From micro level data to macro level indicators: an attempt to aggregate bank balance sheet data into one-dimensional measures for domestic bank sector risk

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Abstract

In this thesis we review the literature on balance sheet based indicators for risk exposure of individual banks and analyze a Bankscope database (2002-2008) consisting of such balance sheet information. From rank correlations and factor analysis, we explore the relationships between different bank risk measures and construct a reduced set of eleven indicators. For the ten countries that we find best documented in our data, we aim to construct risk indicators at a domestic bank sector level. We suggest two simple risk aggregation methods and apply these to our set of indicators. In this thesis, we find commonly associated factor loadings and high correlations between nationally aggregated indicators for credit and earnings risk. Also, at a national level we find high correlations between management and earnings risk. In a final aggregation step, we construct one-dimensional bank risk indications per country. Our results show for each one-dimensional indicator in every country that domestic bank sector risk increases steeply at the outbreak of the global financial crisis in 2007. Moreover our observations suggest that an indicator not depending on management and sensitivity to market risk –concepts that can be hard to assess from balance sheet data– may be a more sensitive measure to such an economic shock.

Preface

This thesis has been performed in cooperation between Tilburg University and the central bank of The Netherlands, De Nederlandsche Bank (DNB). While I am enrolled as a MSc student Quantitative Finance and Actuarial Science in Tilburg, a great part of the research process has taken place during a four-month internship with the Economics and Research Division of DNB. During these four months I have been given the chance to work in an ambitious, challenging and stimulating environment part of a unique institution in The Netherlands. I am thankful to have worked in such an environment with colleagues that as well professionally as personally have enriched myself and my thesis. My special thanks go out to the Head of Research at DNB and my supervisor, prof. dr. Jakob de Haan, who has provided me with all his useful suggestions and excellent supervision throughout the entire research process.

Next to the time spent at DNB in Amsterdam, I have spent a significant amount of time at Tilburg University. A main reason to do so has without a doubt been the constructive feedback, excellent guidance and refreshing views that I, throughout the research, have received from my Tilburg University supervisor, prof. dr. Hans Schumacher. Special thanks go also out to him and mostly the support of my supervisors has greatly motivated me while performing this thesis.

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Contents

1 Introduction

The macro-economic externalities of banking failures are undesirable and therefore, in order to prevent the situation to occur, it is of significant importance to accurately determine the position of banks and whether or not they find themselves at risk. A variable for 'banking risk' is, however, not directly measurable and moreover banking risk arguably is a multifaceted concept (see Klomp and De Haan (2012)).

Nowadays the risks that banks take are a hot discussion topic in public media, often not without being judged: "This so-called crisis is being run by and for banks. They were burned by the credit crunch, by their own reckless lending to a housing bubble [...] Declaring themselves too big to fail, they demanded policies whose sole virtue was to see their loans secured, at whatever cost to the European economy. They do not want a collapse of even a part of the euro, as that would jeopardize their balance sheets."[1] Banks take certain risks that influence the probability of failure and, as a result, indicators for banking risk are an attractive research topic.

In this research, we focus on the broadly researched concept of banking risk and the differences between various indicators of this concept. An attempt is made to review the main banking risk indicators used in previous research and to contemplate the arguments that these indicators have been used with (section 2). Moreover, this thesis aims to extract and analyze proxies for the most important indicators from individual bank data (which is obtained from Klomp and De Haan (2012)). Comparisons between the different indicators help to understand the different identity of these proxies and to address the relationship between the various measures (section 3). Whereas in section 3 we mainly look at risk measures on the micro-level, i.e. we reason from the risk position of individual banks, we aim to increasingly take a macro-level perspective in the continuation of this thesis. section 4 addresses the representativeness of the dataset used in this research and section 5 describes methods that can be used to construct national level indicators from bank level data. In section 6 we present the results that follow from constructing national indicators. Section 7 concludes this thesis.

[1] Passage from "Eurozone crisis: the bankers are happy to play Nero as Europe burns", The Guardian (July 31, 2012)

2 Previous literature: an overview of banking risk indicators

2.1 CAMEL framework

Directly following The Great Depression, Fisher (1933) explained the failure of banks from the economic cycle of debt accumulation and the ultimate collapse of such a macroeconomic bubble. This collapse occurs when people en masse decide to liquidate their debts at banks; hence causing liquidity stress to individual banks and macroeconomic reactions, such as deflation to the system. The latter creating even more unfavorable circumstances within the system and the first one putting instant pressure on banks. As a result of the crucial position in society that banks have occupied over time and moreover stimulated by the occurrence of severe financial crises[2], early attempts were made to capture the 'soundness' of individual banks.

From the 1930s literature on banking risk roughly jumps to the 1970s, not surprisingly an interval in which few significant financial crises were documented. Nevertheless, the boost to banking risk literature in the 1970s indirectly still relates to the 1930s. In 1933 the American Federal Deposit Insurance Corporation (FDIC) was founded "to insure bank deposits and reduce the economic disruptions caused by bank failures." (FDIC, 1984) In the late 1970s, it was also the FDIC that –after a period of US economic recession– introduced the so-called CAMEL framework which was meant to determine individual financial institutions' soundness. The framework initially relied on five categories[3] described as the adequacy of capital and reserves, asset quality, management quality, earnings and liquidity (IMF, 2000). Ultimately, the framework allocates a multinomial score between one and five (where one indicates low banking risk and five indicates high risk) to financial institutions.

The adequacy of a bank's capital and reserves reveals whether the bank has a buffer to cope with losses. One can imagine that 'the more fat the bank has on its bones', the less risk the organization bears that it will indeed face bankruptcy. Often used measures to capture capital adequacy are the relative value of equity to total assets or loans and the value of total capital to the riskiness of assets (e.g. in Klomp and De Haan (2012)). A second dimension under the CAMEL framework is labeled as 'asset quality'. Two banks, where one has a differentiated portfolio with loans to high-credibility governments and the other possesses an equally large portfolio with private microfinance loans, face different probabilities that their debtors will default. A risky asset portfolio implies a higher credit risk to the bank and the occurrence of unfavorable events could lead a bank into solvency issues, i.e. the level of the bank's assets compared to the level of its liabilities. Barnhill, Papapanagiotou and Schumacher (2000)

[2]As a famous example, The Great Depression (1929-1933) caused throughout its entire period over 40% of American banks to fail. See "A refresher on the 1930s", The Economist (September 17, 1998)

[3]Years after its initiation the framework got extended with a sixth category, i.e. the sensitivity of a financial institution to market risk (IMF, 2000)

find that the credit quality of a bank's loan portfolio is the most important risk factor to banks. To address the issue of credit vulnerability, an analysis of a bank's loan portfolio can provide insight into debtors' soundness. Typically used measures are the share of non-performing loans (NPLs) to total loans and the share of weak loans to total loans (IMF, 2000).

Management quality is a third concept used to address banking risk under the CAMEL framework. The concept is different from the others within the framework in the sense that it requires a more qualitative judgment to determine a financial organization's quality of management than the other CAMEL concepts, which result more directly from balance-sheet figures. Among others, Sarkar and Sriram (2001) endorse this argument and focus on changes in financial status reflected through financial ratios. They argue that all institutional failures can ultimately be traced down to inferior and risky managerial decisions, but that such decisions are not easily observable at a point in time. Barr and Siems (1994) argue that not involving management performance gives a rather curious paradox as failing management is often considered to be the leading reason for (bank) failure.[4] The IMF (2000) argues that to some extent management quality is observable from balance sheet information. Management quality then is best described as a measure of efficiency, i.e. with which means management can achieve which results. Measures that quantify this idea are the ratio of total costs over total income and the bank's profit over the total number of employees, as e.g. used in Klomp and De Haan (2012). Another feature in the CAMEL model relates to a bank's ability to generate income, commonly addressed by means of its revenues –earnings– and its revenues corrected for costs –profitability-. Profitability and earnings determine the success of a private company and over time profitability is a direct indicator for a company's success in that period. Increasing levels of profitability and earnings positively influence successful continuation and consistently are associated with lower banking risk. Measures used to determine company's –relative– profit are return on equity, return on assets and the spread of current earnings compared to the historical average earnings.

A fifth category part of the CAMEL framework is labeled as the liquidity dimension. That banks can be threatened by a shortage of liquidity is an important feature also in the current euro crisis. Banks may face serious bankruptcy threats in case of insufficient liquidity buffers that will protect against possible deposit outflows or severe losses on loans. A balance sheet contains items, such

[4]Famous is the case of ABN Amro, which, in the largest bank acquisition until then (2007), was acquired by the bank consortium Royal Bank of Scotland (RBS), Fortis and Banco Santander. Soon after the acquisition in 2008 both RBS and Fortis failed which led to criticism towards the management responsible for the deal. In response to the failed deal, the British Financial Services Authority (2011) investigated the role of RBS and concluded "with hindsight it is clear that poor decisions by RBS's management and Board during 2006 and 2007 were crucial to RBS's failure" and "a pattern of decisions that may reasonably be considered poor, at the time or with hindsight, suggests the probability of underlying deficiencies in: a bank's management capabilities and style; governance arrangements; checks and balances; mechanisms for oversight and challenge; and in its culture, particularly its attitude to the balance between risk and growth."

as liquid assets –compared to total assets– which proxy for the liquidity level. Other liquidity indicators can be e.g. the cash position relative to the total assets or the total loans relative to the total deposits (used by Zhao, Sinha and Ge (2009)). Van den End (2012) discusses banks' funding liquidity (the ability to raise cash to fund asset holdings) and how it interacts with market liquidity (the ability to convert assets into cash at a given price at short notice). He argues that there are multiple dimensions of liquidity risk and dynamics that –whilst not easy– need to be quantified in order to assess liquidity risk in the financial sector.

Not originally part of the CAMEL framework is a sixth category which proxies for sensitivity to market risk. The IMF (2002) describes this factor as the bank's diversified operations all of which involve one or more factors of market risk, such as interest risk, stock risk and exchange rate risk. According to the IMF (2002), good measures for this bank sensitivity to the market are durations of assets and liabilities and net positions in equities and foreign currencies.

Initially invented to locate banks with high probability of failure and to prevent actual failure, the CAMEL framework soon became a popular measure for banking risk. Lane, Looney and Wansley (1986), Whalen and Thomson (1988), Thomson (1991), Barr and Siems (1994), Cole and Gunther (1995) and Zhao et al. (2009) use CAMEL variables to explain the binary variable 'bank failure'. A first advantage mentioned by Barr and Siems (1994) is that the CAMEL framework is well established and allows many previously invented indicator variables for banking risk to be categorized under the CAMEL framework. Moreover, Barr and Siems (1994) emphasize the widespread use of the model because of its simplicity and its use by regulators. Zhao et al. (2009) conclude that most of the previously used indicators for banking risk can be classified under the CAMEL ratings. They also find that financial ratios, while still simple to use, improve proxies for banking risk significantly compared to the situation where plain, non-relative accounting measures are used. Also Zhao et al. (2009) stress the importance of objectivity that accounting numbers exhibit. Whalen and Thomson (1988) add that on-site examination of measures can be rather costly and time-consuming, which makes it beneficial that in the CAMEL framework mainly accounting measures play a role and these can be more easily observed. However, CAMEL ratings also have certain features that make them less attractive. On a practical note, using the CAMEL framework results in an –at least– five dimensional construct for banking risk. This feature may be still practical when banking risk is used as an independent variable (e.g. to explain bank failure, such as in Zhao et al. (2009)), but when risk is the variable to be explained a low-dimensional proxy could be preferred for its use in practice. Also from observing several researches, such as those discussed in the previous paragraph, it instantly becomes clear that the five main categories within the CAMEL framework are not unambiguously defined. In particular, these five constructs leave space to come up with new and different specific measures to capture each category. As Zhao et al. (2009) put it: "while most studies have followed the CAMEL framework in general, the specific measures they have used are often substantially different." Lane, Looney and Wansley (1986) moreover note that in the literature there is little agreement which accounting measures are best for off-site screening.

2.2 Deviations from the CAMEL framework

Despite its official FDIC character and its widespread use in previous literature, not all research sticks exactly to the CAMEL framework in an attempt to capture bank fragility. In some cases, the deviation from the framework is very minimal in the sense that only one of the six labels is altered or dropped. This is the case in several researches that omit the construct for management quality. Tam and Kiang (1992) decide to closely follow the CAMEL framework as a guideline which ratios to use as a proxy for banking risk, however, they use no explicit measure to proxy management performance because the quality of management –which is difficult to quantify– will in their belief be eventually reflected by the ratios for the other categories. Sarkar and Sriram (2001) also stress the qualitative assessment needed in order to judge management quality and decide to rely on financial ratios. Also, the IMF (2003) excludes management quality –as the only CAMEL variable– from a core set of financial soundness indicators. Between their so-called core set and encouraged set of indicators the difference is that the indicators in the core set are -due to their importance for assessing risk to financial stability and because their underlying data generally being available- considered highly relevant in a wide range of countries. Moreover the IMF (2003) believes that for the indicators in the core set there is a clear understanding of how they should be used.

