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How Well Do Aggregate Bank Ratios Identify Banking Problems?

Martin Čihák and Klaus Schaeck

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Monetary and Capital Markets Department

How Well Do Aggregate Bank Ratios Identify Banking Problems?

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Abstract

The paper provides an empirical analysis of aggregate banking system ratios during systemic banking crises. Drawing upon a wide cross-country dataset, we utilize parametric and nonparametric tests to assess the power of these ratios to discriminate between sound and unsound banking systems. We also estimate a duration model to investigate whether the ratios help determine the timing of a banking crisis. Despite some weaknesses in the available data, our findings offer initial evidence that some indicators are precursors for the likelihood and timing of systemic banking problems. Nevertheless, we caution against sole reliance on these indicators and advocate supplementing them with other tools and techniques.

JEL Classification Numbers: E44, G21, G28

Keywords: Financial soundness indicators; banking crises; macroprudential analysis

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I. Introduction

Reflecting the high costs of banking crises and their increased frequency, banking sector stability has received increased attention in policy discussions in the past decade.[2] One of the key questions emerging from those discussions is how to best identify an impending crisis, so that appropriate measures can be taken well in advance.

Various studies have proposed early warning indicators of impending turmoil in banking systems (e.g., Demirgüç-Kunt and Detragiache, 1998, 1999, 2005; Hardy and Pazarbaşioğlu, 1999; Hutchinson and McDill, 1999; Hutchinson; 2002; European Central Bank, 2005). However, full agreement on how to measure systemic banking problems and which explanatory variables to include has not yet been reached.

The need for appropriate tools to assess strengths and weaknesses of financial systems led to efforts to define sets of so-called "core" and "encouraged" financial soundness indicators (FSIs), designed to monitor the health and soundness of financial institutions and markets, and of their corporate and household counterparts (Sundararajan and others, 2002). The precise definitions of the core and encouraged FSIs were laid down in the Compilation Guide on Financial Soundness Indicators (IMF, 2004). In 2004, a Coordinated Compilation Exercise (CCE) was spearheaded by the IMF, aiming to coordinate efforts of national authorities to compile and disseminate internationally comparable FSI data (and the related metadata).[3] The selection of FSIs was based not only on theoretical considerations, but also on surveys of country authorities' views on the usefulness and availability of indicators.[4] The early warning indicator literature has so far made little use of aggregate bank data such as the FSIs. This phenomenon partly reflects the fact that—despite substantial progress in the recent past—there is still no universal database of these indicators to facilitate cross-country research.

Drawing upon a subset of aggregate bank ratios for 100 developed and developing economies, we present the first econometric analysis of the applicability of these ratios for the identification of banking problems. Parametric and nonparametric techniques are employed to establish whether a set of aggregate bank ratios is sufficient to explain the

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[2] As regards the costs, Hoggarth and others (2002) suggest that output losses during banking crises can amount to 15–20 percent of annual GDP. As regards the frequency, Bordo and others (2001) report that simultaneously occurring banking and currency crises ("twin crises") have become more commonplace since early 1970. Surveying 21 countries, they find only one banking crisis in the 25 years after 1945, but 19 since 1970.

[3] For more details on the Coordinated Compilation Exercise, see IMF (2007 a,b). The data and metadata from the exercise can be found at http://www.imf.org/external/np/sta/fsi/eng/cce/index.htm.

[4] The term "country" as used in this paper covers not only states, but also some territorial entities that are not states but for which statistical data are maintained on a separate and independent basis.

emergence of a banking crisis. Additionally, we investigate whether these ratios convey important information on the timing of banking crises.

This paper contributes to the existing literature in several respects. In particular, it is the first paper trying to systematically use aggregate bank ratios to find whether they are beneficial for the identification of banking crises. It is also the first paper, as far as we know, that uses a duration model to analyze the timing of banking crises. Finally, unlike most of the existing early warning system literature, the models presented here attempt to include indicators reflecting the financial soundness of the non-financial sector.

The bulk of our results suggests that certain indicators such as return on equity of banks and corporate leverage are appropriate indicators for the detection of banking system vulnerabilities. We also find that the contemporaneous capital adequacy ratio and the contemporaneous ratio of nonperforming loans to total loans provide signals for systemic banking problems, whereas return on equity of banks additionally serves as an indicator for the timing of a crisis.

Since our study is of an exploratory nature, we qualify our findings along several dimensions.

- First, data availability constrains our sample to a comparatively short period between 1994 and 2004 and to only a few selected indicators from both the core and the encouraged sets of FSIs that are currently available.

- Second, although the currently available sets of FSIs were collected during FSAP and Article IV missions, and although substantial efforts went into ensuring comparability of these indicators, we highlight that there are deviations from the *Compilation Guide on Financial Soundness Indicators* (IMF, 2004). This means that different countries use somewhat different definitions of, for example, nonperforming loans, which may impact the results of our study. Nevertheless, we do find empirical evidence supportive of the hypothesis that these indicators are useful for macroprudential analysis and therefore view our initial findings as a rationale for future work at supranational institutions and central banks to collect bank data on the aggregate level for surveillance activities.[5]

- Third, while we acknowledge that the regulatory and institutional setting is considered to be one determinant of financial system soundness, we do not account for this in our study since it is beyond the scope of this research to investigate the

[5] Future work on FSIs should benefit from the compilation activities (such as the CCE, mentioned earlier), which result in a greater availability of both data and metadata on FSIs, making it clearer which data are comparable, and ultimately improving the quality of these indicators.

interaction between bank data on the aggregate level and the institutional setting in which banks operate.

- Fourth, the classification of crisis observations gives rise to ambiguity. We therefore follow two commonly utilized sources for the information on crisis observations. The study by Demirgüç-Kunt and Detragiache (2005) and the data provided by Honohan and Laeven (2005) which draws upon information and data collected by Caprio and Klingebiel (2003) are standard in the literature on early warning models for banking problems, and we therefore follow their dating scheme.

The paper is structured as follows. Section II elaborates on FSIs and their role in macroprudential analysis. Section III overviews the literature on early warning systems for banking crises. Section IV describes the dataset. Section V presents the methodological approach and the results of parametric and nonparametric tests. Section VI concludes.

II. Macroprudential Analysis and Financial Soundness Indicators

The increased interest in understanding banking crises led to the creation of a new body of analysis, termed macroprudential analysis, which aims to limit the risk of episodes of financial distress leading to significant macroeconomic losses (Borio, 2003). Its key tools include analysis of macroprudential indicators, stress tests, and qualitative analysis of the legal, regulatory, and institutional framework for the financial system (IMF, 2005). The key subgroup of the macroprudential indicators are financial soundness indicators (FSIs), which include both aggregated information on financial institutions and indicators describing markets in which financial institutions operate (Sundararajan, 2002). [6]

Appendix I provides an overview of the FSIs identified in the *Compilation Guide on Financial Soundness Indicators* (IMF, 2004). The development of these indicators was accompanied by a thorough consideration of the feasibility of compiling the data on the national level. FSIs are divided into a core set and an encouraged set. The core set includes banking sector indicators that should have priority in compilation and monitoring, and in practice are already collected by many countries. These indicators closely follow the CAMELS framework adopted by many bank regulators and supervisors to evaluate individual institutions' soundness.[7] The encouraged set includes additional banking indicators, as well as data on other sectors and markets that are relevant in assessing financial

[6] Macroprudential indicators include FSIs and other indicators that are useful for assessing the strengths and vulnerabilities of financial systems, such as credit growth or GDP growth.

[7] CAMELS stands for capital adequacy, asset quality, management soundness, earnings liquidity, and sensitivity to market risk (Sahajwala and van den Bergh, 2000). Management soundness is excluded in FSI consideration as this is usually approximated by qualitative information by bank regulators at the firm level.

stability—the corporate sector, the real estate market, and nonbank financial institutions and markets. (Sundararajan and others, 2002).

III. Survey of the Literature on Econometric Models for Banking Crises

A comprehensive body of literature exists on econometric models for banking crises. However, its findings to date are far from conclusive, highlighting a need to further investigate the causes of banking crises. The following is a brief overview of the models, based on their often used classification into four generations (Breuer, 2004).[8]

First-generation models (e.g., Miskhin, 1978) draw upon the experience of the Great Depression in the U.S. It is hypothesized that a dire macroeconomic setting adversely affects banks' borrowers and subsequently impacts upon the depositories themselves, thereby setting off bank runs that ultimately lead to the closure of financial institutions. Calomiris and Mason (1997), using data from the 1932 Chicago bank panic, analyze the frequently contemplated contagion effects on other institutions that arise from deposit withdrawals. However, they do not find that such contagion effects lead to insolvency.

Second-generation models focus on depositor behavior and view banking crises as self-fulfilling prophecies or "sunspot" events. Diamond and Dybvig (1983) contend that banking crises are unrelated to the business cycle. Rather, sudden shifts in depositors' expectations can trigger a crisis. By contrast, Gorton (1988) rejects the randomness of bank runs. Using long-term U.S. data, he finds a systematic association between bank runs and recessions that cause depositors to change their perception of risk.

Third-generation models underscore the role played by boom and bust cycles in the economy. Gavin and Hausman (1996) is considered to be the seminal work for this type of model. Others, such as Hardy and Pazarbaşioğlu (1998), Demirgüç-Kunt and Detragiache (1999), and the European Central Bank (2005), corroborated these findings. Contrary to the second-generation models, banking problems are understood to arise on the asset side of the institutions. During periods of economic upswing, banks engage in excessive lending against collateral such as real estate and equities that appreciate in value, thus facilitating a lending boom. A sudden bust results in collapsing asset prices and financial institutions scale back their lending. Ultimately, a credit crunch translates into an economic slowdown that increases borrower default rates. Third-generation models use predetermined (lagged) macro variables as leading indicators. They typically do not account for the institutional environment in which financial institutions operate.

[8] Most of the papers reviewed in this section belong to the early warning systems literature, which focuses on crisis prediction. However, some of the papers, such as Barth, Caprio, and Levine (2004), are intended to test hypotheses about the causes of financial crises, and provide a more ex-post assessment.

