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Reassessing the Use of Aggregate Prudential Ratios to Identify Banking System Problems

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Abstract

Building on an early warning baseline model, this paper analyzes the application of macroprudential banking ratios for an economy's five largest financial institutions, constructed from balance-sheet data, on the probability of systemic banking crises occurring relative to the sector-wide aggregates that are commonly used by the International Monetary Fund (IMF) and other authorities. The investigation is motivated by the observation that the distribution of bank assets is highly asymmetric in advanced economies, the fact that an economy's largest banks are often implicated in systemic banking crises, as well as theory and empirical evidence demonstrating the large impact of shocks originating at large banks. For a sample of 25 advanced economies between 1997-2008, a multivariate logit model estimates the effect of a vector of commonly applied macroeconomic indicator control variables, as well as the aforementioned banking ratios for large banks and the banking sector aggregates. The findings support the hypothesis that some characteristics in large financial institutions can be used to identify banking sector turmoil more accurately than their aggregate analogues, however exclusive reliance on these indicators is not advisable.

Suggested Keywords: Financial Soundness Indicators, Macroprudential Analysis, Banking Crises, Financial Fragility

JEL Codes: E44, G21, G28

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Table of Contents

1. Introduction

With hopes for a permanent great moderation in advanced countries dashed with the recent Global Financial Crisis (GFC), many observers were reminded that modern societies have been subject to banking crises for a long period. Qian, Reinhart and Rogoff (2010) show that banking crises occurred frequently in a significant share of high-income countries until the Second World War and staged a strong comeback culminating in the recent GFC after a “hiatus in banking crises across both groups of countries during the years of financial depression from World War II until the 1970s” (Qian, Reinhart, & Rogoff, 2010, p. 19).

During the height of the GFC, some of the largest and most renowned financial institutions around the world were liquidated, had to merge with other institutions, or were bailed out by governments (Acharya, Philippon, Richardson, & Roubini, 2009). These life-extending measures in the form of blanket deposit guarantees, open-ended liquidity support, repeated partial recapitalizations, debtor bailouts or regulatory forbearance are associated with large fiscal costs (Honohan & Klingebiel, 2003; Laeven & Valencia, 2008). Examining samples of countries dating from the 1970s, two studies obtain estimates that governments incurred fiscal costs between 12.8% and 13.3% of gross domestic product to repair the damage that was done to the financial system (Honohan & Klingebiel, 2003; Laeven & Valencia, 2008). However, these estimates only reflect a portion of the true costs of banking crises, and do not consider the difficult-to-measure costs that arise through a slowdown in economic activity as “resources are driven out of the formal financial sector (and into less efficient uses), bank credit [is] curtailed, investment plans [are] cut back and stabilization programs [are] derailed” (Honohan & Klingebiel, 2003, p. 1542). Given the adverse consequences of banking crises on the real economy, a vast amount of economic research has been devoted to examining the root causes of banking crises and establishing early warning systems to detect fragility in financial systems.

Amongst these efforts, the International Monetary Fund (IMF) has organized the collection and analysis of Financial Soundness Indicators (FSIs) to help monitor the financial systems. These statistics are computed as banking sector-wide aggregates and encompass measures for capitalization, asset quality, management, earnings and liquidity for the financial sector. In their analysis of these potential signals, Čihák and Schaeck (2010) develop an early warning system for banking system distress. They conclude that "aggregate data can often 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" (Čihák & Schaeck, 2007, p.33). Their concerns are supported by various theoretical considerations regarding the use of indicators on a sector-wide level. The distribution of assets across the banking sector yields interesting insights as both Demirgüç-Kunt and Huizinga (2011) and Blank et al. (2009) demonstrate that bank assets are distributed asymmetrically within the banking sector. In fact, the vast majority of banks control relatively few assets relative to GDP and are of little systemic importance, whereas few banks possess assets that can exceed the size of their respective country's GDP. Amongst the countries considered in our analysis, banking assets are distributed highly asymmetrically, as demonstrated in 2008 (Figure 1).

Hence, the goal of this paper is to determine whether data for large banks provides adequate or better indicators and estimation of crises in a macroprudential context than aggregate data, and whether data monitoring and collection efforts should be more centered on large banks rather than the broad sector-level perspective being employed by regulators in line with the IMF's FSIs. In order to examine this hypothesis, various multivariate logit model specifications are run to estimate the effects of the aforementioned aggregate and large bank ratios, as well as a vector of commonly applied macroeconomic indicator controls, on the probability of a banking crisis occurring for a sample of 25 advanced economies in the period between 1997 and 2008. Robustness checks account for the sensitivity of results due to a bias that occurs through abnormal behavior of explanatory variables following banking crisis episodes, as well as different crisis classification specifications, and the existing literature's preference for the logit model over the probit.

The key finding of the paper is that data for a country's largest financial institutions is at least as well suited as aggregate data to be used as early warning indicators for systemic banking distress in the literature's standard multivariate logit model context. This is based on similar or even higher levels of significance of key indicators as well as better overall accuracy of the estimated models. However, from a practical point of view, caution is advisable as using large bank data without taking into account the larger macroeconomic environment may lead to missing important signs of early distress. These findings have large efficiency implications for the collection indicators as well as for the potentially more frequent and continuous oversight of financial systems.

The remainder of the paper is organized as follows. Section II reviews the literature on early warning systems and banking crises in a macroprudential context, Section III provides an overview of the methodology employed, and Section IV describes the dataset. Section V presents the main results, Section VI describes the robustness checks and Section VII concludes.

2. Literature Review

2.1 Banking Crises as "Equal Opportunity Menaces"

As the majority of systemic banking crises during the 1990s involved emerging economies (Qian, Reinhart and Rogoff, 2010), the majority of recent banking crises studies have been centered on emerging economies. Reinhart, Rogoff and Savastano (2003) find that developed economies can sustain a higher level of public debt than emerging economies by examining a large historical dataset on external default crises from 1800 to recent times. Building on this finding, Qian, Reinhart and Rogoff (2010) included inflation crises and banking crises into the same dataset. While advanced economies have graduated from external default and inflation crises over the course of the past 200 years, banking crises still occur in both sets of countries, as was made patently clear by the recent Global Financial Crisis. As highly developed economies have historically led developing countries in terms of financial development, a closer analysis of the determinants of banking crises in developed countries can offer lessons for financial development in the world's less developed economies.

2.2 Big Bank Behavior

To set up our research question, several contributions to the research on the unique nature of large banks within the global banking sector are worth reviewing. Demsetz and Strahan (1995) find that large bank holding corporations (BHCs) are better diversified than small BHCs. This does not lead, however, to lower levels of risk as large BHCs have lower capital ratios, larger commercial and industrial loan portfolios and make use of derivatives to a larger extent (Demsetz & Strahan, 1995).

In a more recent paper, Demirgüç-Kunt and Huizinga (2011) present findings that point in a similar direction. Using an international sample of banks, they analyze how absolute and systemic sizes are correlated with banks' risk and return profiles, its activity mix and funding strategy. A bank's absolute size is defined as the log of its total assets in constant dollars while systematically large banks are those with high liabilities relative to the GDP of the country in which they are located. They conclude that large banks are different along several dimensions. Banks with larger absolute size tend to be more profitable but also incur higher bank risk. While absolute size has a positive effect on the risk-return profile of banks, systemic size reduces the return without reducing the overall risk of a bank and also increases its funding costs. These facts point to the potentially destabilizing effects of large banks, which are often implicated in banking crises.