A further deviation from the CAMEL framework can be found in research where just one of the CAMEL categories is used to express bank riskiness. An example of such an approach is the paper by Estrella, Park and Peristiani (2000) in which various capital ratios are separately used as measures for banking risk. Used in official bank regulation documents for over decades[5], capital buffers have implicitly been associated with the risk of individual banks to fail. Estrella et al. (2000) believe that a capital indicator should consist of two parts such that it reflects a bank's capital position relative to some balance-based measure of absolute risk. The authors conclude that simple capital ratios, despite being one-dimensional and less sophisticated measures for bank riskiness, are valuable as predictors for bank failure and almost costless to compute, which makes them more attractive to use.

The capital adequacy indicator is not the only CAMEL variable used as a separate measure for banking risk. As one of the possible measures to determine quality of assets, the share of NPLs indicates whether or not credit risk is an issue. Podpiera (2006) uses the ratio of NPLs to total loans as an indicator of bank fragility with the argument that “while there may be different reasons for an increase in NPLs, a high level of NPLs almost universally indicates serious

[5]International regulations were initiated with Basel I (1988) and evolved into Basel II (2008), current updates are proposed in Basel III. See also Bank for International Settlements, Compilation of documents that form the global regulatory framework for capital and liquidity, http://www.bis.org/bcbs/basel3/compilation.htm

problems in the banking sector." In their model to check for the influence of banking supervision and regulation, Barth, Caprio and Levine (2004) use non-performing loans relative to total assets as a one-dimensional measure for bank fragility. Das, Quintyn and Chenard (2004) construct an index for financial system soundness and use the share of NPLs combined with a capital risk indicator. The share of NPLs is a sign for a bank to be able to perform one of its basic tasks –collecting the money they lend– and an ultimate indicator of credit risk. In previous research the argument has been made that credit risk is such a major determinant of the more general term bank risk that it can be useful as a separate measure (see González (2005)). Das et al. (2004) argue that both credit and capital ratios are important risk measures, which are widely available. However, the use of NPLs has been criticized (e.g. by Demirgüç-Kunt and Detragiache (2011)) from the point of view that accounting standards differ per nation and as a result it is difficult to consistently measure NPLs over countries.

Many of the deviations from the CAMEL framework result in a lower dimensional indicator of banking soundness. This can be because of theoretical arguments to omit certain variables as well as by use of a more statistical approach. One such a statistical approach used in previous research to reduce the dimension of a CAMEL banking risk measure is factor analysis, an approach that uses the covariance between measures to construct so-called factors. These factors than serve as a lower dimensional construct for the same concept, i.e. banking risk. One of the first attempts to apply factor analysis to CAMEL setting measures has been made by West (1985), although not reducing his nineteen CAMEL-based measures to less than five. However, the eight constructed factors provide a reduction of the initial nineteen separate measures. More recently, Klomp and De Haan (2012) apply factor analysis to a set of twenty-five CAMEL-based measures. The number of factors reduced to is decided upon by using the Kaiser criterion and the scree test. These criteria suggest that factors with eigenvalues lower than one should be dropped and that the ideal number of factors is just before where eigenvalues plotted against the number of factors start decreasing in –approximately– a linear way. Using these two criteria the authors define two banking risk factors which are labeled as capital and asset risk and liquidity and market risk, as a result of the specific factor loadings on each measure.

2.3 Z-scores

Boyd and Runkle (1993) defined banking risk as the risk that the bank will run out of its reserves. More specifically, when a bank's losses exceed the value of its reserves, failure will occur. When profitability is measured relative to a company's assets, then also reserves should be weighed by total assets. Assuming that relative profitability is normally distributed allows transforming that same particular variable into a standard normally distributed variable. From here, it is possible to calculate the probability of failure and also the critical level of profitability below which failure will occur. This second characteristic expresses the number of standard deviations that a bank's profitability should fall from the average profitability to become insolvent and is better known as the z-score. Boyd and Runkle (1993) use this one-dimensional z-score as a measure for riskiness, because the higher this score, the smaller the chance that a bank will run out of its reserves and fail. Subsequently, several researches have adopted the idea to express banking risk as a one-dimensional z-score. Interesting to see is that, under the CAMEL framework, it can be incorporated as one of the measures for earnings and profitability (as in Klomp and de Haan (2012)). Demirgüç-Kunt and Huizinga (2010) mention that a higher z-score corresponds with a lower probability of bank insolvency and thus risk. García-Marco and Robles Fernández (2008, p. 339) summarize the usefulness of z-scores as a measure for banking risk as follows: "This indicator reveals the degree of exposure to operating losses, which reduce capital reserves that could be used to offset adverse shocks. Entities with low capital and a weak financial margin relative to the volatility of their returns will score high on this indicator. Since this indicator assigns great importance to the solvency and profitability record of financial institutions, it is a measure of their weakness or strength." Demirgüç-Kunt and Detragiache (2011) and Demirgüç-Kunt, Detragiache and Tressel (2008) implement z-scores as a risk measure. Demirgüç-Kunt, Detragiache and Tressel (2008) note that z-scores are easily obtainable from accounting data and can be determined for any bank. Demirgüç-Kunt and Detragiache (2011) apply z-scores in their research because it allows them to use a larger sample size and because they believe that it is a less difficult measure to compare across countries than, for example, NPLs, which is a concept relatively more vulnerable to reporting rules. Moreover they argue that other accounting measures, such as loan spreads, net interest margins and capital ratios, are affected by many other (macro-economic) forces than just financial fragility.

2.4 Loan spreads

As an alternative to previous measures, the spread between lending rates and risk-free rates (lending spread) could serve as a signal of bank soundness. The idea is that the spread between both rates signals how efficient banks are in the sense that higher lending rates are an indication for higher costs of banking intermediation. Compared to other banking risk measures spreads do not just rely on accounting data, but –by means of interest rates– particularly use information from the market. One of the first studies to use this 'market measure' for banking risk (in a setting related to compliance with Basel regulations) was Sundararajan, Marston and Basu (2001). Podpiera (2006) applies the spread measure under the name of net interest margin measure and associates high spreads with inefficient banking, monopoly power and high risk lending operations. However he also notes that, although associated with lower banking risk, extremely low spreads could also signal heavy competition in the banking market and could accordingly be a threat to financial stability. Gropp, Vesala and Vulpes (2004) use a slightly changed spread measure defined as the interest rate paid to subordinated debt holders minus the risk-free rate. An argument for this measure is that subordinated debt holders are in a more extreme risk position than regular debt holders and in an expectedly larger spread could signal better information. Gropp et al. (2004) assert that a measure for financial fragility should at least be consistent in the sense that higher fragility should correspond with lower earnings, higher risk of earnings and higher financial leverage. They find that subordinated debt spreads meet these criteria. In their earlier paper, Gropp, Vesala and Vulpes (2002) find empirical support for the use of subordinated spread as a risk indicator, but moreover they find that this measure's predictive power is especially useful in the short term –up to six months–, whereas a z-score indicator is performing better in bank failure models with a longer time horizon.

2.5 Credit ratings and default swaps

Whereas CAMEL tries to capture banking risk as a whole based on different critical categories, other ratings focus on a more narrow part of the pie. Private rating agencies, such as Moody's, Standard & Poor's and Fitch, attach credit ratings to financial institutions that issue debt. These credit ratings are an attempt to capture an organization's risk of default and are often regarded as a bank's overall risk. An advantage of using these credit ratings such as Moody's is, according to Demirgüç-Kunt, Detragiache and Tressel (2008), that rating agencies' analysts have access to both quantitative and qualitative information about banks and their operating environment. Therefore the authors believe that ratings should be a more accurate measure of bank soundness than indicators built using only balance sheet variables, such as nonperforming loans or z-scores. A major drawback of using credit ratings as a risk measure is (according to Demirgüç-Kunt and Detragiache (2011)) that small financial institutions and lower income countries are often not rated and this may lead to significant reduction of sample size. Another important remark from Demirgüç-Kunt and Detragiache (2011) is that after the 2007-2010 global financial credit crisis, the credibility of credit ratings as indicators of banking risk has not been empirically backed up.[6]

A second pricing mechanism for credit risk is the market for credit default swaps. These credit derivatives have as an underlying the credit position of a company, which means that the derivative seller will pay out in case the company defaults. A credit default swap on a bank could therefore be expected to have a higher price in a situation that the bank involves high credit risk. Duffee and Zhou (2001) stress that banks often have superior information about their own credit portfolio. This creates an asymmetric information issue which may allow banks to circumvent the 'lemons problem' and to take advantage of their informational advantage. For swap buyers to assess a bank's true risk position may be costly and bring up uncertainty in the valuation process. Yorulmazer

[6] Credit rating agencies initially gave positive ratings to what later turned out to be insolvent financial institutions, such as Lehman Brothers. However, the role that rating agencies play in the current financial markets (especially in the euro crisis countries) remains highly influential. See also "The Credit Rating Controversy", Council on Foreign Relations, January 19, 2012 (http://www.cfr.org/united-states/credit-rating-controversy/p22328)

(2012) moreover discusses how credit default swaps can lead to increased bank risk taking which is not reflected in the default swap's price.

2.6 Models involving banking risk and compliance

The global financial crisis of 2007-2010 has brought the financial world under an increasingly critical scope of attention. The collapse of banks, such as Lehman Brothers, raised the question of whether these banks take too much risk and whether or not there is sufficient supervision to check on these institution's practices. Designing improved regulatory frameworks (such as Basel II and III) can serve as a limitation to risk-taking, but compliance with these regulations is a crucial next step to be taken by banks and enforcing institutions. Because of the crisis' severe consequences and because of the question of whether or not banks' (non-)compliance to the rules has been sufficiently supervised, this particularly created breeding ground for studies discussing bank regulation in relation to banks taking risk, see e.g. Demirgüç-Kunt and Detragiache (2011). Important complementary issues in bank risk and compliance studies are the –behavioral– issues caused by deposit insurance and bank concentration, see e.g. Caprio and Levine (2002). Deposit insurance relates to the idea that banks can end up taking excessive risk because the deposits they manage are insured (e.g. by the government) for the reason that failure of the bank would induce too much damage to society. Especially big banks will be considered important not to fail, which might cause a serious moral hazard problem for banks that are 'too big to fail'. Agency problems occur when bank ownership is widely dispersed and none of the many small shareholders has a strong incentive to actively monitor the bank's decision makers. In such a case of free riding shareholders, managers can relatively easily take excessive risk.

2.7 From a micro prudential level to a macro prudential level

The balance-based risk indicators discussed in this literature review mainly measure risks at the individual bank level. Over the past decade, the International Monetary Fund (IMF) has spent significant efforts towards an increased focus on the broader risk perspective. Under such a macro perspective, analysis gets more focused on the health and stability of financial systems, whereas micro prudential analysis deals with the condition of individual financial institutions (IMF, 2002). Macro prudential analysis is particularly useful to provide a broader picture of economic and financial circumstances (IMF, 2006). Inputs to such a macro-level analysis can be macro-economic by nature as well as micro prudential data that are aggregated. The IMF (2000) determines a set of key financial indicators that can be seen as the core micro inputs in macro analysis. In addition, macro indicators give further information about economic and financial circumstances. Examples of such indicators are credit growth, GDP growth, inflation, exchange rate, institutional frameworks, fiscal account balance and the structure of the financial system (IMF, 2007a).

The efforts by the IMF are ultimately aiming at enhanced compilation and dissemination practices. Compilation deals with the construction of aggregated risk indicators whereas dissemination underlines the importance of correct and complete data availability. With their compilation guide, the IMF (2006, 2008) encourages the compilation of individual indicators in order to increase cross-country comparability of data. Already before, The Bank of England (2004) underlined the importance of the guide's concept by stating: "FSIs (financial soundness indicators) seem likely to become an important tool for providing insight into the health and soundness of the financial sector of a country. They will give valuable information on financial stability for a large number of emerging and developing countries, in particular helping to identify potential financial stability risks at an early stage. While directly comparing individual countries' FSIs may be problematic, it will be possible to look at trends amongst the data for different countries. This may give an indication of any potential financial stability issues."

The IMF (2006) framework specifies different rules and guidelines to be kept in mind in the process of aggregation. These rules apply to topics, such as correct accounting principles, consolidation standards, definitions of financial ratios and preferred indicators. Besides these rules the framework is designed to give direction towards a more appropriate dissemination of data. As noted by Van den Bergh and Enoch (2001), much work remains to produce data on indicators such that a higher degree of international comparability is achieved. The content of the available data determines whether and to what extent cross-country comparison is possible. Oosterloo, De Haan and Jong-A-Pin (2007) conclude that the publication of IMF indicators widely differs over various financial stability reports. These stability reports have been encouraged by the European Central Bank (ECB), which over the past decade engaged in the development of a framework for financial stability analysis, driven by the increasing integration of national financial systems in the European Union (EU) and on account of its commitment to contribute to policies relating to the prudential supervision of credit institutions and the stability of the financial system (ECB, 2008). The ECB (2005) also developed its own analytical framework for evaluating financial soundness, which is different from the IMF compilation approach in the sense that it focuses only on application to the financial sector. Both frameworks also overlap to a great extent, which is e.g. noticed in the compilation application to the Czech banking sector by Geršl and Heřmánek (2007).