Fourth-generation models aim to identify the features of the institutional environment that set the stage for the build-up of macroeconomic imbalances, which subsequently give rise to banking problems. These models accentuate the role of the bureaucracy, protection of shareholder and creditor rights, rule of law and contract enforcement, sophistication of supervisory and regulatory frameworks, incentive schemes created by deposit insurance and the socioeconomic environment. An early warning system for banking crises that takes account of the institutional environment can be found in Demirgüç-Kunt and Detragiache (1998). Hutchinson and McDill (1999), Eichengreen and Arteta (2000), and Hutchinson (2002) extend the number of institutional variables in their analyses. Beck, Demirgüç-Kunt, and Levine (2005) additionally consider concentration in the banking industry for their analysis of banking crises, whereas Barth, Caprio, and Levine (2004) draw upon a World Bank database for bank regulation and supervision. Evidence for the impact of the institutional setting on the probability of observing systemic events in banking systems is, however, mixed. While the generous design of deposit insurance schemes tends to destabilize banking systems, in particular if the political setting is insufficiently developed (Demirgüç-Kunt and Detragiache, 2005), Barth, Caprio, and Levine (2004) fall short in providing statistically significant evidence for the hypothesis that a strong regulatory environment bolsters financial soundness. More recent research by Das, Quintyn, and Chenard (2005) finds some evidence that countries with a higher quality of financial sector policies are better able to contain the effects of macroeconomic pressures on the overall level of stress in the financial system.

Recent work by Gropp and others (2004) suggests market based indicators, such as the distance to default or the subordinated debt spread, as early warning indicators for banking problems on the micro level, whereas DeNicolo and others (2005) use the distance to default to assess the exposure to systemic risks. Whilst this approach draws heavily upon forward looking information, its sole reliance on the availability of market prices considerably limits its applicability to banking systems where such information cannot be obtained. Fox and others (2005) propose a systemic risk matrix, illustrating the relationship between a banking system indicator that averages Fitch's individual institutions' ratings and a set of macroprudential indicators that capture unsustainable departures of asset prices from their trend and credit booms. The benefit of this matrix is its ability to simultaneously embrace two sources of banking vulnerabilities. While the build-up of banking problems on the micro level is reflected in the banking system indicator, macroeconomic imbalances that are likely to impact upon the financial system are captured in the macroprudential indicators. An earlier paper by Pazarbasioglu and others (1997) used a very similar approach for Mexico, first using bank-specific factors and macroeconomic conditions to measure individual bank soundness, and then aggregating the bank-by-bank estimates into an index of banking system soundness.

Table 1 provides an overview of statistically significant variables in selected third and fourth generation models. It illustrates that the incorporation of institutional variables has become commonplace, but none of these models takes account of the non-financial sector and the importance of real estate prices for the early signaling of banking crises. Likewise, models that place great emphasis on the institutional setting fail to sufficiently control for the macroeconomic environment. The use of aggregate bank ratios in early warning models is limited at best. The only exception we are aware of is the study by the European Central Bank (2005), which includes some bank ratios in a logistic regression model for 15 advanced economies (see Table 1).

The related micro-level literature aims to identify individual failing banks. The micro-models traditionally estimate the future state of financial institutions using CAMELS-type financial ratios and macroeconomic variables. More recently, forward looking variables such as stock prices also have been incorporated into these models. Demirgüç-Kunt (1989) provides a detailed account of the early literature in the field. Sahajwala and van den Bergh (2000) survey the early warning systems in place at supervisory agencies and bank regulators in various G10 countries, whereas King and others (2005) offer a synopsis of recent advancements in the literature. The time to failure of individual institutions was investigated by Lane and others (1986) and Whalen (1991). However, while these models are of crucial importance for the surveillance work of bank supervisory agencies, they omit a consideration of cross-sectional and intertemporal correlations between failing institutions and therefore fall short in addressing the question of financial stability from a macroprudential perspective.

Overall, no clear agreement has yet been reached in the literature on models for systemic banking problems. One of the main open questions is the development of a commonly agreed set of leading indicators for the build-up of banking system vulnerabilities.

Table 1. Significant Explanatory Variables in Selected Studies

	Explanatory variables	Hardy and Pazarbaşioğlu (1998)	Demirgüç-Kunt and Detragiache (1998)	Demirgüç-Kunt and Detragiache (1999)	Hutchinson and McDill (1999)	Eichengreen and Areta (2000)	Hutchinson (2002)	Beck, Demirgüç-Kunt, and Levine (2003)	Barth, Caprio, and Levine (2004)	European Central Bank (2005)
Macro variables	GDP growth	■	■	■	■		■	■		
	Real interest rates	■	■	■				■		
	Inflation	■	■	■			■		■	
	Change in terms of trade		■							
	M2/reserves		■	■		■				
	Credit growth		■	■	■	■	■	■		
	Domestic credit to the private sector/GDP	■	■							■
	Capital inflows	■								
	Real exchange rate	■								
	Real exchange rate pressure						■			
	Import growth	■								
	'Northern' interest rates					■				
	'Northern' output growth					■				
	Budget surplus					■				
	GDP/capita		■					■		
	Deposits at banks/GDP	■								
	Gross foreign liabilities/GDP		■							
	Banking sector return on equity									■
	Banking sector loans to nonbank deposits									■
	Growth in GDP/capita									■
	Residential property prices									■
	Stock price index				■					
	Region , country, or OECD dummy	■			■					
	Industry concentration							■		
Institutional variables	'Law and order' index		■							
	Deposit insurance dummy		■		■					
	Central bank independence				■					
	Liberalisation				■	■	■			
	Moral hazard index							■	■	
	Diversification index								■	
	Government						■			
	Contract enforcement						■			
	Accounting disclosure						■			
	Capital regulations								■	
	Bank entry and activity restrictions						■	■	■	
	Ownership							■	■	
	Economic freedom							■		
	Banking freedom							■		
	Institutional environment							■		

IV. REVIEW OF THE DATA

A. Dataset

The dataset for this study includes 13 explanatory variables for 100 countries between 1994 and 2004. A detailed overview of the explanatory variables and sources is given in Appendix II. The countries included in the sample are listed in Appendix III.

In order to draw upon a sufficiently large dataset, we focused on the core FSIs (on regulatory capital, asset quality, and profitability of deposit taking institutions) and additionally on two FSIs for the nonbank corporate sector (namely profitability and leverage). The choice of this subset is driven by availability considerations. Only for the utilized variables was a sufficient number of observations recorded. Additionally, multicollinearity problems deter us from entering variables that capture the same risk category in our econometric models and we therefore decided on using parsimonious specifications. Descriptive statistics for the aggregate bank ratios used in our study are presented in Table 2.

The data on the aggregate bank ratios used in this study were collected in Financial Sector Assessment Program (FSAP) and Article IV missions. These are aggregate data that do not contain confidential information. The quality of the ratios used in this study reflects the quality of data in Fund missions collected from country authorities. The FSAP and Article IV mission teams generally strived to ensure that the indicators are consistent with the definitions put forth in the *Compilation Guide on Financial Soundness Indicators* (IMF, 2004). Nonetheless, many countries still deviate from the *Guide's* methodology, as the *Guide* was finalized only in 2004, and adjusting to the *Guide's* methodology takes time. Thus, some of the data employed in our study may suffer from these deviations, which are likely to increase the "noise" in the cross-country data that we study. This has to be borne in mind when interpreting our findings. Especially proxies for asset quality, such as the ratio of nonperforming loans to total loans and the ratio of nonperforming loans net of provisions to capital suffer from this problem, since national regulators and supervisory agencies follow national regulations that are not necessarily aligned yet with the FSI Compilation Guide.[9]

The length of the time series was limited to 11 years. Many data in FSAP reports start only in 1994, reflecting the fact that the FSAP started in 1999, and Article IV missions started to include FSIs more regularly only around the same time. The data typically end in 2003, since the data in a number of countries are available with a substantial lag. The data are annual (some countries provide also quarterly FSIs, but cross-country comparable data are available

[9] To the extent possible, the mission data on FSIs used in this study have been checked against the data from the CCE, and the differences have been relatively minor. However, this cross-check was possible only for the latest period for which CCE data are available.

on an annual basis only). Table 2 depicts descriptive statistics of the bank ratios used in this study. The table indicates a substantial degree of variability in the ratios covered in the sample.

To calculate the dependent variable, we need to establish whether there was a systemic banking crisis in a given country in a given year. For this purpose, we closely follow the literature on early warning models for banking crises and utilize two key sources for the identification of crisis countries:

- **Demirgüç-Kunt and Detragiache (2005)** provide a more recent survey of systemic banking crises, and report 77 systemic banking crises in 1980–2002. To classify a crisis as systemic, they require that at least one of the following conditions be met: (i) nonperforming assets exceeded 10 percent of total assets in the banking system; (ii) the cost of the rescue operation was at least 2 percent of GDP; (iii) banking sector problems resulted in a large scale nationalization of banks; or (iv) extensive bank runs took place or emergency measures such as deposit freezes, prolonged bank holidays, or generalized deposit guarantees were enacted by the government in response to the crisis.

- **Honohan and Laeven (2005)** update the database by Caprio and Klingebiel (2003) who offer an overview of systemic and nonsystemic banking problems since the 1970s. They define systemic banking crises as episodes during which much or all bank capital was being exhausted—as compared to nonsystemic banking crises, i.e. episodes of banking problems of a smaller magnitude. Using these criteria, they identify 117 systemic banking crises in 95 countries since the early 1970s. The benefit of employing the data provided by Honohan and Laeven (2005) lies in the fact that they distinguish clearly between systemic and nonsystemic problems and we therefore focus only on countries that are classified as having suffered a systemic crisis.

We use both these databases for the coding of our dependent variable. Since availability of aggregate bank ratios constrains our sample to the period 1994–2004, we disregard banking problems prior to 1994 and only report the crisis episodes identified in the two sources for the time horizon for which the banking ratios are available. In total, 51 countries experienced episodes of banking problems during that time. Table 3 provides an overview of these countries.