2.3 The Limited Dependent Variable Approach to Early Warning Systems

Several types of early warning system models were developed out of the banking crisis literature by both academics and central bank researchers to detect banking system distress. These models utilize macroeconomic indicators and other variables to monitor the health of the banking system and draw inferences on the key variables with regards to banking system health. In surveys on more recent models, both Davis and Karim (2008) and Demirgüç-Kunt and Detragiache (2005) identify two main empirical approaches to finding the causes of banking crises: the signal and the limited dependent variable approaches.

In the limited dependent variable approach, a multivariate logit model is typically used to examine the causes that potentially lead to a systemic banking crisis. A variety of indicators including macroeconomic, financial, and institutional variables can be used to estimate the likelihood of a banking crisis. The dependent variable generally takes on the value of 1 if a crisis occurred in a country in a specific year and 0 if not, according to certain criteria for the episode. As noted in Davis and Karim (2008), this approach allows researchers to take into account the interdependencies of explanatory variables that together can cause a banking crisis.

Demirgüç-Kunt and Detragiache (2000) first employed the multivariate logit model to estimate banking crisis probabilities for a sample of developed and developing economies between 1980 and 1995. They analyzed a set of macroeconomic variables including real GDP growth, changes in the terms of trade, exchange rate depreciation, the inflation rate and fiscal surplus as a share of GDP, in addition to a vector of financial sector variables, such as bank credit growth lagged by two periods and the ratio of broad money to foreign exchange reserves. The estimated coefficients for the variables GDP growth, the real interest rate, inflation, broad money to reserves and credit growth all have the expected signs and are significant in explaining the probability of a banking crisis (Demirgüç-Kunt & Detragiache, 2000). Eichengreen and Arteta (2000) conducted a similar empirical exercise but with a probit model to test the effects of various explanatory variables on the probability of crises occurring in emerging markets.

Another early contribution to the development of these models was made by Gonzalez-Hermosillo (1999), which estimated logit models including measures for nonperforming loans, capital equity and other measures that proxy market risk, credit risk, liquidity risk and moral hazard. The addition of macroeconomic variables leads to a significant increase in the predictive power of the model (Gonzalez-Hermosillo, 1999). The results showed the expected effects with a lower ratio of capital equity to total assets and a higher ratio of nonperforming loans to total assets increasing the probability of a banking crisis. Using the coverage ratio – the ratio of capital equity and loan reserves minus nonperforming loans to total assets – is the better alternative to account for individual bank trouble since it differentiates between banks with a similar nonperforming loans exposure that take different measures in order to bolster their capital equity or their reserves (Gonzalez-Hermosillo, 1999).

In more recent research, Čihák and Schaeck (2010) applied a multivariate logit model to test the effects of aggregate banking ratios on the likelihood of a banking crisis, while controlling for a vector of applied macroeconomic variables commonly applied in the literature. Their analysis investigates the performance of the Financial Soundness Indicators (FSIs) disseminated by the IMF, in assessing the strengths and weaknesses of financial systems. The authors find that aggregate banking ratios can help to detect the buildup of imbalances in the banking sector, yet they notably caution the use of aggregate indicators for predicting a forthcoming banking crisis. Still, the authors demonstrate that the contemporaneous aggregate return-on-equity variable is a significant indicator across all of their specifications.

Several studies have been undertaken along this line of research following the recent Global Financial Crisis. Notably, Gourinchas and Obstfeld (2011) examine what causes the outbreak of default, banking and currency crises in advanced, as well as emerging economies, by estimating a panel logit model with fixed effects. Focusing on examining the determinants of the 2008 global financial crisis, the authors assemble a vector of hypothesized indicators, including the level of public debt, the current account balance and the level of domestic credit, all relative to output. They also include the real exchange rate and the output gap (Gourinchas & Obstfeld, 2011). Measures for official reserves and short-term external debt are added for emerging countries. The results yield significant yet quantitatively irrelevant results for banking crises in advanced economies, as, according to the authors, there are too few crisis events during the sample period.

The multivariate logit model has also been applied to estimating the likelihood of individual bank distress. Čihák and Poghosyan (2009) examine bank distress on an individual bank levels for European banks. The paper focuses on the early warning power of so-called CAMEL (capitalization, asset quality, management, earnings and liquidity) indicators. To obtain the balance sheet data for their independent variables, the authors utilize the Bureau van Dijk BankScope database (Čihák & Poghosyan, 2009). They also employ a logit regression using clustered standard errors to provide for the possibility that observations are correlated within individual banks (Čihák & Poghosyan, 2009). They obtain the expected signs for three of the five CAMEL variables, as higher levels of capitalization and earnings reduce the probability of individual banking distress, while higher loan loss provisions (indicating a lower quality of banks' loan portfolios) increase the probability of distress. Notably, banking sector aggregates for several of these variables were utilized in Čihák and Schaeck (2010).

Despite an extensive existing literature, the analysis of micro-macro links has not been widely applied to banking crises. The IMF's Financial Soundness Indicators (FSIs) were developed with the intention of providing tools for the macroprudential analysis of financial systems in different countries (IMF, 2005). While the IMF collects the FSIs from participating countries at an aggregate level, the distribution of assets in the banking system casts doubt on the representative nature of these variables and suggests potential noise in these indicators introduced through the consolidation process. As recommended to reporting countries, banking ratios are constructed by taking the total values for the numerators and denominators in the banking sector. The aggregation of the entire sector leads to the inclusion of many weakly-linked and inconsequential banks, in terms of providing early warning indicators.

As shown in Gabaix (2011), when the distribution of firm-sizes in an industry is fat-tailed as in Figure 1, idiosyncratic shocks to larger firms have the potential to generate aggregate shocks that affect the entire industry and broader economy and can serve as key determinants of business cycle fluctuations. Building on Gabaix's research, a similar proposition was analyzed for the German banking industry in Blank et al. (2009). The researchers found that shocks to profitability and asset quality originating in the country's ten largest banks, ranked by total assets and operating income, affected the probability of distress at small and mid-sized banks, in line with work on bank contagion. Simply put, large banks have been shown to behave differently with implications for the entire banking sector, and, in fact, are often at the center of banking crises. Therefore, early warning systems utilizing variables for the top five banks in an economy is a potentially more precise tool for identifying banking problems than when simply computing overall aggregates.

3. Methodology

3.1 Econometric Model and Variables of Interest

In line with early warning indicator models previously developed in Demirgüç-Kunt and Detragiache (1998), and modified in Eichengreen and Arteta (2000), and, more recently, in Čihák and Schaeck (2010), we test the relative applicability of monitoring banking ratios by estimating the probability of a banking crisis, using a multivariate panel logit model without fixed effects. This allows us to include countries that have not experienced banking crises over the sample period (e.g. Australia, Norway, and New Zealand) as controls, since there is no variation in the dependent variable for those countries. For valid statistical inference, we calculated robust standard errors as applied in Čihák and Schaeck (2010), as well as Demirgüç-Kunt and Detragiache (1998), to obtain heteroskedasticity-consistent standard errors.