3 Individual bank risk indicators

3.1 Data treatment

From the literature reviewed we find several balance sheet-based bank risk indicators that have been used in the past. In this empirical work we aim to distill the most important indicators whereas at the same time we have to cope with the limitations of our dataset. The data used in this study is from Bankscope of Bureau Van Dijk[7] and has been used in Klomp and De Haan (2012) previously. In this research, the authors reduce their raw dataset to a subset of roughly 200 individual banks, each with balance sheet data available for the period 2002 to 2008. The different set-up of this thesis compared to Klomp and De Haan (2012) is the main reason that from the same raw data we can extract a different final dataset which consists of roughly 800 individual banks with data collected over the same time period.

Important to note is that the panel data we use in this thesis is not complete. The initial raw dataset includes more than 4500 banks of which individual data is in many cases not or to a limited extent available. In order to select the useful data for our research we define the criterion that a bank's data can only be used if it has at least two-thirds of its 'crucial data' complete. More specifically, at least 67% of the selected risk indicators over the entire period 2002 to 2008 have to be available for a bank in order to be included. We notice that the stricter we make the conditions on availability of data, the more banks we lose in our final sample. The other way around, in order to increase the number of banks for our research we can decrease the crucial data percentage. Choosing the minimum percentage of 67% data availability per bank we consider reasonable and this condition ultimately results in the outcome that we have less than 23% of missing values in our final data set. As a last step, we check for unreasonable individual data points (e.g. ratio of NPLs to total loans greater than one, proportion of liquid assets in total assets greater than one etc.) and remove the banks with such occurrences from our sample. Table 3.1 lists the number of banks per country in our sample.

[7] Find more information online at http://www.bvdinfo.com/Products/Company-Information/International/Bankscope

Table 3.1. Density of banks split out after country

Country	# of banks in sample
Argentina	7
Belgium	4
Bosnia-Herzegovina	6
Brazil	37
Bulgaria	4
Canada	9
China	20
Denmark	17
France	25
Germany	21
Greece	12
Hong Kong	18
Hungary	6
India	17
Indonesia	6
Ireland	6
Italy	26
Japan	10
Latvia	7
Luxembourg	6
Netherlands	10
Norway	33
Portugal	8
Romania	7
Russia	75
Spain	40
Sweden	67
Switzerland	170
Taiwan	12
Thailand	8
Ukraine	16
United Kingdom	28
United States	30

3.2 Indicators

Inherent to the wide range of suggested indicators to measure banking risk is the decision which specific ones to include in a single research. We consider the prevalence of specific measures in –recent– literature and the availability of the right information in our dataset. As such, we construct z-scores (see e.g. Demirgüç-Kunt, 2011), NPLs (see Barth et al. 2004) and net interest margins (see Podpiera, 2006) as single-dimensional measures of banking risk. On the other side, we choose not to include possible one-dimensional measures such as credit ratings and credit default swaps. The reasoning for this is two-fold. We do not have appropriate data available and, in addition, recent discussions reveal that turbulences in the market may be an indication that both credit ratings (see Demirgüç-Kunt, 2011) and credit default swap prices (see Yorulmazer, 2012) might not be good reflections of risk.

Previous studies involving banking risk have extensively used the CAMEL risk categories. For each risk category –plus an additional category aiming to capture a bank's sensitivity to the market– we decide which specific measures to use as proxies for bank risk. Again, we choose our measures based on their persistence in literature and the availability of corresponding data in our dataset. An overview of measures used in this study is presented in Table 3.2.

The majority of balance-sheet measures in Table 3.2 is rather straightforward to interpret, but for a few we will provide some additional explanation. The z-score is defined by Boyd and Runkle (1993) as:

$$P(\Pi < -E) \;=\; P\left(\frac{\frac{\Pi}{A}-\mu}{\sigma} < \frac{\frac{-E}{A}-\mu}{\sigma}\right) \;=\; P\left(X < \frac{\frac{-E}{A}-\mu}{\sigma}\right) \;=\; P(X < (*))$$

in which Π denotes the bank's profit, E the total equity and A the total assets. μ defines the mean profit over assets (the mean return on assets) and σ the standard deviation of the return on assets. X is standard normally distributed, assuming that bank profits Π follow a normal distribution. The smaller the value of (*), the lower the risk that profit will fall below the reserve. In other words, the greater the absolute value of (*) the lower the risk that profit falls below the bank's reserve. In this way, z-scores provide a straightforward measure to compare bank solvency positions. The higher a bank's z-score, the better its solvency position.

We define the net interest margin in accordance with Podpiera (2006). The classification of non-performing loans we adopt directly from our accounting data. The measure can be interpreted as one of the asset quality measures. One of the capital indicators taken into account in Basel II is the total capital ratio, which can be interpreted as capital relative to a bank's risk-weighted assets. Loans due to commercial banks show to what extent a bank is in debt to colleague banks (as opposed to being in debt to a central bank) which might reflect a more narrow liquidity base.

Table 3.2. Definition of indicators used in this study

Indicator category	Indicator
Z-score	Z-score
Non-Performing Loans	Non-Performing Loans / Total Loans
Loan Spreads	Net Interest Margin
Capital Adequacy	Total Equity / Total Assets
	Total Capital Ratio
	Total Equity / Total Loans
Asset Quality	Loan Loss Provision / Total Loans
	Total Loans / Total Equity
Management Performance	Total Cost / Total Income
	Overhead Costs / Total Assets
Earnings And Profitability	Return On Equity
	Return On Assets
	Net Interest Margin / Income
Liquidity	Liquid Assets / Total Assets
	Total Loans / Total Deposits
	Fixed Assets / Total Assets
	Due To Commercial Banks / Total Equity
Sensitivity To Market	Off-Balance Sheet Items / Total Assets

3.3 Relationships between indicators

From a theoretical perspective, one can reason why each separate indicator from Table 3.2 influences a bank's risky position. We have categorized the indicators based on their use in previous research. The aim of this section is to find out if each indicator leads to a genuinely different classification of banks, or that some of these indicators lead to highly comparable outcomes.

Pairwise correlations can give a first insight into how indicators are related. A first look at our measures shows relatively low pairwise correlations that generally do not exceed absolute values of 0.5 (see Table 3.3). Two exceptions occur. The estimated correlation coefficient of the measures total equity relative to total assets and total capital ratio in our data sample is roughly 0.54. Both measures serve as an indicator of bank capital adequacy and from that point of view it is reasonable that their pairwise correlation is high. Also the correlation of total loans relative to equity and the measure loans due to commercial banks relative to equity exceeds 0.5. The first we use as a measure for asset quality, whereas the second is used as a measure for bank liquidity. However, both constructs look fairly similar from the viewpoint that the denominators are the same and also the numerators are somehow related –being loan-related concepts. At least it seems realistic that when a bank increases its total loans, it might also need to attract more funding and this can be done by taking more loans from other banks. Table 3.3 displays these standard Pearson correlation coefficients which are calculated from actual data values. Instead of considering these actual values we can rank our observations and explore whether different indicators lead to roughly similar rankings or not. Thereto, per indicator, we can rank observations from high to low and add these per indicator rankings as new variables. Instead of calculating pairwise correlations based on actual values, we now use explicit rank numbers to compute Spearman correlation coefficients (see concept definition in Appendix A). An advantage of this ordinal technique is that it is less sensitive to outliers and that it –contrary to Pearson correlations– does not necessarily approach the original data from a linear perspective. Observations are qualified as good or bad according to their relative position to the medium ranking. When highly ranked observations for one indicator are also top-ranked for another indicator, and vice versa for low-ranked observations, the Spearman correlation is positive. When observations are typically high-ranked for one indicator and low-ranked for another indicator, the correlation is negative. In order to control for the fact that every bank has seven observations per indicator and that these values might not be independent we do not just calculate rank correlations based on our full sample, but we do so also based on mean and median indicator scores per bank. The results derived from the full sample method are displayed in Table 3.4; the mean and median method show roughly similar results (see results in Tables A.1 and A.2).

As the technique is similar, yet with different inputs, we interpret Spearman correlations analogously to Pearson correlations (Table 3.3). Just as in the Pearson case, the 'stand-alone' indicators –z-scores, NPLs and net interest margins– have low Spearman rank correlations between each other. This does not hold for the capital adequacy measures, which -between each other- all have rank correlations greater than 0.5. Measures for asset quality, management quality and earnings capability each have at least one measure mostly uncorrelated with all other measures. Liquidity and market sensitivity measures have generally low correlations. The liquidity measure loans due to commercial banks over equity has higher correlations in few cases. We note again that this measure could, besides a liquidity dimension, as well capture a loan dimension.

More specifically, looking at the capital measures equity over assets, total capital ratio and equity over loans we observe these are highly correlated in ranking. This is not unreasonable, as these measures all aim to rank banks based on –a different aspect of– their capital dimension. One of the measures for asset quality, equity over loans, ranks banks in a similar order as do capital measures. A hint towards the idea that this measure might capture more a capital dimension than a credit dimension. Except for the median method, we qualify return on equity and return on assets as highly rank correlated. Both measures aim to address bank soundness based on earnings and are therefore to some extent similar. Finally, we look at the indicators net interest margin over income, overhead costs over assets and net interest margins. These are either qualified as an indicator of earnings, management quality and efficiency or competition. Overhead costs over assets carries a relatively straightforward capital characteristic –assets– in its definition, but also the indicators related to net interest margins seem highly correlated to capital measures. A potential explanation could be that higher capital adequacy makes banks feel more comfortable to increase the margin between its lending rate and the risk-free rate, or that, vice versa, higher lending spreads pave the road towards a greater capital reserve for banks.

Kendall correlations (see definition in Appendix A) provide another non-parametric way to look at ranked relationships. Different from the Spearman method, Kendall's technique compares consistency between pairs, i.e. a pair is concordant when both on indicator A and B observation X is consistently ranked higher or lower than observation Y. A discordant pair is characterized by non-consistence in ranking between X and Y on indicator A and B. Rather than considering how far an observation is away from the benchmark, this technique looks in a binary way at (non-) consistency between pairs. Fredricks and Nelsen (2007) discuss how Spearman and Kendall correlations can be expected to differ, with Spearman correlations expected to be about 50% larger than Kendall correlations. From performing Kendall tests on all observations, median observations and mean observations we find, despite the different magnitude, results corresponding to Spearman outcomes (see Tables A.3, A.4 and A.5 for complete results).

Table 3.3. Pearson correlation coefficients between all measures defined in Table 3.2

	(1)	(2)	(3)	(4)	(5)	(6)	)7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
z-score (1)	1.000																	
NPLs (2)	-0.101	1.000																
net interest margin (3)	-0.072	0.189	1.000															
tot.equity/tot.assets (4)	0.136	0.116	0.293	1.000														
total capital ratio (5)	0.037	0.047	-0.025	0.542***	1.000													
tot.equity/tot.loans (6)	0.003	-0.012	0.014	0.190	0.035	1.000												
loan loss prov./tot.loans (7)	-0.017	0.283	0.006	0.016	0.044	0.018	1.000											
tot.loans/tot.equity (8)	-0.008	-0.128	-0.152	-0.305	-0.180	-0.017	-0.017	1.000										
tot.cost/tot.income (9)	-0.050	0.086	-0.019	0.088	0.077	-0.044	-0.020	-0.006	1.000									
overh.costs/tot.assets (10)	-0.034	0.149	0.274	0.372	0.147	-0.006	0.018	-0.131	0.218	1.000								
return on equity (11)	-0.034	-0.056	0.113	-0.036	-0.062	-0.007	-0.014	-0.076	-0.344	-0.047	1.000							
return on assets (12)	-0.015	-0.026	0.284	0.309	0.094	0.046	-0.009	-0.149	-0.397	0.087	0.479	1.000						
net int.margin/tot.income (13)	0.112	0.037	0.043	0.149	0.001	0.002	-0.001	-0.020	0.018	0.040	-0.014	0.023	1.000					
liq.assets/tot.assets (14)	0.114	0.002	-0.128	-0.154	0.009	0.073	-0.026	0.318	0.020	-0.121	-0.047	-0.044	-0.018	1.000				
tot.loans/tot.deposits (15)	-0.011	-0.011	0.009	0.005	0.002	-0.001	-0.001	-0.009	-0.056	-0.013	0.024	0.026	-0.002	-0.034	1.000			
fix.assets/tot.assets (16)	0.009	0.050	0.078	0.268	0.123	-0.013	-0.007	-0.110	0.130	0.145	-0.036	-0.001	-0.004	-0.116	-0.017	1.000		
due to com.banks/tot.equity (17)	-0.020	-0.029	-0.050	-0.066	-0.105	-0.004	0.002	0.694***	-0.008	-0.042	-0.112	-0.045	-0.003	0.046	-0.005	-0.048	1.000	
off-balance items/tot.assets (18)	-0.018	-0.001	0.004	0.022	-0.015	-0.003	0.179	-0.069	-0.052	0.008	0.038	0.039	-0.015	-0.088	-0.008	-0.020	-0.005	1.000

Correlation coefficients larger than 0.5 in absolute value are marked as (***).