Table 2. Descriptive Statistics of the Banking Ratios in the Sample

	Variable	Mean	Standard Deviation	Min	Max
Core set	Regulatory capital to risk-weighted assets	15.11	6.11	-5	65.7
Core set	Nonperforming loans to total gross loans	8.66	7.83	0.3	37.9
Core set	Nonperforming loans net of provisions to capital	35.58	53.32	-15.3	422.62
Core set	Return on equity	15.55	13.64	-78.6	114.8
Encouraged set	Capital to assets	8.90	4.42	2	49.7
Encouraged set	Total debt to equity	74.83	47.01	0.38	416.27
Encouraged set	Return on equity	9.30	9.53	-18.70	54.09

Table 3. Banking Crises since 1994

Economy	Crisis	Economy	Crisis
Argentina	1995, 2001–2004	Latvia	1995–1996
Armenia	1994–1996	Lithuania	1995–1996
Azerbaijan	1995–1996	Malaysia	1997–2001
Bangladesh	1994–1996	Mexico	1994–2000
Bolivia	1994–2004	Mozambique	1994–2002
Bosnia and Herzegovina	1994–2004	Nicaragua	1994–2004
Brazil	1994–1999	Nigeria	1994–1995
Bulgaria	1996–1997	Paraguay	1995–2000
Cameroon	1995–1998	Philippines	1998–2002
China	1994–2004	Poland	1994–1995
Colombia	1999–2000	Romania	1994–1996
Costa Rica	1994–1997	Russian Federation	1995, 1998–1999
Croatia	1996	Sierra Leone	1994–1996
Ecuador	1995–2004	Slovak Rep.	1994–1995
Estonia	1994–1995	Slovenia	1994
Finland	1994	Sweden	1994
Ghana	1997–2004	Thailand	1997–2004
Hungary	1994–1995	Tunisia	1994–1995
India	1994	Turkey	1994, 2000–2004
Indonesia	1994–1995, 1997–2004	Uganda	1994–1997
Italy	1994–1995	Ukraine	1997–1998
Jamaica	1996–2000	Uruguay	2002–2004
Japan	1994–2004	Venezuela	1994–1997
Kenya	1994–1995	Zambia	1995
Korea, Rep. of	1997–2002	Zimbabwe	1995–1996
Kyrgyz Rep.	1994–2002		

B. Behavior of Financial Soundness Indicators in Crises

Prior to undertaking a rigorous econometric analysis, it is useful to inspect visually how selected banking ratios evolve in times of crisis. In this section, we present the development of five of these ratios three years before and three years after the crisis. However, this preliminary inspection of the dataset does not account for differences in countries' regulatory and supervisory environment, since these diagrams cannot capture the nature and structure of the individual countries' financial systems, their supervision and their monetary operations. We do, however, regard this visual inspection of aggregate bank data as beneficial as an initial exploration of the behavior of the indicators under consideration. This conjecture is supported by the fact that some of the indicators behave in the anticipated manner, suggesting that they provide good signals for the build-up of banking problems.

The evolution of regulatory capital/risk weighted assets, capital/assets, nonperforming loans (NPLs) /total gross loans, NPLs net of provisions to capital and return on equity is plotted in Figures 1 to 5. Included are crisis episodes as identified in Table 3, given that a sufficient number of observations per country were available to draw these diagrams. The horizontal axis records the number of years before and after the crisis and the vertical axis records the level in percent of the FSI under consideration. The solid line represents the mean for all the crisis countries available and the dotted lines denote plus/minus one standard deviation. Figure 6 contrasts mean values and standard deviations of three of the selected ratios with non-crisis countries.

Figure 1 illustrates that the cross country variation of regulatory capital dips slightly at the time of the crisis. However, it cannot be inferred that the capital adequacy ratio (CAR) sends a strong signal in the run up to a banking crisis. In the aftermath of a crisis, regulatory capital increases, which is due to the frequently higher capital requirements in the period after an episode of financial turmoil and the shoring up of reserves in financial institutions.

In contrast to the CAR, capital to assets increases considerably in the period prior to the crisis. This may be because institutions are building up capital buffers in anticipation of regulatory pressure to increase reserves against asset malfunction. An alternative explanation is that high incomes result from cyclically large increases in retained earnings.

The ratio of NPLs to total gross loans behaves intuitively. The rise prior to a crisis implies deteriorating asset quality in financial institutions. When a crisis fully materializes, nonperforming loans are fully recognized with a time lag and the level decreases again in subsequent years. This pattern is fully aligned with theory.

Figure 1. Regulatory Capital to Risk-Weighted Assets

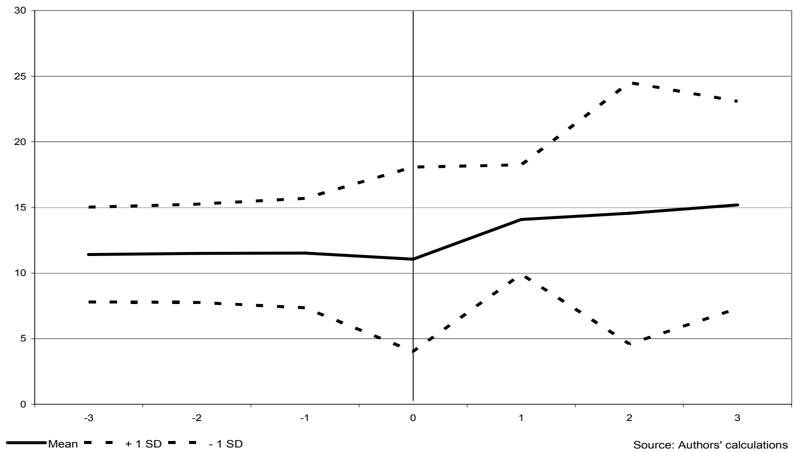


Figure 2. Capital to Assets

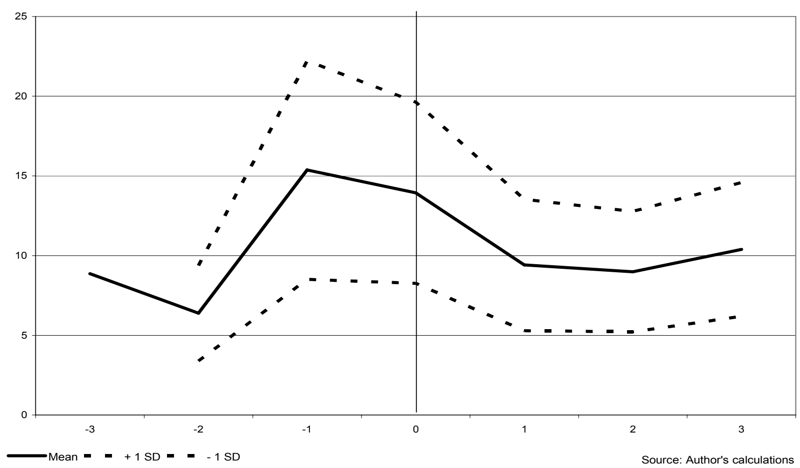
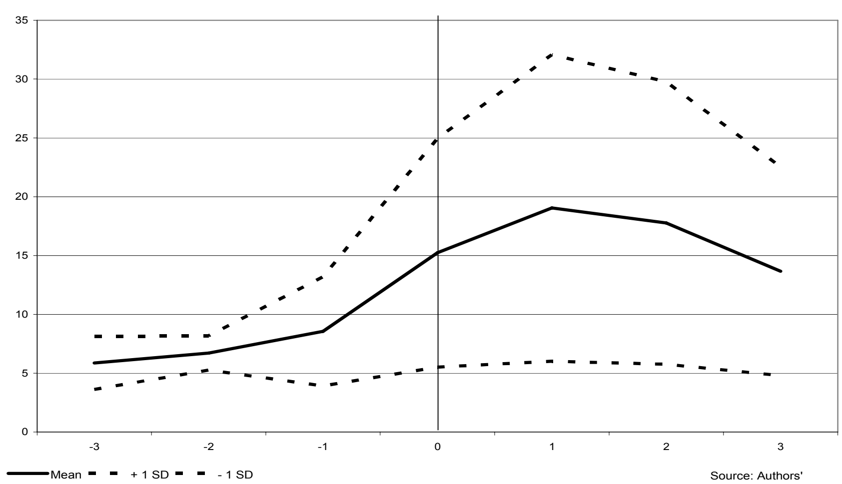


Figure 3. Nonperforming Loans to Total Gross Loans



Similar to the previous chart, Figure 4 provides further support to the hypothesis that NPLs are an appropriate indicator for asset quality. NPLs net of provisions to capital increase in the run up to a crisis, indicating that financial systems recognize poor asset quality; it seems to also indicate that provisioning lags behind the recognition of NPLs before crises, which may affect inter alia perceptions of vulnerability. A further increase follows after the onset of a systemic problem. Both plots show large degrees of variation in the data, which suggests that these measures are very ‘noisy’ in character.

Figure 4. Nonperforming Loans Net of Provisions to Capital

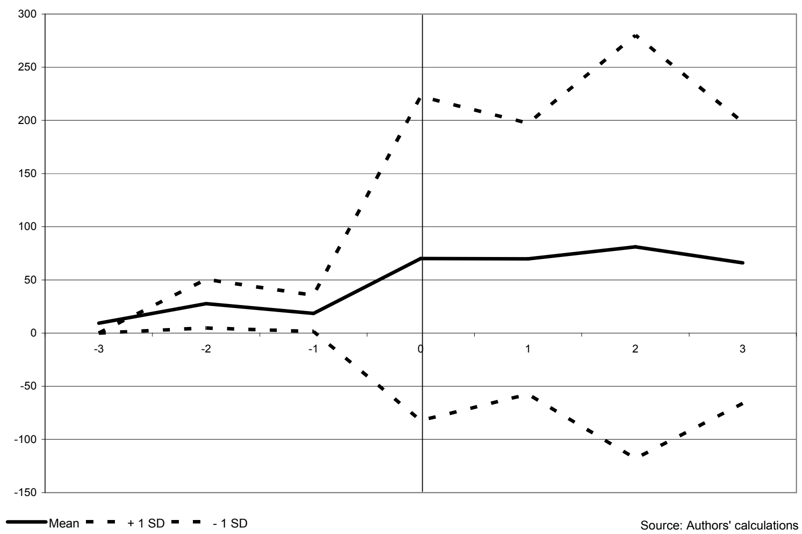


Figure 5 depicts that return on equity remains fairly stable in the period immediately prior to the crisis and declines afterwards. The lack of any deterioration of return on equity at the time of a crisis may be due to the increased risk taking behavior of bank managers as they become aware of impending problems. They might “gamble for resurrection” at that time and boost profits in the short run by undertaking risky investments. Only after the onset of a crisis, the ratio declines considerably, indicating substantial problems in banking systems.