In this model, the probability that a country *i* will experience a crisis at time *t* is hypothesized to be a function of a vector $X_{i,t}$ of n variables, including the prudential variables and controls. The dummy variable $P_{i,t}$ takes the value of one in the event of a banking crisis in country *i* at time *t*, and zero when no crisis occurs. The estimated log-likelihood function is:

$$\ln L = \sum_{i=1}^{T} \sum_{i=1}^{n} \left\{ P_{i,t} \ln\left[F\left(\beta' X_{i,t}\right)\right] + \left(1 - P_{i,t}\right) \ln\left[1 - F\left(\beta' X_{i,t}\right)\right]\right\}$$

Here, β is a vector of n coefficients and $F\left(\beta' X_{i,t}\right)$ is the cumulative probability distribution function evaluated at $\beta' X_{i,t}$ using the logistic functional form for F. To demonstrate that the results are not dependent on the functional form, we also ran regressions using the inverse standard normal distribution (or probit model specification). The estimated coefficients from this regression represent the effect of a change in explanatory variables on $\ln\left[P_{i,t} /(1 - P_{i,t})\right]$. As pointed out in Demirgüç-Kunt and Detragiache (1998) and according to standard theory, the sign of the coefficient indicates the direction of the change, and the magnitude depends on the slope of the cumulative distribution function at $\beta' X_{i,t}$.

To make our results directly comparable with earlier work, our empirical investigation focused on the same banking prudential variables and control variables in Čihák and Schaeck (2010), as well as extended this model to the 2008 onset of banking crises. This allowed us to exploit the recent variation in the dependent variable and reassess the initial model's performance over a larger and more turbulent period. As Čihák and Schaeck (2010) note, the initial model may have failed to provide indicators of the 2007 crises in the US and UK, yet it may have indicative power for other crises occurring thereafter. Regressions were run including just the macroeconomic controls and subsequently with the contemporaneous aggregate banking sector ratios in specifications the first two model specifications. The next baseline model specification (3) focused on examining the use of balance-sheet data from each economy's largest five banks (by asset size) to calculate the prudential ratios.

The accuracy of the different model specifications can be compared along several dimensions. As in Demirgüç-Kunt and Detragiache (1998), a crisis is deemed to be accurately predicted when the estimated probability exceeds the frequency of crisis observations in the sample (6.67%). From this cutoff rule, different model specifications can be evaluated. To first compare the classification accuracy and strength of the Early Warning System (EWS) model specifications, Type I and Type II errors were calculated for all specifications. Type I errors refer to the mistaken classification of a crisis as an episode of no banking problems, while Type II errors are those that classify an episode with no banking problems as a crisis. Although the costs of each error ultimately need to be considered when discriminating between models, these statistics can serve as a guide to evaluating model precision. As in Kaminsky and Reinhart (1999), we then computed each model's noise-to-signal ratio, given by the ratio of the Type II error to (1 - Type I error), as a way to evaluate the overall accuracy without making assumptions about potential costs associated with each error. Lastly, following the accuracy criterion in Demirgüç-Kunt and Detragiache (1998), we reported the percentage of observations that are correctly classified to further help assess the predictive accuracy of each specification.

A major issue when employing early warning system approaches in binary-dependent variable models is the post-crisis bias that arises from utilizing observations occurring after the onset of the crisis in the sample. As Bussiere and Fratzscher (2006) demonstrate, the bias arises when the model fails to distinguish between tranquil periods and post-crisis periods when economic variables undergo adjustment processes. For instance, an increase in fiscal deficits and decrease of real interest rates could be associated with the onset of crises, even though they may be stimulus tools being employed to combat the already existing crisis. Table 4 presents a summary of variables and their averages at different periods relative to crises. As we evaluate crisis determinants, the relevant comparison should be made between tranquil years in column 1 and the years of the onset of crises, column 2. The inclusion of columns 3-5 could lead to erroneous conclusions. Also, as the aim of the model is to determine the factors associated with the onset of a banking crisis, excluding these years does not present problems aside from the loss of observations. As employed by Demirgüç-Kunt and Detragiache (1998) and more recently in Obstfeld and Gourinchas (2011), we addressed the post-crisis bias by eliminating the crisis observations for the years following the onset and years following the last crisis year. Analyzing the behavior of the variables in the years following the last crisis year in Table 4, we eliminated observations for the first three years after the last crisis year in specifications 4 and 5. We see this as a significant improvement compared to the methodology employed by Čihák and Schaeck (2010).

To further compare the early warning power of the aggregate macroprudential ratios with the top five ratios, all specifications included one-year lags of the banking variables for each group. This testing of lag structures can potentially provide important warnings to regulators for impending crises. To examine the sensitivity of our results to the somewhat arbitrary determination of banking crises, we follow Laeven and Valencia (2008) in using a slightly modified set of dependent variables where borderline crisis observations for seven European countries are treated as non-crises in specifications 6-8.

To demonstrate that the results are not dependent on the functional form, we also ran regressions using the inverse standard normal distribution (or probit model specification). Although the logit model has been the primary model utilized in this literature and one that we utilized to make our findings comparable with earlier research, the probit specification allows an additional opportunity to test the sensitivity of our main findings. The analogous testing of lag structures was also performed using the probit specification.

4. Dataset

As earlier demonstrated, the banking sector is highly concentrated in advanced and less-developed countries. This is particularly striking with regards to the advanced countries in our sample, as seen in Figure 1. Drawing from the facts that large banks, when measured by asset and systemic size, behave differently and that their behavior has large effects on the entire sector, we have constructed banking sector variables based on these unique and more influential firms in the sector.

Balance sheet level data for financial institutions was obtained through Bureau van Dijk's BankScope database, which includes data from 1987 to the present. The identification of the largest institutions in each country involved sorting countries by total assets in each year and then screening them to only include bank holding companies, commercial banks, savings banks, investment banks, and real-estate banks. Specialized governmental credit institutions were the main type of financial institution excluded in this process.

Within an economy, a high degree of persistence among the top five banks is evident over time, however the sample period of 1997-2008 was characterized by a high degree of consolidation in the sector. BankScope does not explicitly identify mergers and acquisitions, and the database often includes both the acquiree and acquired banks during the first years after a merger or acquisition. Problems can arise with regards to sudden dramatic changes in banking balance sheet data and also problems due to double-counting. Following the correction employed by Demirgüç-Kunt et al. (2006), both banks involved in a merger were treated as one bank from the beginning of the sample period. To identify all mergers and acquisitions amongst the largest banks, FACTIVA and the websites of financial institutions were consulted.

To deal with missing observations amongst the top five banks, we employed a simple algorithm. If data for specific variables was not available for more than half of the banks comprising the top five (including non-merged entities in the group), then no value was assigned for the observation. Rather than making our sample too dependent on the availability of data in BankScope, we decided to only utilize available data from the largest institutions. Otherwise, this would have conflicted with our aim to analyze the behavior of the largest banks. The BankScope database coverage has improved significantly over time, and we have data for 64.7% of all observations in our sample period.

We focused our empirical investigation on a sample of twenty-five advanced countries partly due to the higher quality balance-sheet sample data that is available for advanced countries. Studies such as Cunningham (2001) and Bhattacharya (2003) have demonstrated that BankScope's coverage in developing countries can omit important banks, resulting in a large selectivity bias. Furthermore, the most recent GFC was primarily, though certainly not exclusively, an advanced country banking crisis phenomenon and serves as a central event in our inquiry. We also removed observations from the years 1994-1996, which were present in the dataset employed by Čihák and Schaeck (2010), due to lower bank coverage and the sudden unexplained disappearance of large banks in the BankScope database.

One drawback of using balance-sheet data is the failure to capture the increasing banking practice of using off-balance sheet transactions to hedge risks or take speculative positions. The rise of these activities has been associated with the most recent banking crises and may represent a key source of omitted variable bias, as these activities may be closely tied to profitability and regulatory capital ratios. As acknowledged by Čihák and Schaeck (2010), banks may engage in creative accounting during traumatic periods to mask their true performance.

