Arellano-Bond method and the

[43] 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.

[44] *Nickell* (1981).

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

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fixed-effects estimations, which is quite robust and suggesting that the bias is small.[46] Second, as *Mehrhoff* (2009) finds, the "Nickell Bias" decreases with increasing T and decreasing α; it should be in an acceptable range in our sample, as T is at least 16 and increasing and α is low. We therefore rely on the results from the fixed-effects model specification.[47]

We start our empirical analysis for all banks without any regressors other than the lagged dependent and control variable as a benchmark model.[48] 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, see related literature and the previous section.[49] To obtain interpretable results, the growth rates of explanatory variables are specified in the estimation equation except for the bank specific control variable. The choice of an optimal model is based on an Akaike Information Criterion (AIC), which is calculated separately.[50] In a robustness check, we also identify the individual optimal lag structure of our set of macroprudential indicators based on the AIC by including them separately in our benchmark model. As this proceeding leads to identical lag structures, we only report the same lag choice for different model specifications.

We find evidence that our data is correlated along two dimensions. The observations of macroprudential indicators are correlated within years, as they capture the effects of economic up and downswings. 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

[46] Regression results for the Arellano-Bond model are not reported and are available upon request.

[47] The Hausmann test reveals a fixed-effects specification to be appropriate.

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

[49] In line with e.g. *Hanschel/Monnin* (2005) or *Borio/Drehmann* (2009b), we consider more than four lags to constitute an irrelevantly long time horizon ahead of banking system (in)stability or crises. The fact that the business cycle is usually characterized by a time horizon of eight years suggests that applying more than four lags to indicate either a boom or a bust phase is inappropriate.

[50] In a robustness check, we also implemented the gap approach suggested by *Borio/Lowe* (2002). However, including the explanatory variables in deviation from their one-sided HP trend did not lead to superior results; in fact, the explanatory power of the overall model specification was lower.

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(i.i.d.) and subject to problems of heteroskedastic and autocorrelated patterns in idiosyncratic error terms, we apply clustered standard errors following *Cameron* et al. (2006).

VI. Results

Our main results reveal a differentiated picture for Germany with regard to the commonly used macroprudential early warning indicators for predicting banking system crises and instability in both industrial and emerging market economies. We present our findings not only for the whole banking system, but also for different banking sectors. As regards our set of macroeconomic, financial and structural explanatory variables, we identify indicators that provide explanatory power and a constant optimal lag structure among various specifications according to the AIC criterion. Whereas some indicators reveal a clear lead in time, others coincidently explain the stability indicator. We argue that the latter are nevertheless useful early warning indicators as they can be monitored at least on a monthly basis, and commonly used forecasts on an annual basis are available. The respective lag is denoted prior to the macroprudential indicator in the result tables, e.g. L1 prior to the real estate price index indicates a one period lag. These indicators will subsequently be 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.

Estimation results can be found in tables 1 and 2 below. 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).

Overall, the explanatory power of several estimated fixed-effects models for all banks is good, as the within-R-squared varies around 29 % except for commercial banks for which the within-R-squared is higher. The estimated coefficient of the dynamic term y_{t-1} is significant and robust among several specifications. It is close to the estimated coefficients from the Arellano-Bond GMM regression model.

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Table 1

Regression Results for the Basket Stability Indicator, All Banks and Commercial Banks