Figure 6 highlights the differences in the banking ratios between crisis and non-crisis countries. It appears counterintuitive that regulatory capital and capital to assets are higher in crisis countries than in non-crisis countries. However, this may be due to the increased pressure in these jurisdictions to shore up capital reserves to absorb losses. Moreover, more volatile markets or more risky markets are encouraged by the Basel Committee on Banking Supervision to consider higher levels of capital. Alternatively, developing economies may consider higher levels of capital adequacy to underpin adherence to the Basel standard or to compensate for a weaker supervisory and regulatory environment. Finally, banks operating in high risk countries can restrain their lending activities by lending only to governments and other low risk borrowers. All these factors are possible explanations for this finding.

Figure 5. Return on Equity

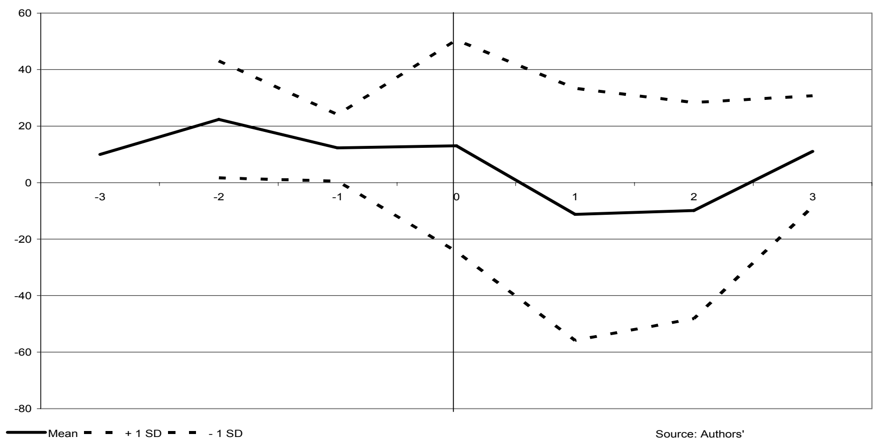
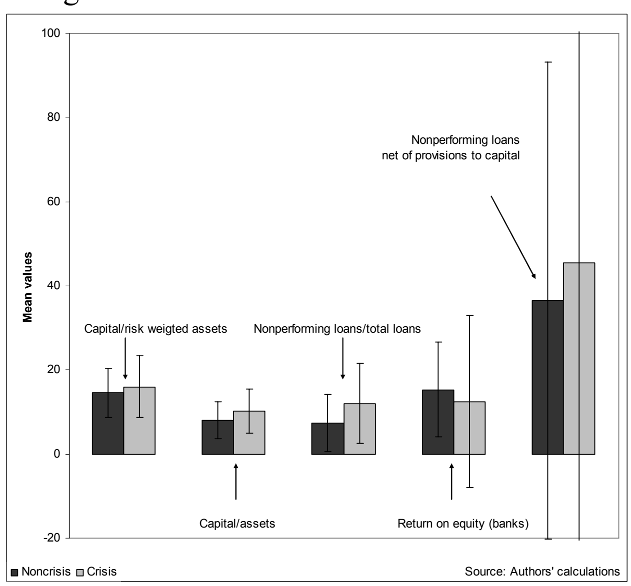


Figure 6. Crisis versus Non-crisis Countries



The higher ratio of NPLs to total gross loans and the higher level of NPLs net of provisions to capital in crisis countries are aligned with theory, and so is the lower ratio of return on equity in crisis countries in comparison to economies that did not suffer banking problems.

In sum, visual inspection of the behavior of the banking ratios around the crisis date suggests that some key ratios are appropriate candidates for the identification of banking problems. In particular, deteriorating asset quality as proxied by the two variables that capture NPLs is a good precursor for deteriorating banking system soundness.[10] As our preliminary analysis does not take account of the relationship between different banking ratios, we now turn to econometric models to account for this.

V. Econometric Analysis

A. Logit Regression Analysis

We test the applicability of the subset of banking ratios for the identification of banking crises using a multivariate logit model for a pooled dataset of 100 countries (listed in Appendix III) for the period 1994– 2004. The probability of observing a banking crisis in country i at point t is modeled as a function of a subset of banking ratios, denoted $FSI_{i,t}$, and a set of macroeconomic control variables, denoted $Macro\_Control_{i,t}$:

$$C_{i,t} = f\left(FSI_{i,t}, Macro\_Control_{i,t}\right). \tag{1}$$

Following Demirgüç-Kunt and Detragiache (1998), we estimate the logit model without the inclusion of a country fixed effect to also include countries that never experienced a banking crisis. The estimated log-likelihood function is

$$LnL = \sum_{t=1\ldots T} \sum_{i=1\ldots n} \{P(i,t)\ln[F(\beta' X(i,t))] + (1-P(i,t))\ln[1-F(\beta' X(i,t))]\}, \tag{2}$$

where $P(i,t)$ characterizes the banking crisis dummy variable that takes on the value 1 if there is a crisis, and zero otherwise. The term β denotes the vector of coefficients and X describes the vector of explanatory variables.

We can only utilize a subset of banking ratios for the following two reasons: First, only a very limited set of ratios is available for the sampling period. This considerably constrains our choice of explanatory variables and future research will help explore whether additional ratios contribute further to the identification of banking system vulnerabilities. Second, many ratios aim to capture similar risk categories. For example, asset quality can be captured by the ratio of nonperforming loans to total gross loans or by the ratio of NPLs net of provisions to capital. Including them in a regression equation simultaneously gives rise to collinearity

[10] An even more favorable interpretation of our plots may be that the dating schemes for crises proposed by Honohan and Laeven (2005) and Demirgüç-Kunt and Detragiache (2005) lag by at least one or two years. This may be due to the establishment of ex-post criteria according to which a banking system is classified as having experienced a crisis. Thus, the FSIs may capture already regulatory adjustments of the data at the time of the crisis and regulatory responses to the build-up of vulnerabilities in banking systems. Analyzing this issue would go beyond the scope of this paper, which takes the dependent variable (presence of a crisis) as given. Nonetheless, it is an interesting question for future research.

problems and we therefore limit the subsequent exposition to a set of three FSIs from the core set and two proxies for FSIs from the encouraged set. The choice of these variables is determined by data availability considerations for the sample.

Table 4 reports the regression results for ten different specifications of the logit model for the pooled dataset. The sample covers 100 countries of which 51 experienced serious banking problems during the period 1994–2004. We start from a parsimonious specification of the equation that only includes commonly utilized macroeconomic variables in the first and second setup of the model. Bank ratios are included in Specifications III–X. The model setup in Specifications III–VI employ contemporaneous bank ratios whereas we lag the ratios in Specifications VII–X by one period. This is a way of testing the sensitivity of the ratios to different lag structures. Specifications II, V, VI, IX, and X also take account of our proxies for credit to the private sector and credit growth.

Our results suggest that several bank ratios provide accurate signals for the probability of observing systemic banking problems and are therefore of benefit for macroprudential analysis. Both the contemporaneous and the lagged ratio of capital to risk-weighted assets consistently show the anticipated negative sign across Specifications III–X. The contemporaneous ratio enters significantly at the 10 percent level in Specifications IV and VI, where the two proxies for the corporate sector are included in the equation. However, capital adequacy is sensitive to the lag structure employed since lagging the variable by one period renders it insignificant. We also find that declining asset quality, reflected in increases of nonperforming loans to total loans, is indicative of impending banking turmoil at the 10 percent level in Specifications III and IV. However, this ratio is only significant when included as a contemporaneous variable. In contemporaneous Specifications V and VI, where the two additional macroeconomic control variables are accounted for, the ratio of nonperforming loans to total loans is close to the 10 percent significance level (p-values 10.5 and 11 percent). Lagging the variable by one period renders it insignificant as illustrated in Specifications VIII–X. This may be due to the fact that deteriorating asset quality is only appropriately accounted for by banks when the crisis is about to fully materialize. By contrast, return on equity (banks) enters at the 1 percent level throughout all specifications where bank ratios are incorporated, irrespective of the lag structure. This indicates that deteriorating profitability is a good predictor for a systemic banking crisis. This result is also substantiated by recent work by the European Central Bank (2005). Whereas return on equity in the corporate sector does not provide any indication of banking problems, corporate leverage as proxied by the debt/equity ratio always enters positively at the 1 percent level in both the contemporaneous and in the lagged model specifications. This underpins the view that increasing corporate debt is a robust precursor for banking system fragility.

Among the control variables, we find a consistently significant and positive relationship between the ratio of M2 to international reserves and banking crises across all specifications.

This is aligned with theory and reiterates that exposure to sudden capital outflows foreshadows the deteriorating soundness of banking systems. Likewise, our variable for the level of economic development, GDP per capita (real), robustly indicates an inverse relationship between the level of development and the probability of suffering a crisis; thus, higher developed countries are less likely to run into systemic banking problems. Contrary to previous studies, we do not find significant relationships between credit growth, inflation, real interest rates and economic prosperity as approximated by the rate of growth of the real GDP and banking system fragility.[11] Similarly, fiscal balance in percent of GDP shows the expected negative sign across all the specifications, but it is also insignificant. The lack of significance for some of the macroeconomic control variables may be attributable to multicollinearity as underscored by Detragiache and Spilimbergo (2001). Since we are not particularly interested in these control variables, but in investigating the impact of bank ratios on the probability of observing a crisis, we keep the macroeconomic variables in the equations.

We assess performance of the logit regression analysis based on the model χ^2 and on Akaike's Information Criterion (AIC). The values for the χ^2 statistic suggest that the null hypothesis that all the partial slope coefficients are equal to zero can be rejected at the 1 percent significance level for all model specifications. The AIC is a model selection statistic and penalizes for adding regressors, whereby the model with the lowest AIC is preferred. Based on the AIC, Specification IV that includes selected bank ratios performs best.