Table 3.4. Spearman rank correlation coefficients between all measures defined in Table 3.2

	(1)	(2)	(3)	(4)	(5)	(6)	)7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
z-score (1)	1.000																	
NPLs (2)	-0.184	1.000																
net interest margin (3)	-0.148	0.336	1.000															
tot.equity/tot.assets (4)	0.187	0.082	**0.684***	1.000														
total capital ratio (5)	0.009	-0.029	0.396	**0.695***	1.000													
tot.equity/tot.loans (6)	0.001	0.079	**0.517***	**0.797***	**0.741***	1.000												
loan loss prov./tot.loans (7)	-0.192	0.439	0.498	0.175	0.083	0.109	1.000											
tot.loans/tot.equity (8)	-0.001	-0.079	**-0.517***	**-0.797***	**-0.741***	**-1.000***	-0.109	1.000										
tot.cost/tot.income (9)	-0.274	0.132	0.077	-0.007	0.035	0.085	0.028	-0.085	1.000									
overh.costs/tot.assets (10)	-0.216	0.332	**0.813***	**0.594***	0.376	**0.511***	0.424	**-0.511***	0.489	1.000								
return on equity (11)	-0.047	0.014	0.070	-0.170	-0.193	-0.098	-0.033	0.098	-0.402	-0.041	1.000							
return on assets (12)	0.162	0.079	**0.530***	**0.568***	0.340	0.483	0.075	-0.483	-0.375	0.342	**0.610***	1.000						
net int.margin/tot.income (13)	-0.060	0.145	**0.667***	**0.644***	0.455	**0.519***	0.197	**-0.519***	0.165	**0.616***	-0.115	0.425	1.000					
liq.assets/tot.assets (14)	-0.181	0.048	0.111	0.143	0.225	0.376	-0.011	-0.376	0.176	0.229	0.056	0.127	0.108	1.000				
tot.loans/tot.deposits (15)	0.121	-0.035	0.085	0.062	-0.185	-0.326	0.141	0.326	-0.098	0.021	-0.086	-0.048	-0.004	-0.342	1.000			
fix.assets/tot.assets (16)	0.205	0.074	0.189	0.105	-0.072	-0.067	0.143	0.065	0.080	0.191	-0.085	0.050	0.130	-0.243	0.042	1.000		
due to com.banks/tot.equity (17)	-0.203	-0.031	-0.437	**-0.588***	-0.462	-0.439	-0.127	0.439	0.055	-0.356	0.027	-0.398	-0.397	0.041	-0.156	-0.077	1.000	
off-balance items/tot.assets (18)	0.270	-0.159	-0.227	-0.122	-0.075	-0.081	-0.097	0.081	-0.185	-0.220	0.127	0.034	-0.234	0.023	-0.092	-0.038	0.013	1.000

Correlation coefficients larger than 0.5 in absolute value are in bold and marked with a (*).

3.4 Factor analysis

Another way to look at our data is to look at the variability between all variables. Factor analysis is a technique that looks at this variability and aims to describe it in fewer variables –now called factors. Previously the technique has been used in a banking risk context by e.g. West (1985) and Klomp and De Haan (2012); more generally this factor approach can be used to reduce the size of data in several types of research.

The eighteen observed variables in our dataset are correlated and these correlations can be exploited by factor analysis to explain in-sample variability. Factor analysis uses the observed variables to find linear combinations of deeper underlying, unobserved variables that explain the observed ones. In a general model setting we write

$$X = \beta' F + \varepsilon \tag{1}$$

where X is the matrix of demeaned observed indicators and F is the matrix of unobserved variables with β the vector of factor loadings. We assume [8] that

$$E(\varepsilon) = 0$$

$$E(F\varepsilon) = 0$$

$$E(F) = 0$$

$$Cov(F) = I$$

As equation (3.1) shows, factor analysis assumes a relationship between the observed variables on the left-hand side and the unobserved factors on the right-hand side. When two observed variables are highly correlated, they will be associated with the same factor and have high loadings on the same factor. West (1985) emphasizes that factors are determined by statistical relationships found in the data and contain information that is distilled from a broader base of variables, so that a small number of factors makes it hard to explain one hundred percent of all original variability. As a consequence, there is a trade-off between the number of factors and the amount of variability left unexplained. In the case of cross-section data, factor analysis can be correctly defined this way. However, in a panel data setting both a cross-section and a time-series dimension occur. Under this kind of multivariate time series setting, dynamic factor models are often used to estimate the parameters while at the same time keeping in mind that the observed variables might be autocorrelated. Here we use factor analysis rather as an exploratory mechanism to analyze indicator relationships and not as a means to extract factors and include these in a model. Therefore we choose to conduct a factor analysis while ignoring the time series dimension, but in parallel checking for differences over time by means of performing separate factor analyses for every year. A disadvantage of factor analysis is that it requires data to be complete and incomplete observations are omitted in the analysis. In our

[8] Assumptions and model derived from Stata Multivariate Statistics Reference Manual, version 12 (2011).

case that leads to losing more than 75% of our observations and therefore we use the EM algorithm from Dempster, Laird and Rubin (1977) to complete some of our missing data.

First, we look at the number of factors that we can abstract from factor analysis on the eighteen measures. We both investigate our complete data sample as well as every separate year sample and use two evaluation criteria to determine how many factors should be retained. The first criterion is the Kaiser (1958) criterion, which states that only factors with an eigenvalue greater than one should be considered. As a second, Cattell's (1966) scree test decides upon the number of factors by looking after which factor the graph of eigenvalues shows a 'kink'. We evaluate both the complete sample as the separate yearly data samples and decide to retain four factors in our further analysis (see appendix B for both estimated factor eigenvalues and loadings).

A factor essentially consists of a vector of correlations (called factor loadings). The greater the (absolute) loading, the more obvious is the linear relationship between the variable and the factor. We decide to look only at loadings larger than 0.6 in absolute value to identify patterns in our data. Comparison between the factor loadings obtained from the total sample and the yearly samples reveals the 'general picture' and local patterns. Both in the overall sample and in the individual yearly ones we observe capital and asset measures consistently associated with the first two factors – the factors with the largest eigenvalues, i.e. the variance accounted for by the factor. Besides capital and asset measures we find the earnings measures return on equity and return on assets mutually persistent as factor loadings over time. From these observations it may not be surprising that capital, asset and both earnings measures also have high correlations in the full sample analysis (see Table 3.5). In contrast, management indicators are hardly associated with any factor in the full sample analysis. However, when looking per year it shows that this is mainly true for the first years in the sample. From 2005 onwards, management indicators seem to correlate more strongly with the factors retained. For liquidity and bank sensitivity to market indicators it is observed that in some years these are not associated with any factor at all. Moreover, when the liquidity measure for loans due to commercial banks over total equity is the only high-correlated liquidity measure this one should be interpreted with caution as this measure technically is a special kind of loan-to-equity ratio that might also have an important credit risk (i.e. asset risk) dimension in it. We note that z-scores and net interest margins are not associated with any common factor at all, nor in an individual year or in the overall sample; both measures show to be relatively unique. As a consequence, neither are these two associated with each other or with the ratio of NPLs, suggesting that choosing these banking risk indicators as different dependent variables implies choosing a significantly different research setting.

Table 3.5. Factor loadings under a four-factor model, using data for the entire period 2002-2008

indicator (risk category)	factor 1	factor 2	factor 3	factor 4	uniqueness
z-score (e)	-0.034	-0.030	0.019	-0.011	0.997
NPLs (a)	0.813**	0.096	0.123	-0.083	0.308
net interest margin (e)	0.033	0.016	0.443	0.215	0.756
tot.equity/tot.assets (c)	0.067	-0.183	0.736**	0.076	0.415
total capital ratio (c)	0.719**	-0.646**	0.008	-0.020	0.065
tot.equity/tot.loans (c)	0.026	-0.007	0.114	0.056	0.983
loan loss prov./tot.loans (a)	0.982**	-0.014	-0.033	0.034	0.033
tot.loans/tot.equity (a)	0.000	0.691**	-0.312	-0.094	0.416
tot.cost/tot.income (m)	0.012	-0.026	0.193	-0.582	0.623
overh.costs/tot.assets (m)	0.055	-0.027	0.515	-0.085	0.724
return on equity (e)	-0.031	-0.072	-0.051	0.591	0.643
return on assets (e)	-0.029	-0.051	0.250	0.709**	0.432
net.int.margin/tot.income (e)	0.012	0.000	0.134	-0.008	0.982
liq.assets/tot.assets (l)	-0.006	0.130	-0.234	-0.041	0.927
tot.loans/tot.deposits (l)	-0.008	-0.033	-0.017	0.059	0.995
fix.assets/tot.assets (l)	-0.003	-0.097	0.291	-0.103	0.895
due to com.banks/tot.equity (l)	-0.009	0.978**	0.010	-0.002	0.043
off-balance items/tot.assets (s)	0.169	-0.014	0.007	0.078	0.965

Correlation coefficients per associated factor and indicator. In column 1, we use (c) for capital risk, (a) for asset risk, (m) for management risk, (e) for earnings and profitability risk, (l) for liquidity risk and (s) for sensitivity to market risk. The degree of uniqueness classifies how much of a measure's variance it has in common with the other measures. Factor loadings larger than 0.6 in absolute value are marked as (**).

3.5 Implications for individual indicators

Pearson correlation coefficients do not show evidence for extensive linear relationships in our data. As a non-linear approach, rank correlations could be used to address the issue of "when an observation is qualified either relatively good or bad on one indicator, is this true for another indicator too?" From the three different ways we used to calculate Spearman and Kendall rank correlations, we find that eleven of our eighteen measures are highly correlated with at least one other measure. Seven of these eleven measures were discussed more specifically in the previous section; each of these seven we could remove while at least leaving an indicator that it is highly similarly ranked to. Complete sample factor analysis as well as yearly models show that especially capital, asset, management and earnings measures are grouped together into factors. From rank correlations, these measures moreover show to be the measures with high correlations. Liquidity and sensitivity measures seem mostly unrelated to other measures from factor analysis, which is in accordance with low scores from our rank correlation analysis. For these reasons, we decide to leave the indicators in Table 3.6 out of consideration from now on in this research.

Table 3.6. List of omitted indicators

Indicator category	Indicator
Loan Spreads	Net Interest Margin
Capital Adequacy	Total Equity / Total Assets
	Total Capital Ratio
Asset Quality	Total Loans / Total Equity
Management Performance	Overhead Costs / Total Assets
Earnings And Profitability	Return On Assets
	Net Interest Margin / Income

4 Data discussion

4.1 An indication for per country representativeness

This section will be used to address some of the implications that result from the data sample used in this research. An issue we would like to check for is how representative our data sample is compared to the complete domestic banking sector. In order to do so, we compare the national, aggregate size of total loans outstanding in our sample to the per-country size of loans as recorded by the World Bank[9]. Note that in the case of Denmark, Greece, Hong Kong, Ireland, The Netherlands, Sweden and United Kingdom coverage ratios in some years are larger than one. This may occur because in our data we cannot separate consolidated results from domestic loans. Therefore we use Table 4.1 as a rough indication rather than an exact test for representativeness.