	All Banks			*Commercial Banks*		
BASKET_SI	(1)	(2)	(3)	(1)	(2)	(3)
L1.BASKET_SI	0.355***	0.335***	0.354***	0.443***	0.424***	0.446***
	(11.480)	(14.672)	(12.874)	(16.026)	(14.792)	(15.084)
Control Variable						
L0.LN_ASSETS	–0.313***	–0.332***	–0.322***	–0.050	–0.053	–0.049
	(–3.410)	(–4.217)	(–5.847)	(–0.998)	(–1.059)	(–1.007)
Regional Variables						
L1.COUNTY_PD	0.041***	0.023*	0.029**	0.008	–0.002	0.010
	(3.678)	(1.992)	(2.932)	(0.430)	(–0.130)	(0.544)
L0.COUNTY_GDP	0.002	–0.005	–0.006	0.004	–0.002	–0.011
	(0.131)	(–0.267)	(–0.374)	(0.188)	(–0.087)	(–0.715)
Macro Variables						
L1.REALEST_PRICE	–0.211***	–0.236***	–0.330***	–0.222***	–0.209**	–0.306***
	(–4.785)	(–3.297)	(–6.408)	(–5.385)	(–2.562)	(–5.960)
L0.IFO_INDEX	0.137**	0.203***	0.192***	0.180***	0.216***	0.213***
	(2.709)	(4.019)	(3.771)	(4.970)	(5.373)	(5.351)
L2.GR_FIXED_INV		0.017	0.142*		–0.011	0.134*
		(0.303)	(2.009)		(–0.185)	(2.024)
L1.CRED_TO_GDP		–0.087	–0.131**		0.015	–0.042
		(–1.659)	(–2.465)		(0.301)	(–0.819)
Financial Variables						
L0.TED_SPREAD	–0.071*	–0.063**	–0.084***	–0.042	–0.038	–0.054**
	(–2.108)	(–2.807)	(–4.799)	(–1.626)	(–1.712)	(–2.870)
L1.3MBUBILL	0.129***	0.145***	0.202***	0.205***	0.204***	0.269***
	(3.031)	(4.779)	(5.724)	(6.025)	(6.116)	(9.065)
International Variable						
L0.VIX	–0.070		–0.148**	–0.081*		–0.160***
	(–1.514)		(–2.564)	(–1.939)		(–3.081)
Observations	32,107	32,107	32,107	2,368	2,368	2,368
Number of times	16	16	16	16	16	16
F statistic	34.28	135.2	118.2	340.9	181.0	330.5
Within-$R2$	0.287	0.289	0.300	0.473	0.465	0.480

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 basket banking stability indicator at the institutional level over the time period 1995 to 2010. The right-hand side of the regression equation is based on the lagged dependent variable, a bank-specific control variable and various macroprudential variables included with different lags. Standardized beta coefficients are reported, t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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1. Macroprudential Indicators

The national commercial real estate price index shows explanatory power in that it precedes 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 25 % of the standard deviation of *y*. Higher growth rates for 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 industrial countries, e.g. *Borio/Drehmann* (2009b).

Turning to leading indicators for the 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. The estimated beta coefficient explains about 18 % of the standard deviation of *y*. Although theoretical evidence suggests that gross fixed investments are a promising leading indicator of the economic outlook and driver of banking system stability, the indicator proved to have little explanatory power. Likewise, *Hanschel/Monnin* (2005) find that European real GDP rather than investments is a robust leading indicator of the stability of the Swiss banking sector, which shows that the country is fairly internationally open.

As for the set of financial indicators, the 3-month Libor over 3-month Bubill spread (TED spread) is robust among several estimation equations coincidently explaining the stability indicator for the banking system according to the AIC criterion. It accounts for about 7 % of the standard deviation of *y*. As higher interbank interest rates are associated with less confidence in the interbank market and more expensive funding, large positive growth rates of the spread lead to less anticipated banking system stability. This underlines the importance of the interbank market in determining the stability of the banking system. With respect to monetary expansion, the ratio of national M2-to-GDP shows little explanatory power and is not robust to various estimation specifications. Instead, the 3-month Bubill reflecting the cycle of key ECB interest rates pre-

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cedes the stability indicator with one lag, explaining about 16 % of the standard deviation of y. Due to its positive sign, we can empirically support recent evidence from the financial crisis of 2008/2009 which suggests that loose monetary policy precedes banking system instability. We conclude that monetary policy affects national banking system stability via the transmission channel of key ECB interest rates rather than via the money supply given by M2.

The most prominent leading indicators of banking system crises and instability in the existing literature are the credit-to-GDP ratio and the credit growth variable. However, our results 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 discussed below. This is important, as it reveals that the indicators might be among the best predictors of banking system crises and instability in various panels of emerging and industrial countries, but they do not prove similar explanatory power for the whole German banking system.[51]

Turning to the set of structural variables, we discuss the relevance of international and regional spillover effects. In our attempts to identify a macroprudential indicator which explains international spillover effects, we find that the VIX index significantly captures current international risk aversion of financial market participants and explains about 11 % of the standard deviation of y. The inclusion of the variable improves explanatory power of the overall model from around 26 % throughout various estimation specifications to about 30 %. It coincidentally explains the stability indicator for the banking system. This implies that a higher growth rate of the VIX index leads to less banking system stability, as increased fluctuations in financial markets 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 believe that this can be attributed to difficulties in constructing the variable using exposures at book values only instead of market-based prices which is due to a lack of adequate data. The construction of indicators which adequately reflect cross-country

[51] See, for example, *Borio/Lowe* (2002), *Borio/Drehmann* (2009b).