To construct our banking crisis binary-outcome dependent variables, we utilized the updated sources obtained in Čihák and Schaeck (2010). In their methodology, Čihák and Schaeck (2010) assign a value of 1, indicating a systemic banking crisis for a country in a particular year, based on two data sources widely used in the EWS literature. The first source is the banking crisis list provided in

Demirgüç-Kunt and Detragiache (2005), which assigns a value of 1, if at least one of the following conditions is met:

i. nonperforming assets exceed 10% of total banking system assets;
ii. the cost of the rescue operation was at least 2% of GDP;
iii. (banking sector problems resulted in large scale nationalizations of banks;
iv. extensive bank runs took place or emergency measures such as deposit freezes, prolonged bank holidays, or generalized deposit guarantees were enacted by the authorities.

Laeven and Valencia (2008) provide another source by updating the widely-cited Caprio and Klingebiel (2005) banking crisis database, but depend more on qualitative criteria by classifying a crisis as a period in which “episodes during which much or all bank capital was exhausted—as compared to non-systemic banking crises, i.e., episodes of banking problems of a smaller magnitude” (Čihák & Schaeck, 2010, p. 132). Following Čihák and Schaeck (2010), if a crisis episode is identified in either dataset for a country in that period, a value of one is assigned to the observation. By extending our model to include the crises of 2008, we consulted the updated database in Laeven and Valencia (2010), to include the large number of banking crises that occurred in 2008. Some of these were classified as “borderline crises”. Including these borderline crises, 6.67% of all observations in the sample were crisis episodes. In an effort to test the sensitivity of our results to these episodes, we ran regressions assigning values of 1 and then 0 to these episodes. The crisis periods are provided in Table 1.

By including banking ratios, as well as established crisis indicators from the earlier literature, we followed the aggregate baseline model of Čihák and Schaeck (2010). Based on an extensive literature survey of the application of econometric models to banking crises, the authors selected ten control variables commonly utilized in the research area’s models. These include the macro variables GDP growth, broad money to reserves, real interest rates, inflation, GDP per capita, fiscal surplus to GDP, credit to the private sector and real credit growth. Given the large percentage of European Monetary Union members in our sample, we were forced to remove the real interest rate and broad to reserves controls. We see this as an appropriate measure since these are not key policy targeting variables for many countries in our sample. Following Alessi and Dektken (2008), we have instead included 10-year bond yields as a market-based indicator for potential banking sector problems.

The selection of the macroprudential ratios from the IMF's FSIs set was based on their importance to central banks, data availability amongst sample countries, and to avoid multicollinearity problems that arise from the inclusion of other relevant ratios that utilize the same numerators or denominators. Nearly all central banks use macroprudential ratios in their stability assessments, such as the non-performing loans ratio which is defined as the ratio of non-performing loans to gross loans, the capital adequacy ratio (the ratio of the sum of Tier 1 and Tier 2 capital to risk-weighted assets), and the return on average equity in the banking system (Čihák, 2006; De Haan et al., 2007). Fortunately, this data was collected at the aggregate level via IMF Staff IV reports and IMF mission reports - following Čihák and Schaeck (2010) - and for individual banks via BankScope. A full list of the explanatory variables and their sources is provided in Table 7.

Several Countries have taken some discretion in calculating the FSIs. In the most recent compilation guide, the IMF admit the difficulty in obtaining comparable data across countries since countries have "different accounting systems and will rely on national sources of data" (International Monetary Fund, 2006). Cost concerns can be a key issue in this process, as particular data series may not be collected by a country's regulatory agency. For instance, ongoing discussions over increasing the frequency of data from the current annual basis have been criticized for the large additional costs they would impose on regulators.[1] Thus, consolidating data for the entire banking sector within an economy can impose significant costs on regulators. For example, in our sample of advanced countries, Sweden provided aggregates for the years 2003-2008 and only provided data on the top four banks in the prior years. Similarly, Canada only reports sector-wide data for the years 2002-2008. Consequently, we have not included these observations from both countries in our

[1] See IMF report on key points and conclusions from November 2011 conference on FSIs, http://www.imf.org/external/pubs/ft/fsi/guide/2012/pdf/020312.pdf.

regressions. As analyzed in the subsequent results section, these missing values often occur during crucial periods and can have very large impacts on estimation techniques.

With cost concerns as an issue, regulators have provided macroprudential data at different rates and in different forms. In his 2003 review of the availability of the FSIs across countries based on survey responses, Slack notes that advanced countries collected and provided a higher percentage of indicators for capital adequacy, asset quality, and profitability than less developed economies. However, these rates were still quite low for utilizing in an empirical framework as only 60% of advanced countries reported data on asset quality and 66% and 80% for profitability and capital adequacy, respectively (Slack, 2003). General data availability has improved significantly however since this time, as we obtained aggregate data for 86.7 percent of all observations (Slack, 2003).

For some countries dominated by few banks, we realize that the aggregate and top5 variables will be quite similar. Analyzing the correlations between the macroprudential ratios for these different specifications, we see a strong positive but imperfect linear relationship for all ratios **(**Table 2**).** Thus we are confident that the different measures can provide much different results when applied to our defined methodology.

The descriptive statistics of the prudential ratios for the top five banks in each country and the IMFs aggregate FSIs used in this study (Table 2) demonstrate a high degree of variation in the sample. Furthermore, t-tests demonstrating the unique behavior of these variables of interest in crisis and non-crisis episodes for both the aggregate and top five macroprudential ratios are presented in Table 3. The selection of these ratios allowed us to obtain estimates and classification results to compare the efficacy of applying aggregate sectorwide or large bank balance-sheet data to our commonly utilized logit model. Banking ratios that may not provide any indication of financial sector turmoil when aggregated at the sector level, may, in fact, provide important insights when analyzed for a country's largest financial institutions and also allow more accurate detection, and therefore lower costs of banking crises.

5. Results

5.1 Main results

The regression results are provided in Appendix A, including the estimated coefficients and standard errors for our various regression model specifications, as well as various model accuracy statistics. The main results obtained through our methodology (Table A1) yield encouraging insights compared to previous research that employed aggregate banking ratios. We find that early warning models using financial information for the five largest banks in an economy can improve the precision of the model and that the indicators can provide more significant and accurate signals than in an aggregate framework. In summary, the models utilizing top five bank data provide at least as good of an early warning system as models utilizing aggregate data.

The noise-to-signal ratio and overall classification accuracy are significantly lower in the baseline regression that employs top five banking ratios compared to the counterpart specifications using aggregate ratios. Furthermore, the Type I error rates are much lower for the top five specifications in most of the pairs, and the Type II rates are nearly identical. Aside from the specifications 4 and 5, in which the post-crisis bias is removed, the improvement of the top five specification's accuracy holds across all types of specifications. Furthermore, the model X^2 statistics indicate that the null hypothesis that all slope coefficients are equal to zero may be rejected at very low significance levels across all specifications for both aggregate and top five bank variables (below 1 percent).

Confirming a key finding in Čihák and Schaeck (2010), the contemporaneous return on equity ratio continues to serve as a highly significant indicator of banking turmoil through the 2008 crises. For both aggregate and top five specifications, the ratio is significant at the 1% level. While the contemporaneous ratio of regulatory capital to risk-weighted assets enters with the unanticipated positive signs in aggregate specifications 4 and 6, the variable enters negatively and significantly at the 5% level in three of the four main regressions using top five bank data. However, although it retains a p-value of .22, the variable's signaling power drops once the post-crisis bias is corrected. Still, the variable remains significant below the 5% level once “borderline” crises are dropped and the post-crisis bias is accounted for. Thus the macroprudential regulatory capital ratio for the top five banks can serve as a valuable and more dependable indicator than the ambiguous aggregate analogue. As in earlier work, the ratio of non-performing loans to gross loans lacks any consistent significance across specifications. These main findings lend evidence to the doubts raised by Čihák and Schaeck (2010) that the use of aggregate banking ratios might not detect the problems in financial institutions that could potentially lead to a full-fledged banking crisis.