[9]Data available at http://data.worldbank.org/indicator/FS.AST.PRVT.GD.ZS

Table 4.1. Bankscope versus World Bank comparison of outstanding domestic credit: coverage ratios

Country name	Year						
	2002	2003	2004	2005	2006	2007	2008
Argentina	0.005	0.010	0.013	0.012	0.028	0.030	0.024
Belgium	0.000	0.000	0.245	0.228	0.281	0.279	0.321
Bosnia-Herzegovina	0.052	0.076	0.091	0.078	0.070	0.087	0.000
Brazil	0.006	0.016	0.022	0.031	0.034	0.043	0.017
Bulgaria	0.016	0.055	0.069	0.058	0.079	0.119	0.000
Canada	0.002	0.002	0.002	0.004	0.003	0.006	0.004
China	0.072	0.167	0.187	0.192	0.196	0.214	0.208
Denmark	0.002	0.006	1.060	1.002	1.141	1.330	1.239
France	0.016	0.020	0.558	0.516	0.612	0.700	0.684
Germany	0.015	0.073	0.099	0.083	0.097	0.134	0.074
Greece	0.002	0.010	0.604	0.545	0.692	0.937	1.006
Hong Kong	0.000	0.000	0.893	0.905	0.919	1.062	1.118
Hungary	0.000	0.000	0.001	0.000	0.000	0.000	0.000
India	0.086	0.101	0.115	0.132	0.151	0.182	0.000
Indonesia	0.000	0.006	0.007	0.008	0.011	0.012	0.011
Ireland	0.009	0.007	1.120	0.992	1.089	1.193	1.055
Italy	0.000	0.000	0.239	0.395	0.419	0.482	0.468
Japan	0.055	0.058	0.053	0.048	0.048	0.055	0.005
Latvia	0.102	0.150	0.185	0.186	0.251	0.329	0.332
Luxembourg	0.122	0.150	0.323	0.342	0.326	0.345	0.130
Netherlands	0.001	0.001	1.004	0.988	1.142	1.124	0.960
Norway	0.020	0.030	0.417	0.379	0.404	-	-
Portugal	0.000	0.000	0.646	0.535	0.571	0.661	0.635
Romania	0.039	0.062	0.086	0.086	0.116	0.128	0.000
Russia	0.014	0.030	0.048	0.079	0.118	0.170	0.101
Spain	0.000	0.000	0.979	0.855	0.935	0.993	0.888
Sweden	0.100	0.127	1.275	1.089	1.223	1.279	1.063
Switzerland	0.057	0.375	0.422	0.393	0.410	0.458	0.408
Taiwan	-	-	-	-	-	-	-
Thailand	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Ukraine	0.010	0.026	0.028	0.048	0.058	0.076	0.011
United Kingdom	0.002	0.003	0.793	0.778	0.866	1.009	0.735
United States	0.001	0.001	0.001	0.001	0.001	0.001	0.001

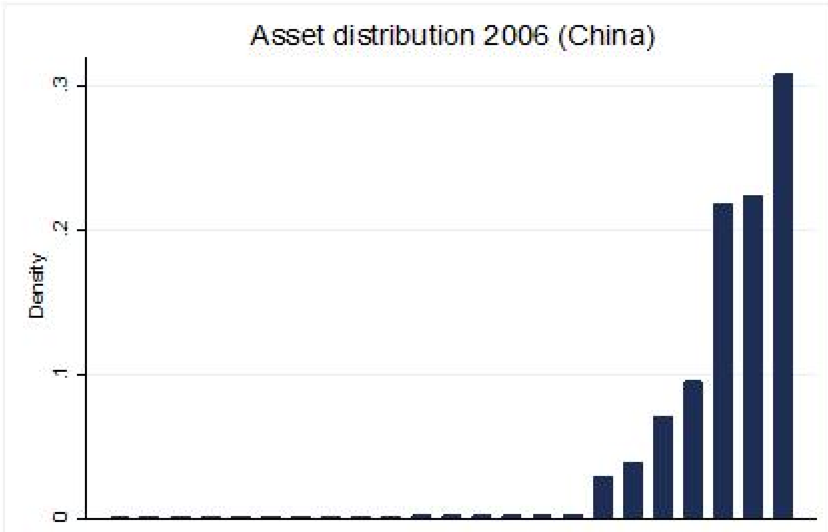
Tabulated ratios are calculated from dividing domestic total loans outstanding (Bankscope) by domestic credit provided (World Bank), both measured in international US dollars. For Taiwan and Norway in 2007 and 2008, we did not observe the required World Bank data.

From Table 4.1 we find that our sample covers very low shares of total loans in every country in 2002. The coverage ratio for some countries slightly goes up in 2003, but for none of the countries we observe a ratio greater than 0.5, i.e. that roughly at least half of the domestic bank sector is represented in our sample. From 2004 and onwards we find ratios consistently greater than 0.5 and for countries Denmark, France, Greece, Hong Kong, Ireland, The Netherlands, Portugal, Spain, Sweden and United Kingdom these stay consistently at that level for the rest of the sample period. From analysis of Table 4.1 we conclude that the data coverage in the years 2002 and 2003 is insufficient and decide to focus our research on the pre-crisis period of 2004-2008.

4.2 Bank size distribution per country

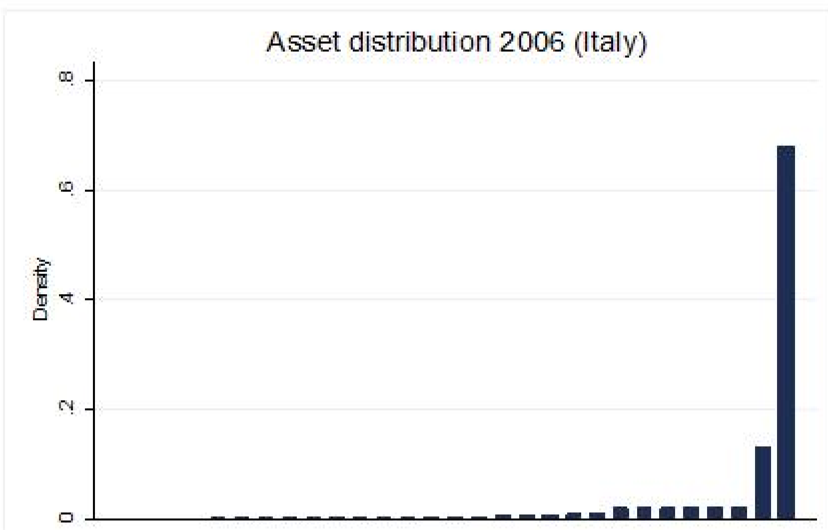
In section 4.1 we looked –from a national perspective– at the loan coverage of our dataset. This gives an important indication of our dataset representativeness, but, as we noticed before, these coverage ratios are not exact tests for the reason that we do not know the exact composition of the loans in our sample. Therefore, we perform a second check focused on the domestic distribution of banks; a check we perform by comparing the size of individual bank assets to the total domestic bank sector assets. Asset distribution functions then show for each country the distribution between big and small banks in our sample, i.e. whether the risk in a country largely depends on one institution or not. Chart 4.1 and Chart 4.2 show example distribution functions for the Chinese and Italian case. For every country in every year we can compose charts as Chart 4.1 and 4.2. In the Chinese case we see that multiple banks play a significant role in the bank sector asset distribution and the largest bank holds roughly 30% of the total assets. However, the distribution in the Italian case reveals that mainly one bank (the largest) in the sample counts for 70% of country's assets. Comparison between distributions for the same country in different years could show whether or not the distribution in the domestic bank sector is changing; which would either suggest a rigorous change in data availability or a shock to the domestic banking sector.

Chart 4.1. Bank asset distribution in China for a chosen year (2006)



For every Chinese bank in the sample, assets are weighed relatively to the total Chinese bank assets per year. Each bar denotes one specific Chinese bank. We then order these banks according to their size and find domestic bank sector asset distributions per year.

Chart 4.2. Bank asset distribution in Italy for a chosen year (2006)



For every Italian bank in the sample, assets are weighed relatively to the total Italian bank assets per year. Each bar denotes a specific Italian bank. We then order these banks according to their size and find domestic bank sector asset distributions per year.

To determine the degree of bank concentration in a country, we examine the total asset size of the five biggest banks relative to the entire sector. The greater the relative size, i.e. the closer the ratio is to one, the more a national bank sector is centered around these five largest banks. For every country and every year, we can determine the share that the largest five banks cover in the total sector (results are available in Table C.1). In order to compare the level of concentration in our sample to actual numbers, we use per-country top five bank shares as provided by the World Bank[10]. When taking the ratio between both, outcomes close to one suggest a great similarity between the actual concentration level and the level of bank concentration in our sample. The results are displayed in Table 4.2. An advantage of considering the five largest banks per country as a measure of sector concentration is that it gives a straightforward idea of how large of a share is taken by few large banks. A disadvantage is that this measure does not explicitly consider how the distribution is between these five banks, i.e. whether the five are different or similar in terms of size. A measure that better accounts for such issues is the Herfindahl index, which is defined as the sum of squared asset shares of all banks in a country. Outcomes close to one reveal very high sector concentration, whereas outcomes close to zero suggest a much lower level of concentration. We calculate yearly indexes based on the Herfindahl method (results available in Table C.2) and –for the EU countries in our sample– and can compare these outcomes to the actual financial sector Herfindahl indexes per country as recorded[11] by the ECB. The compared results are displayed in Table 4.3. Italy is one of the countries for which we find an index that is more than a factor ten larger than its actual Herfindahl index, which indicates that in our Bankscope sample some Italian banks with an important influence on the domestic bank size distribution are missing.

From Table 4.1, we analyzed that the countries Denmark, France, Greece, Hong Kong, Ireland, The Netherlands, Portugal, Spain, Sweden and the United Kingdom appeared most representative in our sample. In Table 4.2, all these countries –except for the United Kingdom in two years– have ratios lower than two, which we regard as an acceptable benchmark for levels of compared concentration in our dataset. From Table 4.3 we find especially the countries Germany, Italy and Luxembourg have higher ratios, but none of these are countries that we selected earlier on from Table 4.1. Hong Kong is not an EU country and we do not have actual Herfindahl indexes available for this country.

In this section, first we determined a selection of countries that from the data seem to be most representative for the actual size of their domestic bank sector. Particularly for these countries, we looked at their yearly bank asset distributions and compare these to actual bank sector concentration levels obtained from the World Bank and the European Central Bank. These comparisons reveal large differences between actual and sample national bank sector concentration levels for some countries. However, we conclude that the range of results

[10]Data available from http://www.worldbank.org/financialdevelopment, Global Financial Development Database (December 2012)

[11]Data available from ECB (September 2010), EU Banking Structures, ISSN 1830-1878 (online)

for the selected group of countries is acceptable. Therefore we will continue this research with data for the countries Denmark, France, Greece, Hong Kong, Ireland, The Netherlands, Portugal, Spain, Sweden and the United Kingdom.

Table 4.2. Bankscope versus World Bank comparison of bank sector concentration

Country name	Year				
	2004	2005	2006	2007	2008
Argentina	1.741	1.778	1.828	1.899	1.957
Belgium	1.113	1.094	1.071	1.062	1.072
Bosnia-Herzegovina	1.425	1.495	1.454	1.579	-
Brazil	1.715	1.867	1.419	1.363	1.228
Bulgaria	1.492	1.688	1.738	1.509	-
Canada	1.449	1.440	1.516	1.523	1.614
China	1.293	1.332	1.223	1.278	1.336
Denmark	1.274	1.291	1.293	1.291	1.281
France	1.510	1.589	1.600	1.598	1.633
Germany	1.994	1.797	1.769	1.667	1.880
Greece	0.853	0.905	1.000	0.957	0.969
Hong Kong	0.928	1.052	1.057	1.031	1.029
Hungary	1.353	1.348	1.297	1.321	-
India	2.124	2.099	2.109	2.146	-
Indonesia	1.493	1.609	1.635	1.581	1.691
Ireland	1.463	1.547	1.707	1.656	1.372
Italy	1.053	2.699	2.704	2.325	2.161
Japan	2.601	2.673	2.550	2.653	2.339
Latvia	1.476	1.362	1.321	1.401	1.361
Luxembourg	2.132	1.994	2.071	2.654	2.780
Netherlands	1.070	1.102	1.075	1.059	1.063
Norway	0.957	1.049	1.027	1.102	1.148
Portugal	1.053	1.138	1.184	1.211	1.165
Romania	1.307	1.265	1.185	1.137	-
Russia	1.303	0.701	0.822	0.830	1.438
Spain	1.009	1.393	1.402	1.365	1.346
Sweden	1.229	1.233	1.237	1.166	1.174
Switzerland	1.139	1.130	1.108	1.101	1.120
Taiwan	-	-	-	-	-
Thailand	1.494	1.567	1.535	1.534	1.639
Ukraine	1.335	1.350	1.576	1.532	2.239
United Kingdom	1.548	2.041	2.001	1.735	1.609
United States	3.572	3.478	3.389	3.373	3.031

In this table, we compare the relative importance of the five largest banks in our sample to actual World Bank numbers. Per country and per year, we determine the total asset share that the five largest banks hold in the country total. This outcome we divide by the 'five largest banks asset share' according to the World Bank. For Taiwan, no according World Bank data were available. In other cases with missing outcomes, we did not have individual bank data for the specific country in the specific year.

Table 4.3. Herfindahl comparison between Bankscope and ECB data

Country name	Year			
	2005	2006	2007	2008
Belgium	4.616	4.784	4.699	5.200
Bulgaria	5.451	5.152	5.165	-
Denmark	3.149	3.293	3.276	2.884
France	3.037	3.081	3.310	3.439
Germany	10.503	9.681	8.324	10.263
Greece	1.455	1.451	1.432	1.363
Hungary	6.381	6.106	5.726	-
Ireland	5.191	4.929	4.661	4.099
Italy	21.729	21.995	15.944	14.253
Latvia	4.084	4.038	4.412	4.368
Luxembourg	11.481	11.423	10.692	34.863
Netherlands	2.264	2.246	2.128	1.901
Portugal	2.496	2.509	2.559	2.580
Romania	2.694	2.292	2.181	-
Spain	3.533	3.416	3.181	3.143
Sweden	3.703	3.588	3.305	3.524
United Kingdom	4.267	4.236	3.760	4.592

The outcomes presented here are ratios. We calculate Herfindahl-based indexes; for every country and for every separate year we calculate sums of squared individual bank asset shares. This outcome we divide by domestic Herfindahl indexes as presented by the European Central Bank (available from 2005 and onwards). For the countries Bulgaria, Hungary and Romania we did not observe any bank in 2008.