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exposures has undoubtedly become important given the 2008/2009 financial crisis and is thus left to future research.[52]

2. *Analyses by Banking Sector*

Banking sector specific early warning models prove to be relevant. 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. The estimated standardized beta coefficients of the lagged dependent variable are significantly higher, see table 1 and table 2 below.

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 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 some explanatory power throughout various specifications for all banks, the variable becomes strongly significant for cooperative banks, while remaining insignificant for commercial banks. The results are mixed for savings banks. A reason for this empirical evidence is that commercial banks and Landesbanks increasingly held cross-border exposures and were thereby dependent on international developments.[53] This contributed to the period of banking system instability we observed in Germany in 2008/2009. A generalized implication is that the ongoing internationalization of EU banking systems needs to be taken into account when assessing domestic banking system stability. Similarly, *Lo Du-*

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

[53] See footnote 38.

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Table 2

Regression Results for the Basket Stability Indicator, Credit Cooperatives and Savings Banks

	Credit Cooperatives			*Savings Banks*		
BASKET_SI	(1)	(2)	(3)	(1)	(2)	(3)
L1.BASKET_SI	0.344***	0.315***	0.333***	0.348***	0.333***	0.351***
	(8.138)	(9.971)	(9.296)	(7.164)	(7.198)	(7.110)
Control Variable						
L0.LN_ASSETS	–0.683***	–0.720***	–0.689***	–0.665***	–0.498*	–0.565***
	(–3.536)	(–4.257)	(–5.397)	(–2.996)	(–2.107)	(–3.033)
Regional Variables						
L1.COUNTY_PD	0.053***	0.030**	0.035***	0.028*	0.016	0.023*
	(4.062)	(2.450)	(3.419)	(2.001)	(1.179)	(1.779)
L0.COUNTY_GDP	0.002	–0.003	–0.004	0.007	–0.001	–0.001
	(0.097)	(–0.152)	(–0.195)	(0.361)	(–0.047)	(–0.051)
Macro Variables						
L1.REALEST_PRICE	–0.183***	–0.222***	–0.308***	–0.199***	–0.192**	–0.292***
	(–3.732)	(–3.262)	(–6.052)	(–5.047)	(–2.568)	(–6.235)
L0.IFO_INDEX	0.131**	0.207***	0.196***	0.137***	0.186***	0.172***
	(2.318)	(3.645)	(3.472)	(3.113)	(4.279)	(3.958)
L2.GR_FIXED_INV		0.019	0.131*		–0.017	0.127*
		(0.358)	(1.762)		(–0.326)	(2.025)
L1.CRED_TO_GDP		–0.136**	–0.173***		–0.013	–0.067
		(–2.598)	(–3.185)		(–0.263)	(–1.503)
Financial Variables						
L0.TED_SPREAD	–0.088**	–0.079***	–0.100***	–0.046*	–0.037*	–0.057***
	(–2.337)	(–3.467)	(–5.101)	(–2.130)	(–1.836)	(–3.596)
L1.3MBUBILL	0.108**	0.129***	0.180***	0.143***	0.139***	0.202***
	(2.242)	(3.933)	(4.671)	(3.746)	(4.276)	(5.810)
International Variable						
L0.VIX	–0.067		–0.134**	–0.094**		–0.166***
	(–1.388)		(–2.268)	(–2.200)		(–2.993)
Observations	22,202	22,202	22,202	7,373	7,373	7,373
Number of times	16	16	16	16	16	16
F statistic	23.45	63.51	63.70	61.57	111.3	64.38
Within-$R2$	0.274	0.286	0.296	0.288	0.281	0.293

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 basket banking stability indicator at the institutional level over the time period 1995 to 2010. The right-hand side of the regression equation is based on the lagged dependent variable, a bank-specific control variable and various macroprudential variables included with different lags. Standardized beta coefficients are reported, t-statistics in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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ca/Peltonen (2011) find that considering domestic and global indicators jointly significantly improves the ability to forecast systemic events.