Classification accuracy can be evaluated in the light of Type I and Type II Error. A Type I Error occurs if a crisis episode is not captured by the model, whereas a Type II Error characterizes the misclassification of a country with a sound banking system as a crisis country. We employ a neutral cut-off probability of 0.2091 that equals the frequency of years with banking crises in the sample for the estimation procedure. In terms of Type I Error, the models classify between 11 and 27 percent of all crisis observations incorrectly. The number of false alarms is higher, and reaches up to 61 percent in the models that omit a consideration of the bank ratios. However, when contemporaneous bank ratios are included, this figure declines considerably to 41 percent in Specification IV, which is according to the AIC the most appropriate model setup. Overall, the model performs well, with up to 74 percent of all crises observations in the sample being correctly indicated in Specification IV, and this underscores the fact that consideration of bank ratios is beneficial for the identification of systemic banking problems.

[11] We also experimented with different lag structures for the real credit growth variable. However, the results were not affected and the variable itself remains insignificant.

To provide a further robustness test of the results, we re-estimated the ten different model specifications using first differences rather than levels. The results confirm the inferences drawn from the Specifications where the variables enter at levels and we therefore do not report the results here for reasons of brevity.[12]

In summary, the logit probability model suggests that bank ratios are of benefit for macroprudential analysis. Of primary importance is the ratio of return on equity of banks, which is is a strong predictor of the build-up of banking vulnerabilities.

[12] The results can be obtained from the authors upon request. We also considered using deltas other than first differences. However, deciding on deltas in such short time series would be very arbitrary, and the delta would be determined by the occurrence of the crisis itself, thereby giving rise to endogeneity problems.

Table 4. Logit Regression Results

Variable and expected sign		**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VII**	**IX**	**X**
Constant		-0.8858***	-0.8691***	-1.2475***	-1.2822***	-1.2369***	-1.2629***	-1.1221***	-1.1699***	-1.1090***	-1.1452***
		(0.1044)	(0.1049)	(0.1394)	(0.1432)	(0.1403)	(0.1445)	(0.1376)	(0.1420)	(0.1393)	(0.1443)
GDP growth (real)	-	0.0001	0.0003	-4.41E-05	-0.0004	0.0003	-0.0002	-0.0001	-0.0003	0.0002	-0.0002
		(0.0013)	(0.0016)	(0.0013)	(0.0012)	(0.0015)	(0.0015)	(0.0013)	(0.0013)	(0.0016)	(0.0016)
M2/international reserves	+	0.0013***	0.0013***	0.0013***	0.0012***	0.0014***	0.0014***	0.0013***	0.0012***	0.0014***	0.0013**
		(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0005)
Real interest rate	+	0.0000	0.0000	0.0001	1.60E-05	0.0001	6.88E-06	3.03E-05	-2.50E-05	2.34E-05	-3.93E-05
		(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Inflation	+	0.0001	0.0002	0.0001	0.0001	0.0001	0.0002	0.0001	0.0002	0.0002	0.0002
		(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
GDP per capita (real)	-	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Fiscal surplus/GDP	-	-7.39E-13	-2.62E-13	-9.53E-13	-3.48E-12	1.21E-13	-2.56E-12	-1.63E-12	-3.99E-12	-8.16E-13	-3.52E-12
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Credit to the private sector	+		-1.99E-05			-0.0003	-0.0002			-0.0002	-2.61E-05
			(0.0007)			(0.0007)	(0.0007)			(0.0007)	(0.0007)
Credit growth (real)	+		-0.0001			-0.0001	-0.0001			-0.0001	-0.0002
			(0.0002)			(0.0002)	(0.0002)			(0.0002)	(0.0002)
Capital/risk weighted assets	-			-0.0004	-0.0005*	-0.0004	-0.0005*				
				(0.0003)	(0.0003)	(0.0003)	(0.0003)				
Nonperforming loans/total loans	+			0.0005*	0.0005*	0.0005	0.0005				
				(0.0003)	(0.0003)	(0.0003)	(0.0003)				
Return on equity (banks)	-			-0.0007***	-0.0007***	-0.0007***	-0.0007***				
				(0.0002)	(0.0003)	(0.0002)	(0.0003)				
Return on equity (corporates)	-				0.0004		0.0004				
					(0.0003)		(0.0003)				
Debt/equity (corporates)	+				0.0001***		0.0001***				
					(0.0000)		(0.0000)				
Capital/risk weighted assets $_{t-1}$	-							-2.02E-05	-0.0001	-2.71E-05	-0.0001
								(0.0003)	(0.0003)	(0.0003)	(0.0003)
Nonperforming loans/total loans $_{t-1}$	+							0.0003	0.0003	0.0003	0.0004
								(0.0003)	(0.0003)	(0.0003)	(0.0003)
Return on equity (banks) $_{t-1}$	-							-0.0007***	-0.0007***	-0.0007***	-0.0007***
								(0.0002)	(0.0002)	(0.0002)	(0.00020
Return on equity (corporates) $_{t-1}$	-								0.0002		0.0002
									(0.0003)		(0.0003)
Debt/equity (corporates) $_{t-1}$	+								0.0001***		0.0001***
									(0.0000)		(0.0000)
Type I Error (percent)		10.90%	12.17%	23.48%	26.52%	23.04%	26.09%	13.04%	14.35%	13.48%	15.22%
Type II Error (percent)		61.03%	60.35%	43.91%	40.58%	44.14%	42.41%	54.02%	47.36%	53.56%	47.24%
χ^2		73.66***	74.64***	93.19***	107.22***	93.94***	108.30***	84.09***	96.93***	84.96***	98.20***
Akaike Information Criterion		0.9746	0.9740	0.9599	0.9499	0.9619	0.9525	0.9672	0.9592	0.9701	0.9617
McFadden R^2		0.0653	0.0661	0.0826	0.0951	0.0833	0.0960	0.0746	0.0859	0.0753	0.0871

Robust standard errors are in parentheses. * denotes significance on the 10 percent, ** on the 5 percent and *** on the 1 percent level.

B. Duration Analysis

To further understand the applicability of the bank ratios for the analysis of banking problems we also estimate a parametric duration model.[13] As far as we know, this is the first time in the literature that the timing of banking crises has been formally investigated using such a model.[14] We therefore start this section by briefly reviewing the key characteristics of this methodological approach.

Duration models are frequently utilized by labor economists to estimate the duration of spells of unemployment of individuals (Lancaster, 1990). A few applications exist in the finance literature for the analysis of 'time until failure' or 'survival time' of individual financial institutions (Lane and others, 1986; Whalen, 1991). Our duration model measures the time for transition from a sound banking system to the occurrence of a systemic crisis. In other words, the key difference from the logit model presented in the previous section is that while the logit model yields the unconditional probability of observing a banking crisis in a certain jurisdiction, the duration model provides the conditional probability of observing a banking crisis at point t, given that no such crisis has occurred in the country until t.

The time until a crisis is observed can be formalized as a probability density function of time t. We estimate the duration model based on the exponential distribution. The exponential distribution assumes a constant hazard rate over time. This is justified, given that countries, contrary to individuals or firms, do not exhibit a "life cycle." Thus, the hazard of experiencing a systemic banking crisis does not depend on the "age" of a country. The model is estimated using the maximum likelihood estimation technique. Commonly employed duration models assume constant covariates from the beginning of the measurement period t_0 to the time of the measurement $T = t_i$. However, as our explanatory variables are varying over the observation period from 1994–2004 the assumption of constant explanatory variables would be misleading, as it is not meaningful to investigate the distribution of a duration conditional upon the values of the regressors at one point in time. To overcome this limitation of commonly used duration models, and to account for the variation in the bank ratios and control variables over time, we estimate the duration model with time varying covariates (Petersen, 1986).

We draw upon the same dataset as for the logit model and observe 100 countries over the period 1994–2004. The number of observations is, however, smaller in the duration model as countries that experience a systemic crisis 'exit' our dataset in the year in which the crisis is

[13] For an introduction to the literature on duration analysis, see Greene (1993) and Lancaster (1990).

[14] There are studies that propose a dating of actual banking crises. These studies use simple pragmatic criteria to distinguish whether a certain system was in a crisis or not. We introduce them in Section IV.B.

first observed. A country's duration is the number of years it remains in the dataset. Thus, the minimum duration is t=1 if the banking crisis was experienced in the first period and the maximum duration is t=11 if the crisis occurred in 2004. Moreover, in countries that have never experienced a systemic crisis, the duration data are "right censored," in the sense that the studied event has not occurred in the observed timeframe. The initial setup of our dataset with six observations per country is well suited for this duration analysis with time varying covariates, as the hazard function is modeled as a step function with different values for the covariates through the intervals between t=0 and t=t_i, the terminal value of the observation, at which either censoring or exit takes place.

The estimated model with time varying covariates divides the sampling period from 0 to t_i into k exhaustive, non-overlapping intervals, $t_o < t_1 < t_2 < ... < t_{k-1}, < t_k$ where $t_0 = 0$ and $t_k = t_i$. This specification permits changing covariates from one interval to the other. Denoting the vector of explanatory variables as x_j, we can write that

$$h(t|x_j) = \text{hazard function from time } t_{j-1} \text{ to } t_j. \tag{3}$$

The relationship between the hazard function and the survival function is given by

$$h_t = -d \log S(t)/dt \tag{4}$$

and

$$\text{Prob}[T \leq t_j | T \geq t_{j-1}] = \exp - \int_{t_{j-1}}^{t_j} h(s|x_j)ds. \tag{5}$$

We therefore write the survival function for duration of t_k or more as

$$S(t_k|x_k) = \prod_{j=1}^{k} \text{Prob}[T \geq t_j | T \geq t_{j-1}] \tag{6}$$

and the density at t_k is

$$f(t_k|x_k) = h(t_k)S(t_k) \ . \tag{7}$$

For one observation, we write the log likelihood function as

$$\log L_i = \delta_i \log h(t_k|x_k) + \log S(t_k) \,, \tag{8}$$

where δ_i equals 0 for the "right censored" observations and 1 for all others.