With the potential to provide regulators with valuable and earlier information, models with lagged macroprudential ratios unfortunately yield uninteresting results (Table A3). The model specifications utilizing top five banking variables do not lead to any significant improvement to the study of Čihák and Schaeck (2010) as the estimated coefficients for the largest banks are insignificant at the 10% level. While the lagged aggregate return on equity variables retain their significance at the 1% level in specifications 2 and 6, the variable’s significance drops dramatically to a p-value of .51 when the post-crisis bias is considered. Thus, it is difficult to draw consistent policy conclusions from these mixed results. In fact, the overall lagged specifications are much less accurate in classifying observations with far higher noise-to-signal ratios than the specifications featuring contemporaneous macroprudential ratios. While the increased significance of some of the control variables and the aggregate banking ratios is notable, the results do not yield any valuable new insights.

5.2 Discussion of results

The fact that models including top five bank variables tend to perform at least as well as the FSIs, in terms of accuracy and the indicative power of macroprudential ratios, has powerful implications for researchers and regulators. Rather than dedicating resources extensively to monitoring the large number of small institutions, resources could potentially be employed more efficiently towards dealing with the largest ones. This conclusion is especially intriguing for countries with very low levels of concentration in the banking sector. As can be seen in Table 5, the correlation between aggregate and top five banking ratios in these countries suggests that the behavior of the biggest banks in the economy captures the asset quality and the levels of regulatory capital to a large extent. Thus our findings may have greater implications from an efficiency-perspective in less concentrated countries, such as the United States, than in more highly concentrated countries, such as Finland, as resources shift towards closer scrutiny of larger banks and away from extensive overall coverage. As banking crises could potentially arise in smaller banks through contagion, we are not advocating for regulators to neglect consideration of small and less systematically important financial institutions.

First steps such as "systemic capital surcharges", i.e. higher regulatory capital to risk ratios for systemically important financial institutions (SIFIs), have been utilized in order to prevent the onset of financial stress (Hannoun, 2010). Our findings also have implications from a research point of view. Previous studies used the so-called CAMEL (capital, asset quality, management, earnings and liquidity) variables to predict systemic and individual bank distress (Čihák & Schaeck, 2007, 2010; Čihák & Poghosyan, 2009). Measurements of the liquidity and management components were not included in these studies**.** However, the experience of the recent Global Financial Crisis shows that liquidity problems marked the beginning of the crisis (Acharya, Philippon, Richardson, & Roubini, 2009). Measures of liquidity for major financial institutions that are comparable across jurisdictions can be utilized to assess their performance as an early warning indicator. This would be a potentially valuable effort that could motivate policymakers to pass legislation addressing this issue.

A major concern with utilizing the FSIs for macroprudential analysis is the timeliness and frequency of sector-wide data. As alluded to in the data section, availability of data is an important issue as the aggregate variables are backward-looking which causes delays in identifying fragility. For example, Iceland has yet to release the NPL to gross loans for the 2007 and 2008 periods, or the return on equity and regulatory capital to risk-weighted assets ratios for 2008. Consequently, we were unable to obtain estimates for a robustness check of a specification utilizing aggregate ratios due to a lack of observations on account of missing data for the 2007-2008 period. The IMF has admitted the existence of timeliness problems in the collection and release of FSIs and the impact for monitoring banking sector fragility. The close monitoring of systemic institutions and release of preliminary data could help resolve this issue. Thus, the IMF is contemplating increasing the frequency of data dissemination for a preliminary sample population to a quarterly basis.[2] This would represent a positive step for researchers and regulators in monitoring banking sectors and developing improved early warning systems.

6. Robustness Tests and Other Findings

6.1 Macroprudential Ratios

Though not at the center of our study, a high level of credit to the private sector is a significant and robust indicator for banking distress across all sensitivity tests. Concerns remain whether this finding can be effectively put to use from a policy perspective as collecting and preparing these backward looking macroeconomic indicators is a time-consuming task for the regulator. Compared to the financial sector indicators mentioned above, macroeconomic fundamentals cannot be considered as reliable indicators for turmoil in the banking sector as the few significant indicators are rendered insignificant with the application of robustness tests.

6.2 Borderline Crisis Sensitivity Analysis

Our first robustness test treats the so-called borderline crisis observations in France, Greece, Hungary, Portugal, Spain, Sweden and Switzerland as non-crises following the dataset of dependent variables provided by Laeven and Valencia (2008). The results obtained confirm the significance of both the aggregate and top five indicators obtained in the baseline regressions, even if we account for post-crisis bias in the sample employing the top five bank ratios (specifications 6 and 7 of Table 1A). The top-5 specification 8 also performs better in terms of accuracy with the top five post-bias correction using these dependent variables correctly predicting over 95% of all observations. Notably, regulatory capital and return on equity are highly significant in predicting turmoil once these borderline crises are removed.

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[2] See IMF report on key points and conclusions from November 2011 conference on FSIs, http://www.imf.org/external/pubs/ft/fsi/guide/2012/pdf/020312.pdf.

6.3 Probit Robustness Checks

Running the regressions using a probit model (Tables A2 and A4), our main findings from the logit results hold. Interestingly, the macroprudential ratios tend to become more highly significant as the contemporaneous return on equity ratio is significant at the 1% level across all specifications for both aggregate and top five data. Notably, the contemporaneous regulatory capital variable also retains high levels of significance in the same specifications 2, 6 and 7 in Table A2. As before, the top five models tend to classify observations moderately better than the aggregate counterparts. Comparing the specifications of one-year lags, the aggregate return on equity variable is highly significant in specifications 1 and 3, however the variable in the probit model also loses its significance once the post-crisis bias is removed.

7. Conclusion

Recent literature has tried to establish early warning systems for financial turmoil based on the explanatory power of variables such as the Financial Soundness Indicators compiled by the IMF. The shortcomings of these papers and the models, particularly through the recent GFC, serve as a motivation for this paper. As noted in post-crisis reviews of FSIs and other indicators conducted by the IMF's International Monetary and Financial Committee (IMFC), regulators need to more closely assess systemic institutions and "variations in the distributions within aggregates".[3] As shown in earlier studies, large banks not only behave uniquely but have significant effects on aggregate sector-wide outcomes. Utilization of the aggregate banking sector introduces noise and might leave undetected problems of the largest banks in the sector. The calculation of simple means to represent the entire sector, especially given the highly asymmetric distribution of key banking characteristics in advanced countries, can introduce noise into macroprudential signals provided by large and systemic institutions and affect the accuracy of early warning system models.

Building on the mixed results of Cihak and Schaeck (2010) regarding the information

[3] See IMF and FSB Secretariat report to G-20 Finance Ministers on information gaps from October 2009. http://www.financialstabilityboard.org/publications/r_091107e.pdf.

and warning content of aggregate ratios, the results of our study suggest that macroprudential indicators based on balance-sheet data from a country's largest banks in a commonly utilized early warning logit panel regression model provide similar or better precision than their aggregate counterparts. In particular, contemporary regulatory capital to risk-weighted assets ratios from the top five banks can be utilized to identify weak banking systems and the return on equity variable performs well as an indicator for the build-up of systemic banking problems. Our results cast serious doubt on the earlier Cihak and Schaeck (2010) finding of the lagged FSI return on equity ratio as an early warning indicator through the GFC period.