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 do indeed show some explanatory power for commercial banks with a lag of one period, but are not robust to several specifications.[54]

3. International and Regional Spillover Effects

Turning to international and regional effects across banking sectors, we again observe heterogeneous determinants of banking system stability that require us to take a different view in our analysis of the German banking system. In the empirical analysis of commercial banks, regional effects become irrelevant in determining stability in the German system. Instead, the 3-month Libor over 3-month Bubill spread and the VIX index capture international effects accurately throughout various estimation equations. The former variable forfeits some of its statistical significance, which might be explained by the fact that we include the 3-month Euro-Libor in the empirical analysis, whereas commercial banks also obtain funding in US dollars on international financial markets. Another reason might be related to an offsetting effect through emergency funding of central banks in times of financial stress. As these institutions have an international focus, they are highly dependent on international developments, whereas regional factors play only 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. Thereby we measure 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

[54] Estimation results are not reported and are available upon request.

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surrounding financial institutions leads to increased banking distress for bank i one period later. Under the assumption that the control variable regional per-capita GDP growth – which is insignificant in most model specifications – is an appropriate proxy for regional real economic stress, we are able to rule out the hypothesis that the real economy (e.g. insolvency of local companies) is in effect driving regional banking stability. This finally limits the channel for regional banking stress to the regional spillover effects we observe. We conclude that, as cooperative banks and savings banks predominantly obtain funding through regional deposits, they are 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 observation that credit cooperatives and savings banks are likewise starting to participate in international financial markets.

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 over 3-month Bubill, the 3-month Bubill and the VIX are shown to be useful macroprudential leading indicators in all models, regional spillover effects and the credit-to-GDP ratio play a significant role for cooperative banks, but are less important for commercial banks. These heterogeneous determinants of banking system stability indicate a diversification effect within Germany's three-pillar banking system (whereby different shocks affect each banking sector in different ways) that may contribute to the stability of the banking system as a whole.

VII. Concluding Remarks

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

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The stability indicator encompasses 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 use the supervisory risk profile assessment as a benchmark for assigning weights to indicator components. Despite a slight recovery in our stability indicator for the overall banking system in 2010, major German banks are still suffering from increased stress in financial markets brought about by the European sovereign debt crisis. Therefore, the importance of our study remains high.

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 monetary indicators are reliable early warning indicators. This underscores the necessity of monitoring macroprudential indicators in banking supervision and highlights the need for regulators to develop regulatory requirements incorporating (anticyclical) business cycle components. 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 significantly affect credit cooperatives, but are less important for commercial banks. These findings imply heterogeneous determinants of banking system stability, which indicates that Germany's three-pillar banking system encompasses a diversification effect, whereby different shocks affect each banking sector in different ways. This might contribute to the stability of the banking system as a whole.

Our results also feed into the ongoing debate on the choice of a suitable conditioning variable on which countercyclical capital buffers should be based, e.g. regarding the ifo index or our suggested short-term monetary indicators. Further research is needed to develop indicators that adequately map financial institutions' increased cross-border exposures. This became especially important with regard to international spillover effects during the financial crisis of 2008/2009 and the subsequent European sovereign debt crisis.

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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 financial 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.

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

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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 bonds. *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: 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 expectations	*IFO_INDEX*	Ifo Institute
		Gross fixed investments	*GR_FIXED_INV*	German Federal Statistical Office
		Regional GDP	*COUNTY_GDP*	German Federal Statistical Office
Financial Variables	*Lending*	National private credit to GDP	*CRED_TO_GDP*	Deutsche Bundesbank
	Monetary indicators	Libor (3-month)	*LIBOR_3M*	British Bankers' Association
		Bubill (3-month)	*3MBUBILL*	Bloomberg
		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
	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

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

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Appendix III: 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 IV: Descriptive Statistics

Variable	Mean	Std. Dev.	Skewness	Kurtosis	P5	P95
BASKET_SI_INST$_{i,t}$	4.37	74.51	–4.09	28.48	–118.50	59.19
LN_ASSETS	19.43	1.44	0.44	2.98	17.26	21.91
COUNTY_PD	–0.24	65.31	–5.18	55.03	–108.97	46.99
COUNTY_GDP	1.35	3.46	0.16	6.79	–5.60	6.35
REALEST_PRICE	98.35	4.39	1.29	4.14	93.55	109.59
IFO_INDEX	100.16	3.83	–0.08	2.57	93.38	105.82
GR_FIXED_INV	93.97	5.10	0.62	2.14	88.26	102.55
CRED_TO_GDP	1.55	0.14	–1.01	2.64	1.25	1.68
TED_SPREAD	–0.96	1.84	–0.70	1.80	–4.38	0.62
3MBUBILL	2.79	1.20	–0.45	3.24	0.31	5.15
VIX_INDEX	21.27	5.99	0.02	2.05	12.42	31.48

Note: Original and rescaled time series j see appendix II.