Equation 8 highlights that each observation contributes the survivor function to the log likelihood function. If an observation is not censored, the density, evaluated at the terminal point, is added. Thus the estimated function is,

$$\log L_i = \delta_i \log h(t_k \,|\, x_k) - \sum_{j=1}^{k} \int_{t_{j-1}}^{t_j} h(s \,|\, x_j) ds. \tag{9}$$

Table 5 reports the results of the duration analysis for six different specifications of the model. The sample consists of 638 observations for 100 countries of which 51 experienced serious banking problems during the period 1994–2004. As with the estimates presented in the previous section, explanatory variables are defined in Appendix II.

We report a parsimonious specification of the equation that only includes commonly utilized macroeconomic variables first.[15] Bank ratios are included in Specifications III-VI, whereby Specifications III and V include FSIs from the core set only and Specifications IV and VI also utilize ratios from the encouraged set. We also add credit growth and credit to the private sector to the equation in Specifications II, V and VI. The interpretation of the signs of the coefficients is contrary to the logit model. We do not experiment with different lag structures in the duration model since the model more appropriately accounts for multiple observations per country. With the dependent variable being duration (in logs), a positive sign suggests an increase in the time to a crisis, implying a higher degree of stability.

The results from the duration analysis confirm the importance of return on equity (banks) for the detection of systemic banking problems. Whenever included in the equation, the variable enters with a positive and highly significant coefficient, providing strong evidence that increasing profitability of financial institutions increases the survival time of banking systems. The two other FSIs from the core set, the capital adequacy ratio and the ratio of NPLs to total loans, enter always with the expected sign but are rendered insignificant. Similarly, when we account for both profitability and leverage of the corporate sector, the variables show the anticipated sign but remain insignificant. The inclusion of the two additional macroeconomic controls, i.e., credit to the private sector and real credit growth, does not alter the significance level of the FSIs under consideration.

Among the control variables, only real GDP per capita consistently shows the anticipated positive relationship with the timing of banking crises. As highlighted in Section V.A. better developed countries are not only less likely to suffer a systemic problem, but time to crisis also increases in countries with a higher degree of economic development. While real GDP growth, the ratio of M2 to international reserves, real interest rate, inflation and credit growth

[15] We drop the variable fiscal surplus/GDP as it hampers convergence of the estimator in the duration models.

show consistently the correct sign, none of these variables assumes any meaningful level of significance in the duration models.

We also estimated the six duration models using first differences rather than levels. The variables GDP growth now enters positively and significantly, suggesting that economic prosperity increases time to crisis, which is intuitive. However, the bank ratios are all rendered insignificant in these additional tests. We do not report the results for reasons of brevity.[16]

In summary, the duration model reiterates the finding from the logit model that bank return on equity on the aggregate level is a strong indicator for increased vulnerability of the banking system and deteriorating profitability shortens time to crisis. The evidence for the other bank ratios is less convincing in this model setup, which imposes more restrictions on the dataset than the logit model. We interpret the findings from the duration model as preliminary evidence for a positive relationship between the return on equity of banks and the timing of systemic crises.

Table 5. Duration Analysis Results

Variable and expected sign	I	II	III	IV	V	VI
Constant	1.8759***	1.8911***	3.8494***	3.7512***	3.9153***	3.8148***
	(0.1978)	(0.2039)	(0.7350)	(0.8210)	(0.7352)	(0.8238)
GDP growth (real)	0.0011	0.0010	0.0019	0.0020	0.0013	0.0013
	(0.0013)	(0.0014)	(0.0038)	(0.0053)	(0.0038)	(0.0052)
M2/international reserves	-0.0001	-0.0001	-0.0003	-0.0003	-0.0003	-0.0004
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0007)
Real interest rate	-0.0003	-0.0004	-0.0003	-0.0003	-0.0004	-0.0004
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)
Inflation	-0.0003	-0.0003	-0.0002	-0.0003	-0.0002	-0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
GDP per capita (real)	0.0001***	0.0001***	0.0001***	0.0001**	0.0001***	0.0001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Credit to the private sector		0.0003			0.0009	0.0010
		(0.0009)			(0.0010)	(0.0010)
Credit growth (real)		-0.0002			-0.0002	-0.0001
		(0.0003)			(0.0003)	(0.0003)
Capital/risk weighted assets			0.0005	0.0005	0.0006	0.0005
			(0.0007)	(0.0008)	(0.0007)	(0.0008)
Nonperforming loans/total loans			-0.0005	-0.0004	-0.0005	-0.0004
			(0.0007)	(0.0007)	(0.0007)	(0.0007)
Return on equity (banks)			0.0023***	0.0023***	0.0023***	0.0023***
			(0.0008)	(0.0008)	(0.0008)	(0.0008)
Return on equity (corporates)				-0.0004		-0.0004
				(0.0005)		(0.0006)
Debt/equity (corporates)				8.13E-06		0.0000
				(0.0001)		(0.0001)
Log likelihood	-164.7704	-164.4979	-148.9624	-148.5545	-148.338	-147.923

[16] The results can be obtained from the authors upon request.

C. Nonparametric Tests

To further investigate our results obtained with the parametric models analyzed so far, we utilize several nonparametric tests for the selected aggregate bank ratios. Nonparametric tests do not impose any distributional assumptions upon the data and the inferences drawn from such tests are therefore considered to be more robust than parametric models. Additional benefits of these nonparametric tests are their intuitive character and their ability to illustrate the classification accuracy of aggregate bank ratios over different threshold levels. The drawback of this approach is the omission of a consideration of both the interaction amongst different indicators and the regulatory and institutional environment in which financial institutions operate.

We acknowledge that benchmarks for such aggregate bank level data may vary across different countries and that hardly any evidence exists in the literature regarding critical threshold levels for certain indicators, such as the CAR or NPL ratio. Nevertheless, we regard the following exposition as useful to illustrate the discriminative power of the selected ratios, since the supportive results for the benefit of some of the indicators obtained from the econometric analysis is (at least partially) confirmed by the nonparametric tests.

Figures 7–9 plot Type I and Type II Error classification accuracy over different cutoff levels for each indicator. The solid line in the diagrams represents Type I Error, the erroneous classification of a crisis as an episode of no banking problems. If the FSI under consideration possesses strong discriminative power, the area under the two curves will be small, while a large area indicates poor discriminative power. Figures 10 and 11 combine two of the most readily available aggregate bank ratios to further underline the findings for the previous plots.

Figure 7 illustrates that the capital adequacy ratio alone does not have strong discriminative power. The area underneath the two curves is sizeable and the plot corroborates the findings from the econometric models that capital adequacy is at best weakly indicative of the build-up of banking problems. For instance, at a cutoff level of 14 percent, more than 50 percent of the observations are misclassified according to this test. Moreover, the diagram questions whether the arbitrary chosen capital adequacy ratio of 8 percent is sufficient and appropriate for both macro- and microprudential analysis.

Figure 7. Type I/Type II Error for Capital Adequacy to Risk Weighted Assets

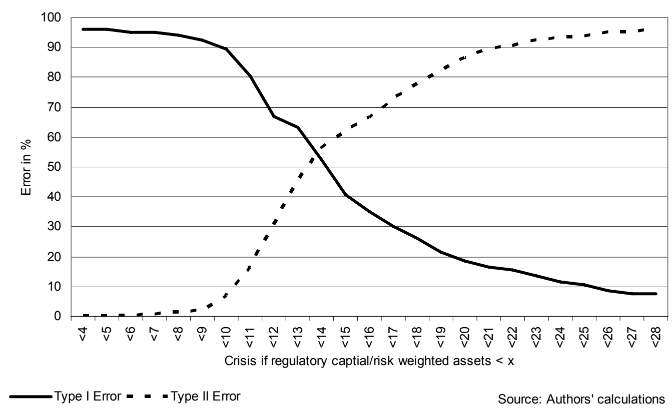
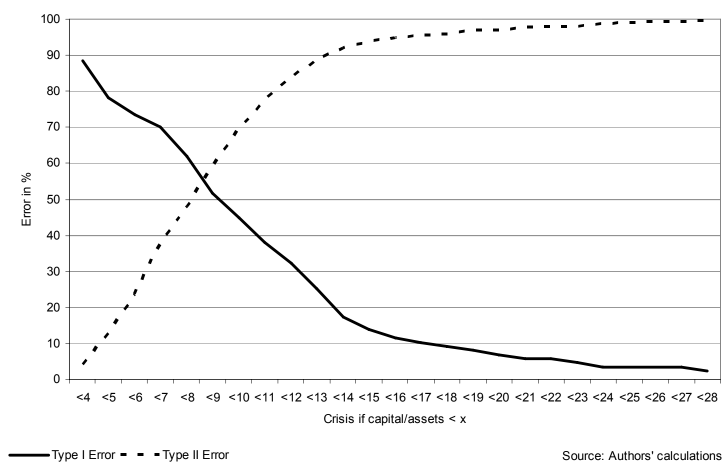


Figure 8 reiterates that capital ratios themselves are only of limited benefit for the discrimination between sound and unsound banking systems. At a cutoff level of 9 percent, only 40 percent of the crises are correctly classified. However, as this broader measure of the capital buffer increases, the misclassification decreases considerably, indicating some discriminative power in the capital to assets ratio.

Figure 8. Type I/Type II Error for Capital to Assets



Contrary to the two measures for capital adequacy, the ratio of NPLs to total gross loans possesses some discriminative power between sound and unsound banking systems. At a comparatively low cutoff level of 3 percent, approximately 94 percent of all crises are correctly classified. However, such low cutoff gives rise to a Type II Error of approximately 66 percent. This indicates that this ratio is a ‘noisy’ indicator and that solely relying on one indicator ought to be avoided. More importantly, it also confirms that the supervisory guidelines indicating when loans are to be classified as nonperforming need to be brought to a common standard. We anticipate the CCE (and subsequent compilation work) to be of substantial benefit in that respect as it will filter out the 'noise' in this indicator by improving both cross-country comparability of these data and the extent of information that is available for data comparison.