5 Aggregated national indicators

In the previous two sections we looked at similar patterns between indicators and the completeness of data per country. Based on these sections, we continue with selected sets of indicators and countries that are displayed in Tables 5.1 and 5.2. In this section, we aim to construct risk indicators at a national level and to aggregate different indicators into first a categorical and an ultimately overall dimension. To do so, we use both a weighted asset method and a minimum or maximum method. In both cases, we use normalized observations to enhance comparability between different indicators –which originally have various outcome ranges. This section describes both methods and the consecutive formulas used in these methods.

Table 5.1. Indicator categories and indicators per category

category	indicator (expected sign in relation to bank risk)
capital	total equity / total assets (-)
asset	loan loss provision / total loans (+)
	non-performing loans / total loans (+)
management	total cost / total income
earning	return on equity (-)
	z-score (-)
liquidity	liquid assets / total assets (-)
	total loans / total deposits (+)
	fixed assets / total sssets (+)
	due to commercial banks / total equity (+)
sensitivity	off balance sheet items / total assets

Table 5.2. Individual banks per country

country	# of banks
Denmark	17
France	25
Greece	12
Hong Kong	18
Ireland	6
Netherlands	10
Portugal	8
Spain	40
Sweden	67
United Kingdom	26

5.1 Country-level indicators based on asset size

In our first aggregation method, we base individual banks' importance on the size of its assets relative to the country total. To obtain outcomes that –for different indicators– are comparable in range we standardize the indicator outcomes. In order to do so, our first step is to determine asset weighed sample means and standard deviations per indicator and country. As a remark, note that in section 3 we noticed that not all of the banks in our sample have complete yearly observations and for that reason we explicitly account for missing values in the formulas presented in this section. Using the country specific means and standard deviations, we calculate standardized individual bank results which in its turn we weigh for their relative asset size. Yearly summations of these weighed results then provide indicator outcomes at the country level. After choosing weights for each of these indicators, aggregation leads to categorical indicators and ultimately a one-dimensional bank risk indicator.

While our initial individual bank data is at a micro rather than at a macro level, the aggregated one-dimensional risk indicator is constructed as a macro indicator over time. For each of the countries considered, this indicator can be used to assess patterns in risk development and to identify periods of relatively high or low risk. Domestic bank sector risk is as a macroeconomic variable that evolves over time and could therefore be related to other indicators of the domestic macroeconomic environment over time. Such indicators may be both relatively specific to the bank sector (e.g. interbank lending rate) or to the economy as a whole (e.g. national GDP growth).

To calculate per country asset weighed sample means (2) and variances (3) for every indicator we write

$$\overline{X}_i(c) \;=\; \frac{\sum_{j=2004}^{2008} \sum_{b \epsilon A_{ij}(c)} (X_{ijb} \, \frac{a_{jb}}{a_{ij}(c)})}{\sum_{j=2004}^{2008} 1 \left\{ A_{ij}(c) \neq \emptyset \right\}} \tag{2}$$

$$s_i^2(c) \;=\; \frac{\sum_{j=2004}^{2008} \sum_{b \epsilon A_{ij}(c)} (X_{ijb} - \overline{X}_i(c))^2 \, \frac{a_{jb}}{a_{ij}(c)}}{\sum_{j=2004}^{2008} 1 \left\{ A_{ij}(c) \neq \emptyset \right\}} \tag{3}$$

I	=	{indicators}
C	=	{countries}
B	=	{all individual banks in the data sample}
a_{jb}	=	total bank assets for bank b in year j
X_{ijb}	=	observation for bank b on indicator i in year j
$\overline{X}_i(c)$	=	weighted average for indicator i in country c
$NA(c)$	=	$\{(i,j,b)$ |no observation available for bank b in country c concerning all indicators i and all years $j\}$
$A_{ij}(c)$	=	$\{b \mid (i,j.b) \not\subseteq NA(c)\}$
$a_{ij}(c)$	=	$\sum_{b \epsilon A_{ij}(c)} a_{jb}$
$s_i^2(c)$	=	average annual variance for indicator i in country c

We denote normalized observations for bank b on indicator i in year j as $\tilde{X}_{ijb}$. Because every individual bank b exactly exists in one country c we have

$$\forall b \,\epsilon\, c, \quad \tilde{X}_{ijb} = \frac{(X_{ijb} - \overline{X}_i(c))}{\sqrt{s_i^2(c)}} \tag{4}$$

The normalized results per measure in (4) are on the level of individual banks b. In order to obtain indicator results at the country level, we weigh every outcome from (4) with its own bank assets relative to the country total and subsequently calculate yearly summations per indicator per country (see (5)). Note that we weighed observed outcomes to obtain indicator averages per country in (2) as well. However, we explicitly undertake the normalization step in (4) and subsequently the weighed aggregation step in (5) to obtain yearly aggregates per indicator per country that are similar in outcome range. This characteristic is useful for the aggregation of multiple indicators into categorical or overall risk indicators.

$$\hat{X}_{ij}(c) = \sum_{b \epsilon A_{ij}(c)} (\tilde{X}_{ijb} \, \frac{a_{jb}}{a_{ij}(c)}) \tag{5}$$

For the one-dimensional risk categories in Table 5.1, using (5) is enough to determine category indicators. However, this is not the case for the categories in Table 5.1 consisting of multiple indicators. When each indicator is given a specific weight, then indicators can be summed into a category indicator. Geršl and Heřmánek (2007) choose weights proportional to the number of indicators per category. We can write this step as

$$R_{j,cat}(c) = \sum_{i \epsilon cat} [(\hat{X}_{ij}(c) \, \frac{1}{n_{cat}}) \, sign_i] \tag{6}$$

$$\begin{aligned} CAT &= \{\text{capital, asset, management, earning, liquidity, sensitivity}\} \\ n_{cat} &= \text{number of indicators per category} \\ sign_i &= \text{expected sign of relationship between indicator } i \text{ and bank risk} \end{aligned}$$

Aggregation by means of (6) is straightforward and simple, but it is not the only possible way to aggregate risks. A well-documented example in a financial problem setting is the Dutch standard for pension fund solvability, described in the FTK (Financieel Toetsingskader, part of the Dutch legal retirement framework as described in the 'Pensioenwet' initiated in 2007). This risk framework aggregates risks that play a role in pension fund solvability by means of a square-root formula. The formula aggregates non-negativerisks and uses a square root to average over the total. In the FTK this is written

$$risk = \sqrt{S_1^2 + \rho S_1 S_2 + S_2^2 + S_3^2 + S_4^2 + S_5^2 + S_6^2} \tag{7}$$

where S_1 to S_6 are non-negative risks in percentages and ρ is the assumed correlation between S_1 and S_2 (interest rate risk and stock market risk). The other risks are assumed to be uncorrelated.[12] The aim of the FTK risk assessment is to determine which solvency buffer a pension fund needs to stay fully funded[13] over the next year, with at least 97.5 per cent probability. The more uncertainty involved with the separate six risk factors, the larger the risk buffer that a fund will need to hold. To address the risk involved with each of the six factors, the FTK proposes a standardized approach which makes use of several pre-defined parameters and assumptions. This approach is useful because customized risk modeling is often complex and time consuming, and the advantage of a standardized approach is that it is easy to implement and moreover that it can be practically used by pension funds different in size (see also Nijman (2006)). To quantify each risk factor from (7), a pension fund's exposure per factor and the magnitude of a reasonable shock need to be quantified, where the latter is mostly set by the FTK. In this way, each risk factor determines a buffer that would be implicitly needed to protect the fund against the shock. These buffers cover possible deviations that could realistically occur with the fund's current risk exposure. The deviations are non-negative and can, similar to a summation of variances, be aggregated by means of the square root formula as in (7).

This example of risk aggregation is well-known in the pension world and deals with the uncertainty of future shocks and the exposure of a pension fund to such shocks. However, in the risk aggregation setting that we consider in this thesis, we do not look at –uncertain– risks in the future and buffers that banks should set accordingly. We rather deal with a dataset consisting of realized indicator values that we normalize according to historic indicator averages and standard deviations per country. Moreover, our risks per category from (6) are scores that can be qualified as negative (below the historic average) or positive (above average). Consistent with Geršl and Heřmánek (2007), we give weights to the categorical indicators obtained in (6) so that we can construct a one-dimensional indicator for bank risk in (8). Geršl and Heřmánek (2007) explain that they do not take into account potential correlations by using this aggregation method. Based on theoretical judgment they determine weights which they use to aggregate categorical indicators. Their starting point however is to choose proportional weights, which they then alter for three categories due to country-specific reasons in the Czech Republic. As we deal with more than just one country in our research, we choose not to alter weights for country-specific reasons and simply use proportional weights.

$$BR_j(c) = \sum_{cat} (w_{cat} \, R_{j,cat}(c)) \tag{8}$$

[12]For a more in-depth discussion of the assumptions and parameters used in the FTK, see "Advies inzake onderbouwing parameters FTK", De Nederlandsche Bank (2006)

[13]For additional information on pension fund-related definitions and topics, we refer to literature such as by Kortleve, N., Nijman, T., Ponds, E., 2006. Fair value and pension fund management. Elsevier B.V.

$$
\begin{array}{lcl}
BR_j(c) & = & \text{aggregate construct for bank risk in country } c \text{ in year } j \\
w_{cat} & = & \text{weight per risk category}
\end{array}
$$

$$
\begin{array}{lcl}
w_{cat} & \geq & 0 \quad \text{for every category} \\
\sum_{cat} w_{cat} & = & 1
\end{array}
$$

5.2 Country-level indicators based on a minimum-maximum criterion

In section 5.1, country-level indicators were constructed by means of weighing individual bank outcomes for their relative asset size. Another way to look at the risk of the domestic bank sector is –instead of weighing all observed banks– by only considering one specifically chosen bank. This case is relevant in contagion theories, which discuss the possibility that failure of one financial institution leads to troubles for others as well. An example is the paper by Brown, Trautmann and Vlahu (2012) in which the authors conclude that deposit withdrawals can be strongly contagious across banks when there are economic linkages between banks' balance sheets. Iyer and Peydro-Alcalde (2011) find that higher interbank exposures to a failed bank and weak bank fundamentals can generate large deposit withdrawals. By means of looking at the worst individual bank on a specific indicator we look at 'how risky the riskiest bank in a country is'. We reason that the failure of one bank could influence the stability of the national banking sector as a whole. However, we control for the relative asset size of a bank, because it may be assumed that a bank needs to be of certain size before it can actually impact the system as a whole.[14]

The first step in this method is to choose which specific indicator we would like to regard. Depending on that indicator's sign in Table 5.1 we look for either a minimum (in case of a negative sign, because then we associate lower values with higher risk) or a maximum (in case of a positive sign). In other words, after choosing an indicator, for every country in every year we look for the lowest (or highest) outcome under the condition that the bank with that outcome is at least of relative asset size T. When an observation is selected as such, we look to which bank this observation belongs and use the indicator outcomes of that specific bank in that year as the national indicator for that country in that year. After this step, we normalize every indicator outcome so that we obtain outcomes that are comparable in range between indicators. For this normalization step, we again use the averages and standard deviations obtained in (2) and (3). We weigh indicators within the same category proportionally and obtain risks per category. Finally, we can weigh category risks to construct a one-dimensional bank risk construct per country.

[14]Most recent case of bank failure in The Netherlands is the case of DSB in 2009. Other Dutch banks and the Dutch government decided not to rescue the bank from bankruptcy after it announced its problems, a decision in which the size of the troubled bank might also have played an important role. See also "Big Dutch banks refuse to rescue failing DSB", NRC (October 16, 2009)

To find either the minimum or maximum, depending on the specifically chosen indicator i^*, we use

$$XM_{ij}(c, i^*) = X_{ijb},\ b = argmin[X_{i^*jb} \mid \frac{a_{jb}}{a_{i^*j}(c)} > T] \tag{9}$$

or

$$XM_{ij}(c, i^*) = X_{ijb},\ b = argmax[X_{i^*jb} \mid \frac{a_{jb}}{a_{i^*j}(c)} > T] \tag{10}$$

i^*	=	the indicator for which we want to find its minimum or maximum
T	=	the required relative size of a bank's assets
$XM_{ij}(c, i^*)$	=	the vector with observations on all indicators i, taken from bank b in country c that minimizes/maximizes the criterion i^* in year j

Subsequently we normalize our observations (we use (9) for a chosen i^* with expected negative sign, instead use (10) in case of an i^* with positive expected sign in Table 5.2)

$$\widetilde{XM}_{ij}(c, i^*) = \frac{XM_{ij}(c, i^*) - \overline{X}_i(c))}{\sqrt{s_i^2(c)}} \tag{11}$$

Similar to (6), we can proportionally aggregate indicators to a category level by means of

$$R_{j,cat}(c, i^*) = \sum_{i \epsilon cat} [(\widetilde{XM}_{ij}(c, i^*) \frac{1}{n_{cat}})\, sign_i] \tag{12}$$

And to a one-dimensional annual national risk level

$$BR_j(c, i^*) = \sum_{cat} (w_{cat}\, R_{j,cat}(c, i^*)) \tag{13}$$

using non-negative weights (as in (8)) that sum up to one.