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References

Aharony, Joseph/*Swary*, Itzhak (1983): Effects of bank failures: evidence from capital markets. Journal of Business, Vol. 56 (3), 305–322.

Arellano, Manuel/*Bond*, Stephen (1991): Some tests of specification for panel data: monte carlo evidence and an application to employment equations. Review of Economic Studies, Vol. 58, Issue 2, 277–297.

Behr, Andreas/*Kamp*, Andreas/*Memmel*, Christoph/*Pfingsten,* Andreas (2007): Diversification and the banks' risk-return characteristics – evidence from loan portfolios of German banks. Deutsche Bundesbank, Series 2, No. 05.

Bekaert, Geert/*Hoerova*, Marie/*Lo Duca,* Marco (2010): Risk, uncertainty and monetary policy. NBER Working Paper, No. 16397.

Bell, James/*Pain,* Darren (2000): Leading indicator models of banking crises – a critical review. Financial Stability Review, Bank of England, December.

Bernanke, Ben/*Gertler*, Mark/*Gilchrist*, Simon (1996): The financial accelerator and the flight to quality. The Review of Economics and Statistics, Vol. 78, No. 1, 1–15.

Borio, Claudio (2003): Towards a macroprudential framework for financial supervision and regulation? BIS Working Papers, No. 128.

Borio, Claudio/*Drehmann*, Mathias (2009a): Towards an operational framework for financial stability: "fuzzy" measurement and its consequences. BIS Working Papers, No. 284.

– (2009b): Assessing the risk of banking crises-revisited. BIS Quarterly Review, March.

Borio, Claudio/*Lowe,* Philip (2002): Assessing the risk of banking crises. BIS Quarterly Review, December.

Cameron, Colin A./*Gelbach*, Jonah B./*Miller*, Douglas L. (2006): Robust inference with multi-way clustering. NBER Working Paper, No. 327.

Clement, Piet (2010): The term "macroprudential": origins and evolution. BIS Quarterly Review, March.

Crockett, A. (2000): Marrying the micro- and macroprudential dimensions of financial stability. BIS Speeches, September.

De Graeve, Ferre/*Kick,* Thomas/*Koetter,* Michael (2008): Monetary policy and financial (in)stability: An integrated micro-macro approach. Journal of Financial Stability, Vol. 4, 205–231.

Demirgüc-Kunt, Asli/*Detragiache,* Enrica (1998): The determinants of banking crises in developing and developed countries. IMF Staff Papers, Vol. 45, No. 1.

– (2005): Cross-country empirical studies of systemic bank distress: a survey. IMF Working Paper, No. 05/96.

Deutsche Bundesbank (2003): Report on the stability of the German financial system. Monthly Report, December.

DOI https://doi.org/10.3790/ccm.47.1.5 | Generated on 2024-07-22 15:24:00
OPEN ACCESS | Licensed under CC BY 4.0 | https://creativecommons.org/about/cclicenses/

Deutsche Bundesbank/BaFin (2008): Guideline on carrying out and ensuring the quality of the ongoing monitoring of credit and financial services institutions by the Deutsche Bundesbank of 21 February 2008. Frankfurt a.M./Bonn: Deutsche Bundesbank and BaFin.

ECB (2005): Measurement challenges in assessing financial stability. Financial Stability Review, December.

– (2007): Progress towards a framework for financial stability assessment, speech by José-Manuel González-Páramo, Member of the Executive Board of the ECB, OECD World Forum on Statistics, Knowledge and Policy, Istanbul.

– (2010): Financial stability review. December.

Fell, John/*Schinasi,* Garry (2005): Assessing financial stability: exploring the boundaries of analysis. National Institute Economic Review, Vol. 192, pp. 102–117.

Fichtner, Ferdinand/*Rüffer*, Rasmus/*Schnatz,* Bernd (2009): Leading indicators in a globalised world. ECB Working Paper, No. 1125.

Financial Stability Forum (2009): Report of the financial stability forum on addressing procyclicality in the financial system. April.