From a policy perspective, the collection of aggregate data to assess the banking sector is costly and may prove inefficient for regulators as a significant share of resources is devoted to institutions that have a minor impact on systemic risk compared to the so-called SIFIs (systemically important financial institutions). Directing resources to the monitoring of large banks can increase efficiency especially in countries with a low concentration of assets in the banking sector. Moreover, this paper drew only on banking characteristics on earnings, asset quality and capital. As an adequate amount of liquidity is key to financial soundness, using data that is consistently defined across different jurisdictions can yield interesting insights for regulators how to monitor the largest financial institutions. Although these findings are supportive of the value of utilizing macroprudential ratios for large financial institutions, it is important to qualify our findings and support the need for regulators to continue using other tools given the high costs of banking crises, while implementing large and systemically important balance-sheet data into early warning system models.

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Appendix

Appendix A: Regression results

Table A1: Logit regression results

Dependent variable: Banking crisis	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
GDP growth $_t$	-0.289*	0.125	-0.372	-0.987**	-0.616	1.048	0.404	0.539
	(0.176)	(0.511)	(0.402)	(0.446)	(0.536)	(0.687)	(0.271)	(0.366)
GDP per capita $_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Credit growth $_t$	-0.032**	0.071	0.008	0.193***	0.006	0.149*	0.011	0.009
	(0.015)	(0.045)	(0.005)	(0.062)	(0.004)	(0.082)	(0.007)	(0.008)
Credit to the private sector $_t$	0.029***	0.044**	0.057***	0.038**	0.048**	0.079***	0.091**	0.083**
	(0.008)	(0.023)	(0.022)	(0.015)	(0.020)	(0.029)	(0.036)	(0.036)
Fiscal surplus $_t$	-0.206**	0.068	-0.276	-0.098	-0.202	0.145	-0.444*	-0.468*
	(0.082)	(0.086)	(0.220)	(0.098)	(0.224)	(0.108)	(0.243)	(0.274)
Inflation $_t$	-0.264	0.576**	0.293	0.870***	0.341	0.954**	-0.693	-0.589
	(0.168)	(0.289)	(0.370)	(0.256)	(0.410)	(0.395)	(0.537)	(0.395)
Government bond yields $_t$	0.667**	0.397	-0.514	0.587	-0.119	2.740**	1.165	1.251
	(0.274)	(0.608)	(0.654)	(0.856)	(0.522)	(1.086)	(0.725)	(0.931)
Non-performing loans $_t$ **(AGG)**		-0.253		-0.681		-0.420		
		(0.253)		(0.426)		(0.329)		
Regulatory capital to assets $_t$ **(AGG)**		-0.280		0.306		0.771*		
		(0.420)		(0.429)		(0.430)		
Return on average equity $_t$ **(AGG)**		-0.485***		-0.445***		-1.110**		
		(0.182)		(0.124)		(0.535)		
Non-performing loans $_t$ **(TOP 5)**			0.166		-0.114		0.828*	0.805
			(0.277)		(0.597)		(0.498)	(0.730)
Regulatory capital to assets $_t$ **(TOP 5)**			-0.883**		-0.569		-1.769***	-2.019**
			(0.401)		(0.427)		(0.434)	(0.900)
Return on average equity $_t$ **(TOP 5)**			-0.260***		-0.254***		-0.366***	-0.388***
			(0.083)		(0.072)		(0.102)	(0.141)
Aggregate or Top 5 banking ratios?	-	*Agg.*	*Top 5*	*Agg.*	*Top 5*	*Agg.*	*Top 5*	*Top 5*
Post-crisis bias correction	*no*	*no*	*no*	*yes*	*yes*	*no*	*no*	*yes*
Exclusion of "borderline" crises	*no*	*no*	*no*	*no*	*no*	*yes*	*yes*	*yes*
Observations	273	233	194	222	178	233	194	178
Chi Square ($\chi 2$)	55.70	93.96	92.91	75.33	70.35	93.64	88.64	44.66
LR test statistic	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Type I Error (%)	5.00	1.07	0.66	1.05	1.39	0.49	0.59	0.00
Type II Error (%)	79.65	56.52	45.45	56.25	67.65	46.43	40.00	50.00
Noise-to-signal ratio	83.84	57.13	45.76	56.85	68.60	46.66	40.24	50.00
% correctly predicted	64.10	87.98	88.14	90.99	85.96	93.99	94.33	95.51

***, **, * indicates significance at the 1%, 5% and 10% level respectively
Standard errors are given in parentheses

Table A2: Probit regression results

Dependent variable: Banking crisis	[1]	[2]	[3]	[4]	[5]	[6]	[7]
GDP growth $_t$	-0.003 (0.174)	-0.265 (0.182)	-0.553*** (0.195)	-0.339* (0.204)	0.473** (0.218)	0.210 (0.146)	0.296 (0.178)
GDP per capita $_t$	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000** (0.000)	0.000 (0.000)
Credit growth $_t$	0.035 (0.024)	0.004 (0.002)	0.101*** (0.030)	0.003 (0.002)	0.076* (0.040)	0.006 (0.003)	0.005 (0.004)
Credit to the private sector $_t$	0.020** (0.008)	0.029*** (0.009)	0.019*** (0.007)	0.025*** (0.009)	0.041*** (0.010)	0.048*** (0.016)	0.046*** (0.017)
Fiscal surplus $_t$	0.046 (0.045)	-0.115 (0.091)	-0.048 (0.050)	-0.084 (0.094)	0.085 (0.053)	-0.234** (0.114)	-0.258* (0.139)
Inflation $_t$	0.264*** (0.099)	0.155 (0.156)	0.458*** (0.123)	0.164 (0.154)	0.474*** (0.139)	-0.354 (0.241)	-0.328 (0.218)
Government bond yields $_t$	0.197 (0.227)	-0.263 (0.285)	0.270 (0.273)	-0.048 (0.246)	1.430*** (0.425)		0.672 (0.464)
Non-performing loans $_t$ **(AGG)**	-0.176 (0.123)		-0.390** (0.180)		-0.207 (0.165)		
Regulatory capital to assets $_t$ **(AGG)**	-0.207 (0.199)		0.124 (0.195)		0.399** (0.151)		
Return on average equity $_t$ **(AGG)**	-0.240*** (0.062)		-0.233*** (0.061)		-0.539*** (0.164)		
Non-performing loans $_t$ **(TOP 5)**		0.095 (0.139)		-0.013 (0.198)		0.480** (0.498)	0.466 (0.314)
Regulatory capital to assets $_t$ **(TOP 5)**		-0.462** (0.213)		-0.324 (0.223)		-1.007*** (0.258)	-1.163*** (0.426)
Return on average equity $_t$ **(TOP 5)**		-0.134*** (0.034)		-0.133*** (0.036)		-0.202*** (0.046)	-0.218*** (0.068)
Aggregate or Top 5 banking ratios?	*Agg.*	*Top 5*	*Agg.*	*Top 5*	*Agg.*	*Top 5*	*Top 5*
Post-crisis bias correction	*no*	*no*	*yes*	*yes*	*no*	*no*	*yes*
Exclusion of "borderline" crises	*no*	*no*	*no*	*no*	*yes*	*yes*	*yes*
Observations	233	194	222	178	233	194	178
Chi Square ($\chi 2$)	93.23	93.07	76.72	56.01	92.76	89.01	45.25
LR test statistic	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Type I Error (%)	1.09	0.67	0.54	1.38	0.49	0.60	0.00
Type II Error (%)	60.00	54.55	58.33	66.67	46.43	42.31	52.94
Noise-to-signal ratio	60.66	54.92	58.65	67.60	46.66	42.57	52.94
% correctly predicted	86.27	87.11	90.09	86.52	93.99	93.81	94.94