6 Results

In this section we use the methods from section 5 to obtain national level risk indicators. Using these national constructs, we first look at the behavior of different indicators that are classified within the same category (these are listed accordingly in Table 5.1). After this first step, indicators are aggregated into categorical indicators. First we will use these categorical aggregates to compare risk patterns per category, and moreover we use them to aggregate another time to an overall bank risk indicator. These one-dimensional, overall indicators per country we analyze relative to indicators for their domestic macro-economic environment. Last, we will use this section to analyze non-standardized indicators per country.

6.1 Intra-category similarity between indicators

In this research, we have defined three risk categories (i.e. assets, earnings and liquidity) that contain more than just one indicator (see Table 5.1). Geršl and Heřmánek (2007) decide to give proportional, identical weights to aggregate these indicators into a single indicator per category. Implicit to such an approach is the independence between indicators. We decide first to check correlations between the intra-category indicators, which we obtain from using the asset-weighted method. Per category, the evolutions of standardized indicators over time are displayed in Graph 6.1 to 6.3. From Graph 6.1 we notice that the share of loan loss provisions and the share of non-performing loans relative to a bank's total loan portfolio behave relatively similar in direction. For the separate earnings and profitability indicators in Graph 6.2, we do not observe an indication that both move to some extent together. Graph 6.3 shows the category that includes most separate indicators –liquidity. The standardized level of liquid assets over total assets does not seem to follow a linear development over time, whereas the indicator with loans due to commercial banks over equity seems to be relatively constant around the zero level. We notice that the risk associated with the share of fixed assets and the development of the loan-deposit ratio to some extent seem to move in opposite directions.

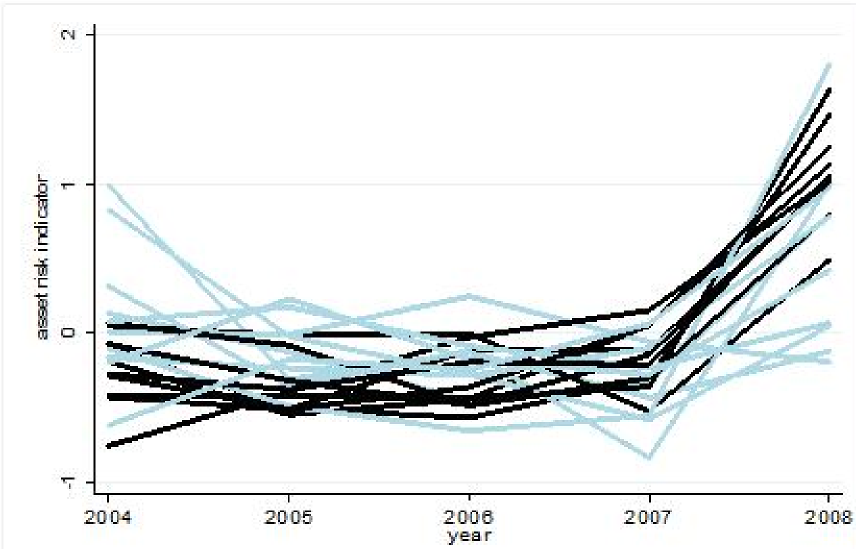
To check correlations between these national level indicators, we calculate pairwise correlations (see Table 6.1) based on the ten countries in our sample. We find a correlation coefficient of 0.60 between the both asset indicators and a negative coefficient of -0.51 between two of the liquidity indicators. In case of the asset indicators the positive coefficient expresses that loan loss provisions and NPLs –at a nationally aggregated level– move together. For the liquidity measures 'share of fixed assets' and the loan-deposit ratio the opposite seems to hold. A possible explanation for this observation could be that banks keep in mind their asset liquidity when determining their loan portfolio. We find that return on equity has a similar risk pattern over time as the asset risk indicators. At the domestic level, this indicates that the adequacy of the total bank sector asset portfolio and the volume of earnings and profitability are positively related.

As we did in section 3, another way to look at linear relationships between variables is by means of factor analysis. From applying this technique to the national-level indicators for asset, earnings and liquidity risk we identify two factors of which one mainly associates with assets and earnings while the other is best described as a liquidity factor (see Table 6.2). The finding that asset and earnings risk correspond to the same factor underlines the linkage that from our data seems to exist between both categories.

To check whether we find similar correlations when using another method to derive national risk indicators, we apply the minimum-maximum method from section 5. This approach we apply six times, with each time an indicator from a different category as the criterion to either minimize or maximize. We notice that in the case of choosing a capital, asset or earnings indicator as the leading argument we obtain correlations similar to the correlations from the weighted asset method (see results in Appendix D). The strength of correlations is lower in the min-max method which we find unsurprising as in this method we use only a fraction of the actual data to obtain indicators representing the national level. To increase the amount of data involved in this method we make a linear combination of the national indicators obtained from respectively using a capital, asset, earning and liquidity risk indicator as the leading argument to find the extreme of. Still, this combination only consists of a subset of the complete data. The correlations we find are similar in sign to the results obtained from using weighed aggregates, but not in magnitude.

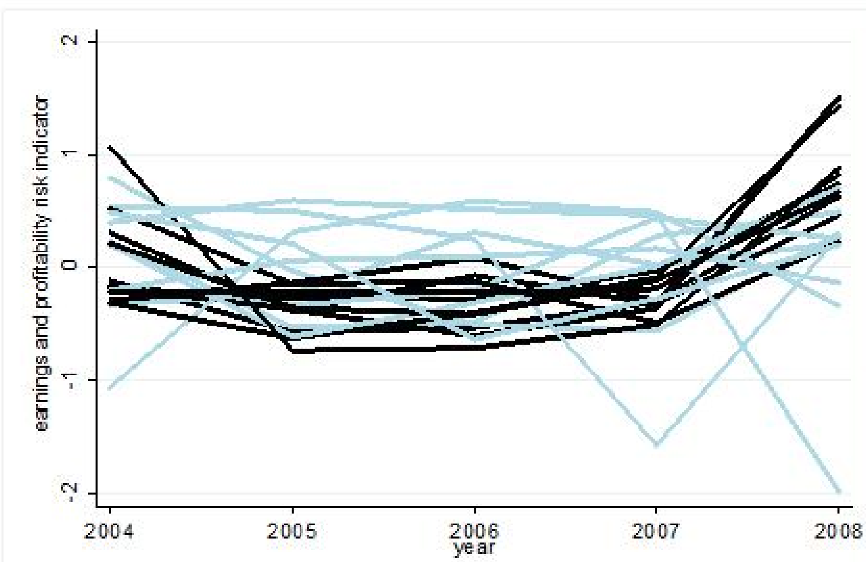
Based on the correlation analysis at the national level in this paragraph, we decide to reduce the number of indicators for the categories asset risk and liquidity risk. Instead of a reduction, one could also think of making another linear combination of indicators. However, infinitely many possibilities for such a combination exist and this spectrum of choices will hardly make a final choice for specific weights less arbitrary. Therefore we use correlations and similarity between indicators as a reasonable argument to obtain risks per category that consist of fewer indicators. Because of their similarity, we omit the share of NPLs and use the share of loan loss provisions to total loans as the indicator for asset risk. For the share of fixed assets and the loan-deposit ratio we have reason to believe that to a certain extent they work in opposite ways and therefore we continue with the other two liquidity indicators.

Graph 6.1. Evolution of asset risk per indicator



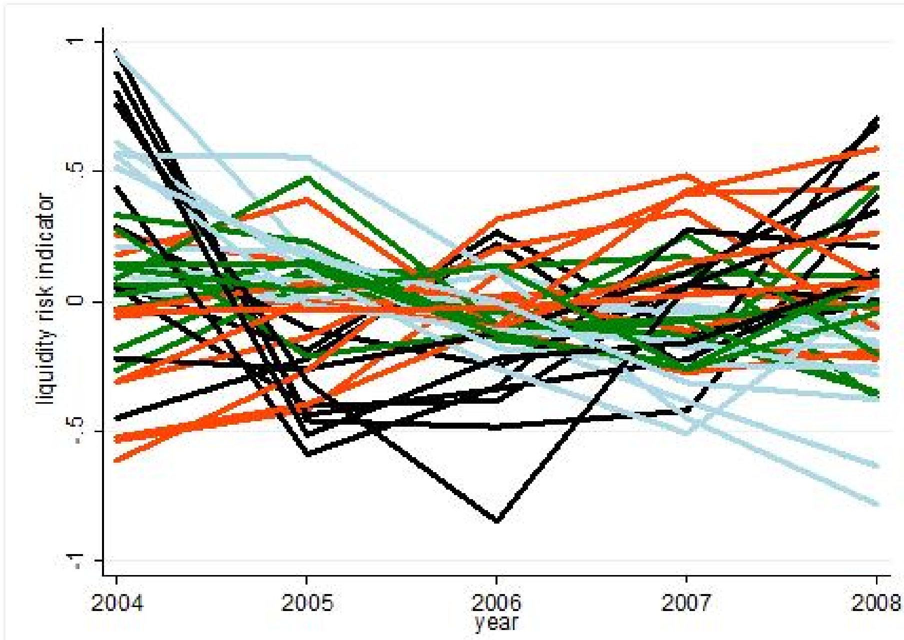
The graph displays standardized developments for asset risk indicators at the national level (obtained using weighted averages). Black lines correspond to the share of loan loss provisions in total loans, light blue lines correspond to the share of NPLs in total loans. Each country from Table 5.2. is represented by one line of each color.

Graph 6.2. Evolution of earnings and profitability risk per indicator



The graph displays standardized developments for earning and profitability risk indicators at the national level (obtained using weighted averages). Black lines correspond to returns on equity, light blue lines correspond to z-scores (both measures are multiplied by minus one so that higher values correspond to higher risk). Each country from Table 5.2. is represented by one line of each color.

Graph 6.3. Evolution of liquidity risk per indicator



The graph displays standardized developments for liquidity risk indicators at the national level (obtained using weighted averages). Black lines correspond to liquid assets relative to total assets (multiplied by minus one so that higher values correspond to higher risk), light blue lines correspond to fixed assets relative to total assets, red-orange lines correspond to total loans relative to total deposits and green lines correspond to the loans that are due to commercial banks over total equity. Each country from Table 5.2. is represented by one line of each color.

Table 6.1. Pearson correlation coefficients between all separate indicators for asset, earnings and liquidity risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) loan loss prov./tot.loans (a)	1.000							
(2) NPLs (a)	**0.599***	1.000						
(3) return on equity (e)	**0.828***	**0.578***	1.000					
(4) z-score (e)	-0.014	-0.029	0.060	1.000				
(5) liq.assets/tot.assets (l)	0.386	0.397	0.381	0.063	1.000			
(6) tot.loans/tot.deposits (l)	0.017	-0.008	-0.127	-0.142	0.153	1.000		
(7) fix.assets/tot.assets (l)	-0.345	-0.157	-0.137	0.056	-0.019	**-0.510***	1.000	
(8) due com.banks/tot.equity (l)	-0.208	-0.214	-0.128	0.008	0.023	-0.290	0.176	1.000

Correlations larger than 0.5 in absolute value are marked in bold and marked with a (*). In column 1, we use (a) for asset risk indicators, (e) for earnings and profitability risk indicators and (l) for liquidity risk indicators.

Table 6.2. Factor loadings for a two-factor model based on eight indicators

variable	factor 1	factor 2	uniqueness
loan loss prov./tot.loans (a)	0.892**	-0.131	0.186
NPLs (a)	0.680**	-0.052	0.534
return on equity (e)	0.875**	-0.101	0.224
z-score (e)	0.034	0.151	0.976
liq.assets/tot.assets (l)	0.468	-0.029	0.780
tot.loans/tot.deposits (l)	-0.028	-0.720**	0.481
fix.assets/tot.assets (l)	-0.212	0.641**	0.544
due to com.banks/tot.equity (l)	-0.177	0.335	0.856

Factor loadings larger than 0.6 in absolurte value are marked with a (**). In column 1, we use (a) for asset risk indicators, (e) for earnings and profitability risk indicators and (l) for liquidity risk indicators.

6.2 Risks per category

Whereas in section 6.1 we focused on the existence of correlations between indicators within the same category, here we shift our focus to the connections that may exist between the different categories. To a great extent, this inter-categorical analysis is similar to the previous intra-categorical analysis. Based on that intra-categorical analysis, we decided to omit three indicators and, as a result, the categories capital risk, asset risk, management risk and sensitivity to market risk here all consist of not more than one indicator. The categories earnings and profitability risk each consist of two indicators which, in both cases, we weigh proportionally to obtain a one-dimensional category indicator. As a first step, we look at plots per category (see Graph 6.4 to 6.9) that we obtained while weighing individual banks for their asset size. These plots show time patterns for every country listed in Table 5.2.