Figure 9. Type I/Type II Error for Nonperforming Loans to Total Gross Loans

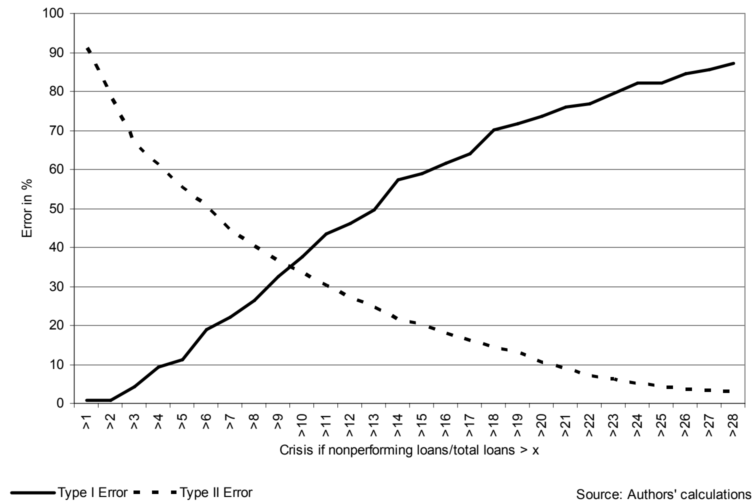
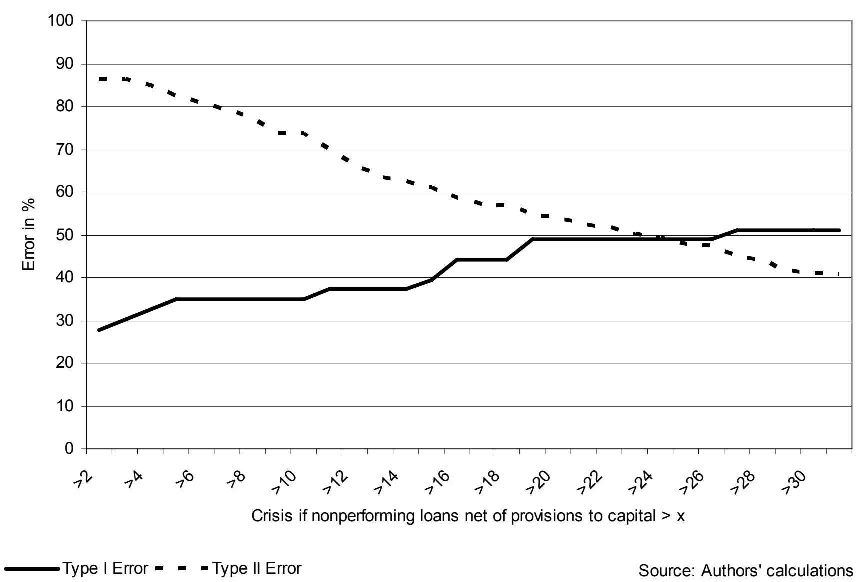
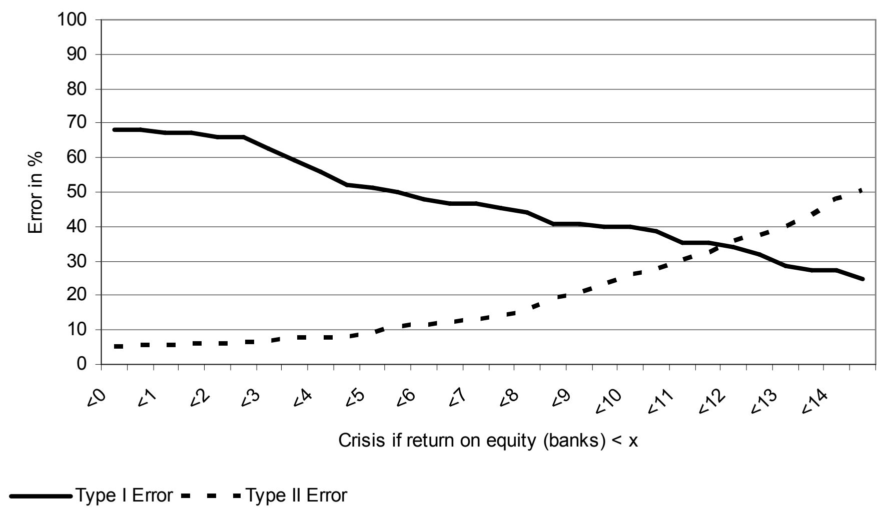


Figure 10. Type I/Type II Error for Nonperforming Loans Net of Provisions to Capital



A slightly lower discriminative power than the ratio of nonperforming loans to total loans reveals the ratio of NPLs net of provisions to capital. More than 66 percent of all crises are correctly classified at a low cutoff level of 10 percent whereas 73 percent of the observations during which no problems surfaced are identified as crisis episodes at this cutoff level. This underscores again that proxies for asset quality are 'noisy' indicators and that future work on commonly agreed and adhered measures for asset quality is necessary to remedy these limitations.

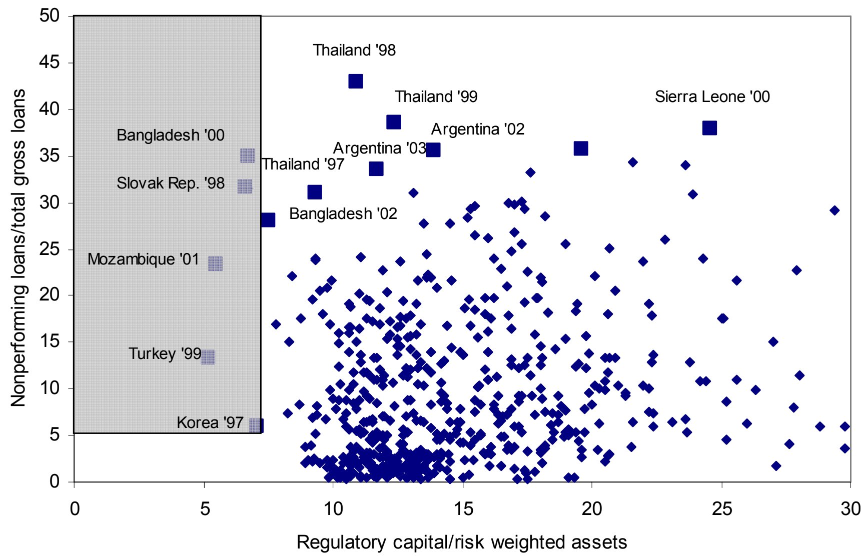
Figure 11. Return on Equity (banks)



As already indicated by the econometric models, return on equity (banks) has a strong discriminative power. This is not only supported by the comparatively small area under the two curves but also by the fact that 64 percent of the crisis observations are correctly classified at a cutoff value of 12 percent and by the low level of 35 percent Type II Error at this cutoff point.

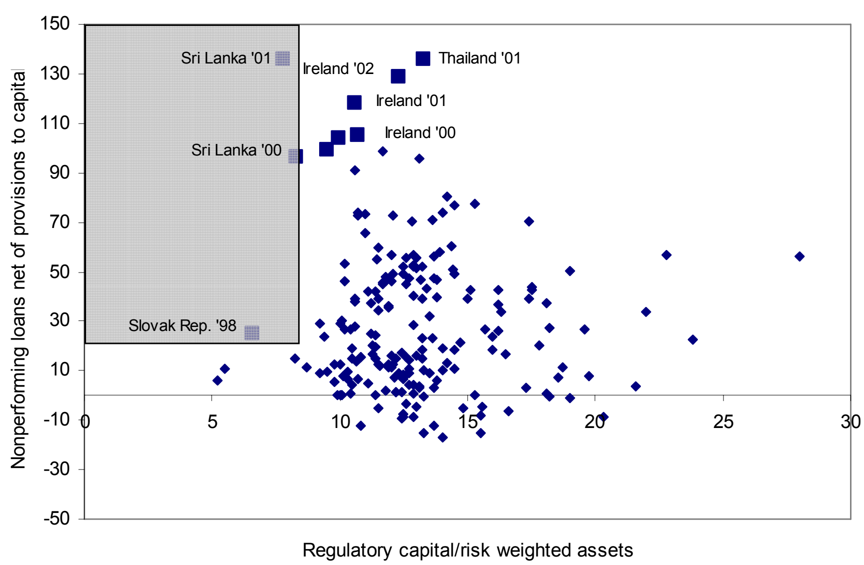
Figure 12 plots the CAR against the ratio of NPLs to total gross loans. Crisis episodes are expected to cluster in the shaded area in the northwest region. While a number of the countries for which we have complete observations for these two variables are indeed located in the shaded area, some others are widely dispersed in the diagram. Thus, two of the commonly most utilized variables for the identification of banking problems do have their justification as widely employed proxies for the assessment of banking system vulnerabilities. However, other banking systems that also experienced episodes of turmoil are more highly capitalized corroborating that reliance on capital ratios can give rise to misleading inferences. This finding cautions against using bank data on the aggregate level without taking account of the institutional environment in which banks operate.

Figure 12. Nonperforming Loans to Total Gross Loans vs. Capital Adequacy



The previous findings are reiterated in Figure 13, which plots the CAR against NPLs net of provisions to capital. Only a few observations are located in the shaded area. The data points are again widely dispersed in the diagram. This suggests that such analysis may be less appropriate than using econometric models for our initial evaluation of bank data on the aggregate level for the identification of banking system turmoil.

Figure 13. NPLs Net of Provisions to Capital vs. Capital Adequacy



In sum, the figures indicate that bank data on the aggregate level provide some benefit for the discrimination between sound and unsound banking systems. While the results from the nonparametric tests indicate that return on equity (banks), NPLs to total loans and return on equity are somewhat indicative of the build-up of banking vulnerabilities, measures for the capital buffer to absorb losses do not seem to be good candidates for the discrimination between sound and fragile banking systems. However, as underscored in the introduction to this section, we caution against solely relying on these indicators without considering the financial system and the surrounding regulatory and supervisory environment due to the fact that nonparametric tests cannot account for these factors. Moreover, it is essential for macroprudential analysts to be aware of the fact that the currently available indicators on the aggregate level may be subject to regulatory smoothing. We anticipate the CCE (and follow-up compilation work) to boost the quality of available indicators (and increase the availability of the metadata) so as to mitigate adverse effects arising from the noise that currently distorts some of the indicators on asset quality.