***, **, * indicates significance at the 1%, 5% and 10% level respectively
Standard errors are given in parentheses

Table A3: Logit regression results (one-year lag)

Dependent Variable: Banking Crisis	[1]	[2]	[3]	[4]	[5]	[6]	[7]
GDP growth $_t$	-0.435**	-0.924***	-0.951***	-0.960***	-0.351	-0.752***	-0.757***
	(0.198)	(0.276)	(0.235)	(0.267)	(0.275)	(0.227)	(0.260)
GDP per capita $_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Credit growth $_t$	0.048	-0.024	0.049	-0.017	0.065	-0.038	-0.021
	(0.039)	(0.031)	(0.052)	(0.024)	(0.041)	(0.032)	(0.021)
Credit to the private sector $_t$	0.023	0.031**	0.012**	0.024	0.024*	0.049**	0.033**
	(0.010)	(0.013)	(0.012)	(0.011)	(0.014)	(0.023)	(0.016)
Fiscal surplus $_t$	-0.082	-0.231**	-0.289**	-0.190*	-0.029	-0.203	-0.138*
	(0.119)	(0.114)	(0.135)	(0.115)	(0.109)	(0.119)	(0.115)
Inflation $_t$	0.144	0.256	0.033	0.172	0.023	-0.176	-0.115
	(0.167)	(0.268)	(0.290)	(0.272)	(0.148)	(0.203)	(0.160)
Government bond yields $_t$	0.314	-0.087	0.486	0.018	0.826***	0.999**	1.004**
	(0.328)	(0.613)	(0.856)	(0.747)	(0.272)	(0.501)	(0.431)
Non-performing loans $_{t-1}$ (**AGG**)	-0.375		-0.726**		-0.363		
	(0.235)		(0.363)		(0.329)		
Regulatory capital to assets $_{t-1}$ (**AGG**)	-0.595**		-0.350		-0.104		
	(0.292)		(0.277)		(0.255)		
Return on average equity $_{t-1}$ (**AGG**)	-0.231***		-0.061		-0.277***		
	(0.070)		(0.092)		(0.095)		
Non-performing loans $_{t-1}$ (**TOP 5**)		0.078		-0.040		0.380	0.163
		(0.247)		(0.267)		(0.244)	(0.458)
Regulatory capital to assets $_{t-1}$ (**TOP 5**)		0.162		0.187		0.131	0.204
		(0.253)		(0.249)		(0.231)	(0.408)
Return on average equity $_{t-1}$ (**TOP 5**)		-0.060		0.013		-0.087	-0.023
		(0.050)		(0.095)		(0.068)	(0.109)
Observations	219	176	206	164	219	176	164
Chi Square ($\chi 2$)	52.10	65.37	41.16	37.90	48.83	65.37	27.07
LR test statistic	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Type I Error (%)	1.95	1.63	1.83	1.72	1.74	1.47	1.50
Type II Error (%)	73.85	64.15	73.81	75.00	76.60	67.50	80.65
Noise-to-signal ratio	75.32	65.21	75.19	76.31	77.96	68.51	81.88
% correctly predicted	76.71	79.55	83.50	76.83	82.19	83.52	83.54

***, **, * indicates significance at the 1%, 5% and 10% level respectively
Standard errors are given in parentheses

Table A4: Probit regression results (one-year lag)

Dependent Variable: Banking Crisis	[1]	[2]	[3]	[4]	[5]	[6]	[7]
GDP growth $_t$	-0.203** (0.108)	-0.511*** (0.125)	-0.514*** (0.118)	-0.511*** (0.122)	-0.351 (0.275)	-0.390*** (0.110)	-0.757*** (0.011)
GDP per capita $_t$	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000* (0.000)	0.000 (0.000)
Credit growth $_t$	0.021 (0.018)	-0.013 (0.015)	0.026 (0.026)	-0.008 (0.011)	0.031* (0.019)	-0.020 (0.017)	-0.011 (0.011)
Credit to the private sector $_t$	0.011** (0.005)	0.016*** (0.006)	0.005 (0.005)	0.012** (0.005)	0.011* (0.006)	0.021** (0.009)	0.015** (0.006)
Fiscal surplus $_t$	-0.036 (0.053)	-0.121** (0.058)	-0.147*** (0.067)	-0.102* (0.057)	-0.017 (0.051)	-0.101 (0.057)	-0.070* (0.053)
Inflation $_t$	0.063 (0.077)	0.137 (0.134)	0.025 (0.142)	0.094 (0.131)	0.438 (0.133)	-0.080 (0.084)	-0.069 (0.076)
Government bond yields $_t$	0.183 (0.154)	-0.041 (0.249)	0.191 (0.856)	0.007 (0.272)	0.826*** (0.272)	0.457** (0.217)	0.474** (0.189)
Non-performing loans $_{t-1}$ (**AGG**)	-0.180* (0.105)		-0.394** (0.166)		-0.156 (0.131)		
Regulatory capital to assets $_{t-1}$ (**AGG**)	-0.278** (0.134)		-0.173 (0.134)		-0.055 (0.110)		
Return on average equity $_{t-1}$ (**AGG**)	-0.113*** (0.033)		0.045 (0.092)		-0.277*** (0.095)		
Non-performing loans $_{t-1}$ (**TOP 5**)		0.061 (0.119)		-0.005 (0.136)		0.206 (0.132)	0.110 (0.187)
Regulatory capital to assets $_{t-1}$ (**TOP 5**)		0.085 (0.120)		0.099 (0.118)		0.070 (0.128)	0.100 (0.163)
Return on average equity $_{t-1}$ (**TOP 5**)		-0.031 (0.026)		0.009 (0.039)		-0.036 (0.027)	0.004 (0.041)
Observations	219	176	206	164	219	176	164
Chi Square ($\chi 2$)	49.89	65.58	41.85	38.55	46.47	60.18	26.94
LR test statistic	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Type I Error (%)	2.07	1.64	1.84	1.72	1.84	1.48	1.52
Type II Error (%)	77.03	64.81	74.42	75.00	80.36	68.29	81.25
Noise-to-signal ratio	78.66	65.89	75.81	76.31	81.87	69.32	82.50
% correctly predicted	72.60	79.55	83.01	76.83	80.36	82.95	82.93

***, **, * indicates significance at the 1%, 5% and 10% level respectively
Standard errors are given in parentheses

Appendix B: Figures and Tables

Figure 1: Distribution of assets relative to GDP in sample economies (2008)