Gadanecz, Blaise/*Jayaram,* Kaushik (2009): Measures of financial stability – a review. IFC Bulletin, No. 38.

Gertler, Mark/*Kiyotaki,* Nobuhiro (2010): Financial intermediation and credit policy in business cycle analysis. Handbook of Monetary Economics, Vol. 3, 547–599.

Hagen, Jürgen von/*Ho,* Tai-Kuang (2007): Money market pressure and the determinants of banking crises. Journal of Money, Credit and Banking, Vol. 39, No. 5.

Hanschel, Elke/*Monnin,* Pierre (2005): Measuring and forecasting stress in the banking sector: evidence from Switzerland. BIS Papers, No. 22.

Hardy, Daniel C./*Pazarbasioglu,* Ceyla (1999): Determinants and leading indicators of banking crises: further evidence. IMF Staff Papers, Vol. 46, No. 3.

Holló, Dániel/*Kremer*, Manfred/*Lo Duca,* Marco (2012): CISS – A composite indicator of systemic stress in the financial system. ECB Working Paper Series, No. 1426.

Hosmer, David W./*Lemshow,* Stanley (2000): Applied logistic regression (2nd ed.). New York: Wiley.

Illing, Mark/*Liu,* Ying (2006): Measuring financial stress in a developed country: an application to Canada. Journal of Financial Stability, Vol. 2, 243–265.

IMF (1998a): Chapter IV, financial crises: characteristics and indicators of vulnerability. World Economic Outlook, Washington, DC.

– (1998b): Chapter III, key aspects of a framework for a sound financial system, World Economic and Financial Surveys, Washington, DC.

– (2003): Managing systemic banking crises. IMF Occasional Paper, No. 224.

DOI https://doi.org/10.3790/ccm.47.1.5 | Generated on 2024-07-22 15:24:00
OPEN ACCESS | Licensed under CC BY 4.0 | https://creativecommons.org/about/cclicenses/

Kick, Thomas/*Koetter,* Michael (2007): Slippery slopes of stress: ordered failure events in German banking. Journal of Financial Stability, Vol. 3, Issue 2, 132–148.

Kick, Thomas/*Pfingsten,* Andreas (2011): The importance of qualitative risk assessment in banking supervision before and during the crisis. Deutsche Bundesbank, Discussion Paper, Series 2, No. 09.

Kiyotaki, Nobuhiro/*Moore,* John (1997): Credit cycles. Journal of Political Economy, Vol. 105, No. 2, pp. 211–248.

Koetter, Michael/*Poghosyan,* Tigran (2008): Real estate markets and bank distress. Deutsche Bundesbank, Discussion Paper, Series 2, No. 18.

Krainer, John/*Lopez,* Jose A. (2008): Using securities market information for bank supervisory monitoring. International Journal of Central Banking, 125–165.

Laeven, Luc/*Valencia,* Fabián (2012): Systemic banking crises database: an update. IMF Working Paper, No. 163.

Lo Duca, Marco/*Peltonen,* Tuomas A. (2011): Macro-financial vulnerabilities and future financial stress. Assessing systemic risks and predicting systemic events. ECB Working Paper Series, No. 1311.

Lorenzoni, G. (2008): Inefficient credit booms. Review of Economic Studies, Vol. 75, Issue 3, 809–833.

Mehrhoff, Jens (2009): A solution to the problem of too many instruments in dynamic panel data GMM. Deutsche Bundesbank, Discussion Paper, Series 1, No. 31.

Misina, Miroslav/*Tkacz,* Greg (2008): Credit, asset prices, and financial stress in Canada. Bank of Canada, Working Paper, No. 2008-10.

Nickell, Stephen (1981): Biases in dynamic models with fixed effects. Econometrica, Vol. 49, No. 6, 1417–1426.

Porath, Daniel (2004): Estimating probabilities of default for German savings banks and credit cooperatives. Deutsche Bundesbank, Discussion Paper, Series 2, No. 06.

Roye, Björn van (2013): Financial stress and economic activity in Germany. Journal of European Economics, May.

Segoviano, Miguel A./*Goodhart,* Charles (2009): Banking stability measures. IMF Working Paper, WP/09/4.

Wooldridge, Jeffrey M. (2010): Econometric analysis of cross-section and panel data. 2nd edition, MIT press, Cambridge, Mass. (et al.).

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