VI. Conclusion

The emergence of banking problems in the past two decades sparked off the development of econometric models that explain the build up of vulnerabilities in banking systems. This paper is an initial attempt to draw upon a set of aggregate bank ratios collected during Fund missions to assess whether these indicators are of benefit for the identification of banking crises and their timing for a panel of 100 countries in the period 1994–2004.

The findings of this study have to be interpreted with caution, for several reasons listed below. These reasons also indicate directions for future research efforts in this area:

- The dataset only covers a comparatively short time horizon for which only a small subset of FSIs was available. This limits the number of crises that can be analyzed. Due to the limited number of observations, we also cannot distinguish between different types of crisis (e.g., by size or by the size of government debt exposure).

- While the FSAP and Article IV missions that collected the FSI data made substantial efforts to ensure consistency with the *Compilation Guide on Financial Soundness Indicators* (IMF, 2004), some deviations from the Guide were inevitable (partly because missions before 2004 used earlier drafts of the Guide), which may affect the cross-country comparability of the data.

- Bank ratios are backward-looking, which limits their usefulness for predicting crises.

- The bank ratios used in this study are based on regulatory data, which are often subject to “smoothing.” This could explain the relatively low variability of the bank ratios observed in crisis countries, as compared with the cross-country variability of the same indicator. For instance, regulatory capital differs from the underlying economic capital and the ratio of NPLs is only a weak proxy for the actual asset quality in a banking system (in both cases, the regulatory data are likely to show lower volatility in case of adverse shocks). In addition, bank resolutions may be implemented before allowing the problems to be reflected in the data. Finally, in some cases, banks may engage in "creative accounting" in very difficult times.

- The bank ratios used in this study are aggregate indicators, while crises are in many cases "bad-apple problems." The use of aggregate data can disguise problems in individual banks or groups of banks. If the crisis begins in a segment of the banking system, and spreads to the rest of the system only later on, it may not show up in the aggregates. It is therefore always useful to look further at the distribution of these ratios across the banking system (there is such information from some FSAPs, but not enough for a systematic cross-country analysis).

- The paper uses a "0/1" definition of crisis, i.e. either there is a crisis or there is no crisis. While this is the dominant approach in the literature, it needs to be recognized that some banking systems can be weak and near crisis without any tell-tale signs of a crisis, such as bank runs, holidays, insolvencies, and liquidity support. In our paper, we have used a definition of crisis that is typically accepted in the early warning systems literature. Nonetheless, the classification and timing of crises in those papers is still open to discussion.

A graphical study of the development of the bank ratios suggests that a number of these ratios behave in an intuitive way in crisis countries, especially those that aim to capture asset quality. The findings from our binomial logit regression model provide preliminary evidence for the benefit of utilizing bank data on the aggregate level for macroprudential analysis. In particular, return on equity of financial institutions and corporate leverage are found to be good indicators for the build up of systemic banking problems. We also find weak evidence that the contemporaneous ratio nonperforming loans to total loans and the contemporaneous capital adequacy ratio are useful for the identification of banking turmoil. Moreover, our results corroborate the hypothesis that banking problems tend to occur in countries that are vulnerable to sudden capital outflows and in less developed economies. A duration model offers further support for the importance of the ratio of return on equity for the timing of banking crises.

The results of the logit and duration models regarding the discriminative power of the bank ratios are partially reiterated by several nonparametric tests. Plots of Type I and Type II Error over different cutoff levels are weakly supportive of the benefit of using aggregate ratios to discriminate between sound and unsound banking systems, although the evidence is less clear cut than in the parametric models.

In sum, the presently available data are supportive of the hypothesis that aggregate bank ratios provide signals for the build up of imbalances in banking systems. They are also of some benefit for the determination of the timing of crises. We conclude that future research is necessary to evaluate the aggregate bank ratios in a more continuous setting so as to validate the conclusions drawn to date. Moreover, the question whether aggregate bank ratios help explain the cost of banking crises has not yet been subject to econometric tests and appears to be an additional avenue of further research.

We therefore contemplate that utilizing aggregate bank ratios for country surveillance offers some benefit to the macroprudential analyst. However, we explicitly underscore the preliminary character of the conclusions drawn to date and highlight that analysis cannot be undertaken mechanically. Aggregate bank ratios need to be considered in the context of other tools of macroprudential analysis, both quantitative (e.g., stress tests or market-based indicators) and qualitative (e.g., assessment of the supervisory, regulatory, and institutional framework for the financial sector). Marked-based and other quantitative indicators can provide information on the probability of a crisis, and stress tests can help quantify the impact of such crisis. The qualitative information on the overall financial sector framework can be used to assess the ability of financial institutions and supervisors to mitigate the impacts of a crisis. Further research is clearly needed on the behavior of aggregate bank ratios and other variables in banking crises.

Increased quality of the available data (through the CCE on FSIs and through ongoing follow-up work) and the increasing quantity of available indicators should make it possible to replicate this type of analysis in the future. In addition, given that the annual frequency of FSIs is one of the drawbacks of these indicators, an analysis based on higher frequency data (e.g., market-based indicators) can be a fruitful avenue for research. Such analysis could cover not only the relationship between these high-frequency indicators and the 0/1 (no crisis/crisis) variable, but also—as a consistency check—the relationship between the high-frequency indicators and aggregate bank ratios.

APPENDIX I. FINANCIAL SOUNDNESS INDICATORS

Core Set	
Deposit-taking institutions	
Capital adequacy	Regulatory capital to risk-weighted assets
	Regulatory tier I capital to risk-weighted assets
	Nonperforming loans net of provisions to capital
Asset quality	Nonperforming loans to total gross loans
	Sectoral distribution of loans to total loans
Earnings and profitability	Return on assets
	Return on equity
	Interest margin to gross income
	Noninterest expenses to gross income
Liquidity	Liquid assets to total assets (liquid asset ratio)
	Liquid assets to short-term liabilities
Sensitivity to market risk	Net open position in foreign exchange to capital
Encouraged Set	
Deposit-taking institutions	Capital to assets
	Large exposures to capital
	Geographical distribution of loans to total loans
	Gross asset position in financial derivatives to capital
	Gross liability position in financial derivatives to capital
	Trading income to total income
	Personnel expenses to noninterest expenses
	Spread between reference lending and deposit rates
	Spread between highest and lowest interbank rate
	Customer deposits to total (noninterbank) loans
	Foreign currency-denominated loans to total loans
	Foreign currency-denominated liabilities to total liabilities
	Net open position in equities to capital
Other financial corporations	Assets to total financial system assets
	Assets to GDP
Nonfinancial corporations sector	Total debt to equity
	Return on equity
	Earnings to interest and principal expenses
	Net foreign exchange exposure to equity
	Number of applications for protection from creditors
Households	Household debt to GDP
	Household debt service and principal payments to income
Market liquidity	Average bid-ask spread in the securities market[2]
	Average daily turnover ratio in the securities market[2]
Real estate markets	Real estate prices
	Residential real estate loans to total loans
	Commercial real estate loans to total loans

Source: International Monetary Fund (2003, 2004).

APPENDIX II. EXPLANATORY VARIABLES

Variable	Definition	Source
GDP growth	Rate of real GDP growth in percent	WDI (World Bank)
M2 to reserves	Ratio of broad money to FX reserves of the central bank	WDI (World Bank)
Real interest rate	Real interest rate in percent	WDI (World Bank)
Inflation	Rate of change of GDP deflator to gauge inflation	WDI (World Bank)
GDP to capita	GDP per capita (constant 2000, in USD)	WDI (World Bank)
Fiscal surplus to GDP	Ratio of government surplus in percent of GDP	WDI (World Bank)
Credit to the private sector	Ratio of domestic credit to the private sector	IFS (IMF)
Credit growth	Rate of real credit growth	IFS (IMF)
Regulatory capital to risk weighted assets 1/	Capital adequacy ratio on the aggregate level	Article IV and FSAP reports (IMF)
Nonperforming loans to total gross loans */	Ratio of nonperforming loans to total gross loans on the aggregate level	Article IV and FSAP reports (IMF)
Return on equity (banks) 1/	Ratio of return on equity on the aggregate level for banks	Article IV and FSAP reports (IMF)
Return on equity (corporates) 1/2/	Ratio of return on equity on the aggregate level for corporates	Corporate Vulnerability Database (IMF)
Debt to equity (corporates) 1/2/	Ratio of debt to equity on the aggregate level for corporates	Corporate Vulnerability Database, (IMF)

Notes: IFS... International Financial Statistics (IMF), WDI....World Development Indicators (World Bank).
1/ For a detailed description, see the Compilation Guide on FSIs (International Monetary Fund, 2004).
2/ The corporate sector data are only available for publicly listed corporations. To account for cross-country differences in the depth of equity markets, these variables are weighted by stock market capitalization to GDP.

APPENDIX III. COUNTRY COMPOSITION OF THE SAMPLE

The sample used in this paper covers the following jurisdictions:

Angola	Kyrgyz Rep.
Argentina	Latvia
Armenia	Lebanon
Australia	Lithuania
Austria	Luxembourg
Azerbaijan	Madagascar
Bangladesh	Malaysia
Belarus	Malta
Belgium	Mexico
Bolivia	Moldova
Bosnia and Herzegovina	Morocco
Botswana	Mozambique
Brazil	New Zealand
Bulgaria	Nicaragua
Cameroon	Nigeria
Canada	Norway
Chile	Pakistan
China	Panama
Colombia	Paraguay
Costa Rica	Peru
Croatia	Philippines
Czech Republic	Poland
Denmark	Portugal
Dominican Rep.	Romania
Ecuador	Russia
Egypt	Saudi Arabia
El Salvador	Senegal
Estonia	Sierra Leone
Finland	Singapore
France	Slovak Republic
Gabon	Slovenia
Germany	South Africa
Ghana	Spain
Greece	Sri Lanka
Honduras	Sweden
Hong Kong SAR	Switzerland
Hungary	Taiwan
Iceland	Thailand
India	Tunisia
Indonesia	Netherlands, the
Ireland	Turkey
Israel	Uganda
Italy	Ukraine
Jamaica	United Arab Emirates
Japan	United Kingdom
Jordan	United States
Kazakhstan	Uruguay
Kenya	Venezuela
Korea, Republic of	Zambia
Kuwait	Zimbabwe

The list of crisis episodes as used in this paper is presented in Table 3.

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