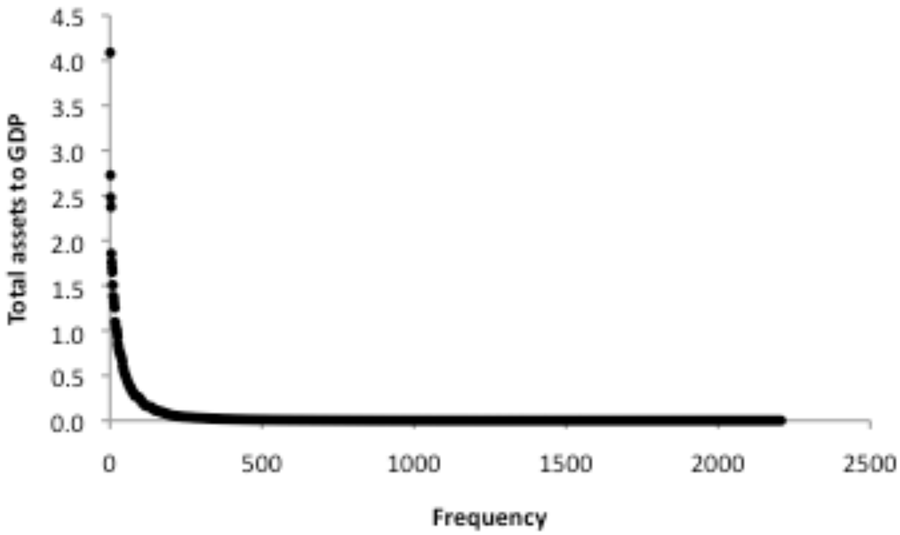

Table 1
Banking crises in advanced countries between 1997 and 2008

Country	Crisis	Country	Crisis
Austria	2008	Japan	1994-2004
Belgium	2008	Korea, Rep. of	1997-2002
Denmark	2008	Netherlands	2008
France*	2008	Portugal*	2008
Germany	2008	Spain*	2008
Greece*	2008	Sweden*	2008
Hungary*	2008	Switzerland*	2008
Iceland	2008	United States	2007-2008
Ireland	2008	United Kingdom	2007-2008

* indicates "borderline crisis" as determined by Laeven and Valencia (2010)

Country in Post-Crisis since 1997	Crisis
Italy	1994-1995
Finland	1994
Sweden	1994

Table 2

a. Key sample descriptive statistics

Variable	**Std. Dev.**	**Min**	**Max**	**Max**
Aggregate IMF FSIs				
Nonperforming loans to gross loans	2.85	0.20	19.00	19.00
Regulatory capital to risk-weighted assets	1.90	7.00	20.60	20.60
Return on equity	10.17	-52.50	41.70	41.70
Top-Five Bank Aggregates				
Nonperforming Loans to Gross Loans	2.13	0.09	13.82	13.82
Regulatory Capital to Risk-Weighted Assets	1.92	7.89	21.12	21.12
Return on Equity	23.66	-368.65	51.58	51.58

b. Correlations between aggregate and Top 5 banking ratios across full sample

		AGGREGATE		
		Nonperforming loans $_t$	Regulatory capital $_t$	Return on equity $_t$
TOP 5	Nonperforming loans $_t$	0.84	-	-
	Regulatory capital $_t$	-	0.82	-
	Return on equity $_t$	-	-	0.79

Table 3

Differences of means between crisis (incl. "borderlines" and non-crisis countries for key variables

Variable	**Crisis Countries (mean)**	**Non-Crisis Countries (mean)**	***t*-test**
Aggregate IMF FSIs			
Nonperforming loans to gross loans	3.71	2.79	1.68
Regulatory capital to risk-weighted assets	11.56	12.27	1.74
Return on equity	-5.01	14.57	11.94
Top 5 Bank Aggregates			
Nonperforming loans to gross loans	3.78	2.22	3.55
Regulatory capital to risk-weighted assets	11.10	11.54	1.16
Return on equity	-16.10	14.75	7.59

Table 4

Variable means in years relative to crisis onset

	tranquil	***crisis***	***after crisis***			
	-1	0	1	*2*	3	4
roe_agg	14.90	-4.26	7.16	8.35	12.35	11.03
npl_agg	2.60	3.69	2.22	4.27	3.38	3.35
regcap_agg	12.33	11.59	11.83	12.26	12.13	11.80
roe_top5	15.05	-15.75	11.68	14.35	15.21	15.21
npl_top5	2.14	3.78	3.30	*2.91*	2.50	1.93
regcap_top5	11.65	11.19	11.21	10.81	11.11	10.17
credit growth	6.91	2.18	2.85	-1.65	-1.44	5.56
credit level	110.86	154.26	139.39	107.75	94.01	96.82
fiscal	0.46	-2.71	-1.57	-2.12	-1.36	-0.31
gdp_growth	3.21	1.37	2.37	*2.84*	3.34	2.94
gdp_per capita	23'664	26'423	25'868	23'755	23'622	24'117
inflation	2.73	2.11	1.17	1.57	1.22	0.92
real gov yield	4.70	4.61	3.07	4.25	4.68	4.15

Table 5
Correlations between aggregate and Top 5 banking ratios

for countries with relatively LOW levels of banking concentration (<0.75)*

		AGGREGATE		
		Nonperforming loans $_t$	Regulatory capital $_t$	Return on equity $_t$
TOP 5	Nonperforming loans $_t$	0.71	-	-
	Regulatory capital $_t$	-	0.63	-
	Return on equity $_t$	-	-	0.81

* Australia, Austria, Canada, France, Germany, Hungary, Ireland, Italy, Japan, Korea, Netherlands, United Kingdom, United States

*for countries with HIGH levels of banking concentration** (>0.75)*

		AGGREGATE		
		Nonperforming loans $_t$	Regulatory capital $_t$	Return on equity $_t$
TOP 5	Nonperforming loans $_t$	0.96	-	-
	Regulatory capital $_t$	-	0.88	-
	Return on equity $_t$	-	-	0.75

** Belgium, Denmark, Finland, Greece, Iceland, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland

Concentration Data Source: Beck and Demirgüç-Kunt (2009)

Table 6
Sample composition for 1997-2008 period

Australia	Finland	Iceland	Netherlands	Spain
Austria	France	Ireland	New Zealand	Sweden
Belgium	Germany	Italy	Norway	Switzerland
Canada	Greece	Japan	Portugal	United Kingdom
Denmark	Hungary	Korea	Singapore	United States

Table 7
Explanatory variables

Variable	Definition	Source
GDP growth	Year-on-year change in real GDP (in %)	World Development Indicators (World Bank)
Real government 10-year bond yields	Annual arithmetic average that uses monthly reportings of yield-to-maturity (in %)	International Financial Statistics (IFS), International Monetary Fund
Inflation	Rate of change of GDP deflator (%)	World Development Indicators (World Bank)
GDP per capita	GDP per capita in 2000 US$	World Development Indicators (World Bank)
Fiscal surplus to GDP	Ratio of government surplus in percent of GDP	World Development Indicators (World Bank)
Credit to the private sector	Ratio of domestic credit to the private sector	International Financial Statistics (IFS), International Monetary Fund
Credit growth	Year-on-year change in real credit (%)	International Financial Statistics (IFS), International Monetary Fund
Capital adequacy ratio (Aggregate)	This FSI is calculated using total regulatory capital as the numerator and risk-weighted assets as the denominator. Data are compiled in accordance with the guidelines of either Basel I or Basel II.	IMF staff reports, International Monetary Fund
Nonperforming loans to total gross loans (Aggregate)	This FSI is calculated by using the value of NPLs as the numerator and the total value of the loan portfolio (including NPLs, and before the deduction of specific loan- loss provisions) as the denominator.	IMF staff reports, International Monetary Fund
Return on equity (Aggregate)	This FSI is calculated by dividing net income before extraordinary items and taxes by the average value of capital over the same period.	IMF staff reports, International Monetary Fund
Capital adequacy ratio (Top 5)	Ratio is the total capital adequacy ratio under the Basel rules. It measures Tier 1 + Tier 2 capital which includes subordinated debt, hybrid capital, loan loss reserves and the valuation reserves as a percentage of risk weighted assets and off balance sheet risks.	Bankscope - Bureau van Dijk
Nonperforming loans to total gross loans (Top 5)	Ratio of non-performing loans to total loans	Bankscope - Bureau van Dijk
Return on equity (Top 5)	Ratio of net income by average equity capital (average between given year's reported equity and previous year's value)	Bankscope - Bureau van Dijk