For asset –i.e. credit– risk we observe for every country a risk increase at the outbreak of the global crisis, the period after 2007. For almost all countries, earnings and profitability risk increases in the period 2006-2008. Moreover this is true for capital and liquidity risk –however, difference between these and, especially, credit risk development is that over the other years the sampled countries seem to be more dispersed for as well capital risk as liquidity risk. Management and sensitivity to market risk are most dispersed with regard to the spectrum of values at the beginning and the end of the sample period, as well as in their behavior per country over time. This could, indeed, be a clear hint for unique developments over time per country, but it could also be a suggestion that both risk categories are not easy to quantify. From the literature on this topic we have noticed that the correct measurability of management risk has been widely discussed. Also in our case, we may doubt whether cost efficiency alone is a complete reflection of the true capabilities of management. In this research, we measure bank sensitivity to the market from the relative level of non-balance sheet items. While this may be one aspect of a banks' vulnerability to changes not on the balance sheet, it may not cover all. One can think a bank's sensitivity to interest rate risk, exchange rate risk, stock market risk etc. These are not specifically represented in our measure for sensitivity risk.

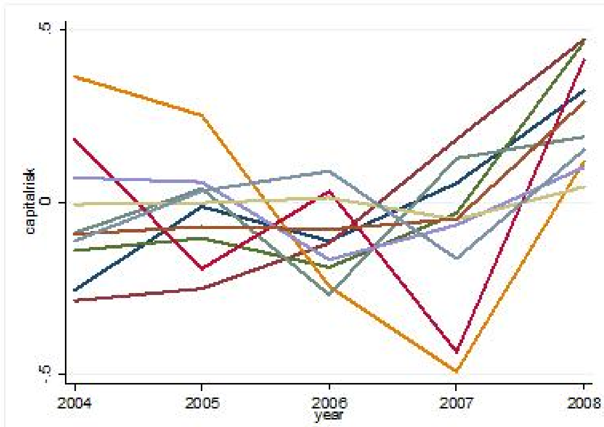
Consistent with previous analysis for 'intra-category' indicators we perform correlation analysis for inter-category risks. The results are displayed in Table 6.3 and reveal especially high correlations between the risk associated with earnings and profits and asset risk, as well as between earnings and profits and management risk. Considering the difficulties involved with the measurement of management risk, it may be uncertain whether the correlation between management and earnings risk is indeed a correct representation of a general relationship. In the case of the correlation between credit risk and earnings and profit risk, balance-sheet indicators have wider acceptance as useful risk indicators. This acceptation gives a stronger foundation to the existence of a plausible relationship.

Table 6.3. Pearson correlation coefficients between capital, asset, management, earnings, liquidity and sensitivity to market risk

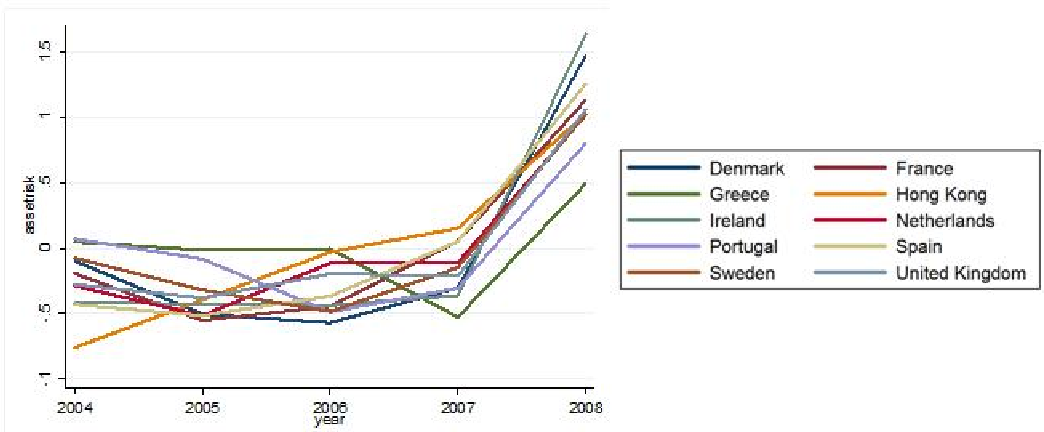
	(1)	(2)	(3)	(4)	(5)	(6)
capital risk (1)	1.000					
asset risk (2)	0.478	1.000				
management risk (3)	0.278	0.350	1.000			
earnings risk (4)	0.350	0.569*	0.554*	1.000		
liquidity risk (5)	0.292	0.258	0.103	0.242	1.000	
sensitivity to market risk (6)	-0.133	-0.135	-0.152	-0.135	0.116	1.000

Correlations larger than 0.5 in absolute value are marked with a (*).

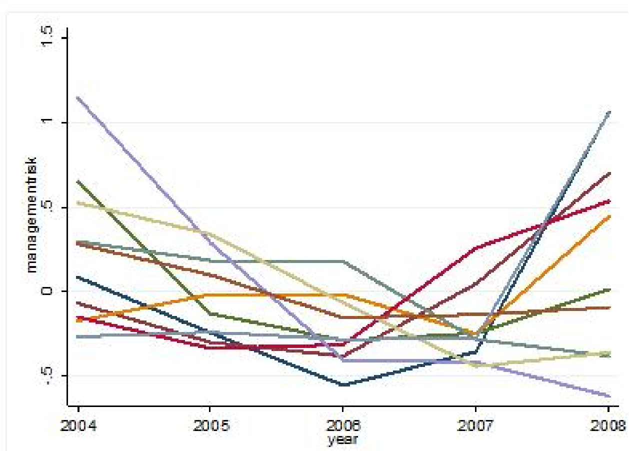
Graph 6.4. Evolution of capital risk for each of the ten countries in our sample



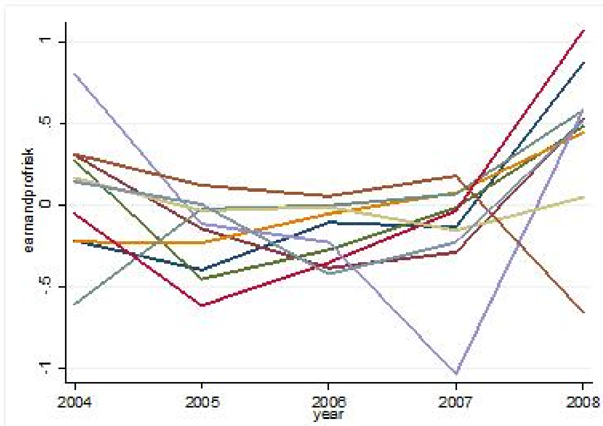
Graph 6.5. Evolution of asset risk for each of the ten countries in our sample



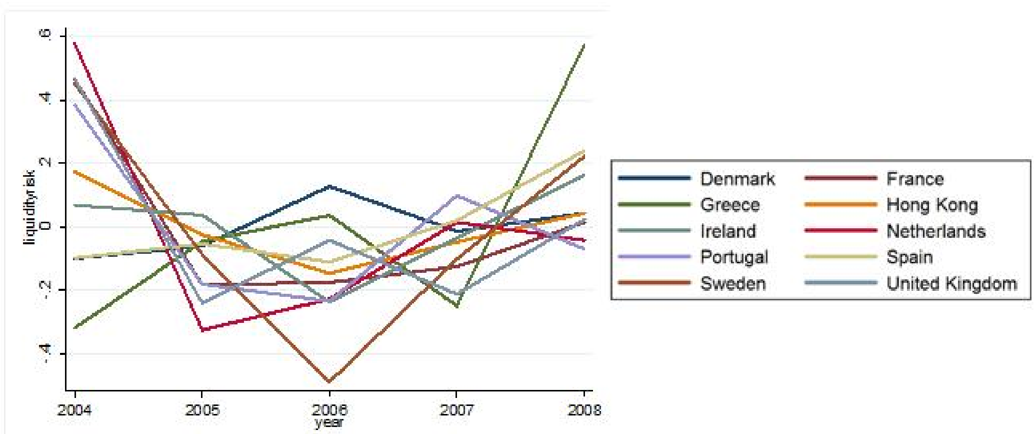
Graph 6.6. Evolution of management risk for each of the ten countries in our sample



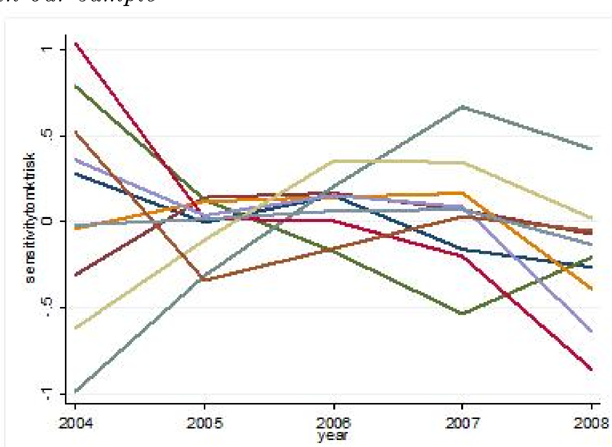
Graph 6.7. Evolution of earnings and profitability risk for each of the ten countries in our sample



Graph 6.8. Evolution of liquidity risk for each of the ten countries in our sample



Graph 6.9. Evolution of sensitivity to market risk for each of the ten countries in our sample



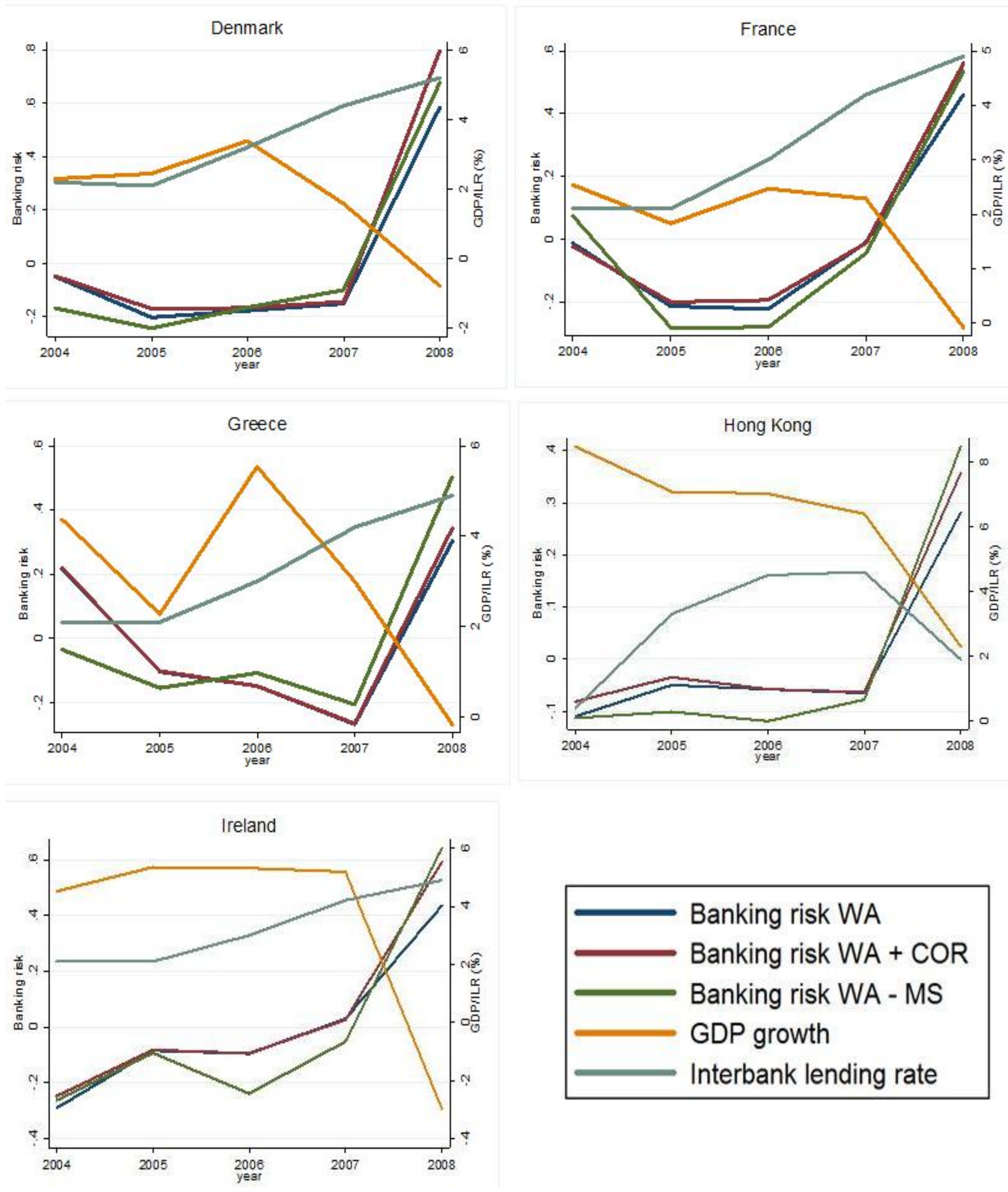
6.3 One-dimensional indication for bank sector risk

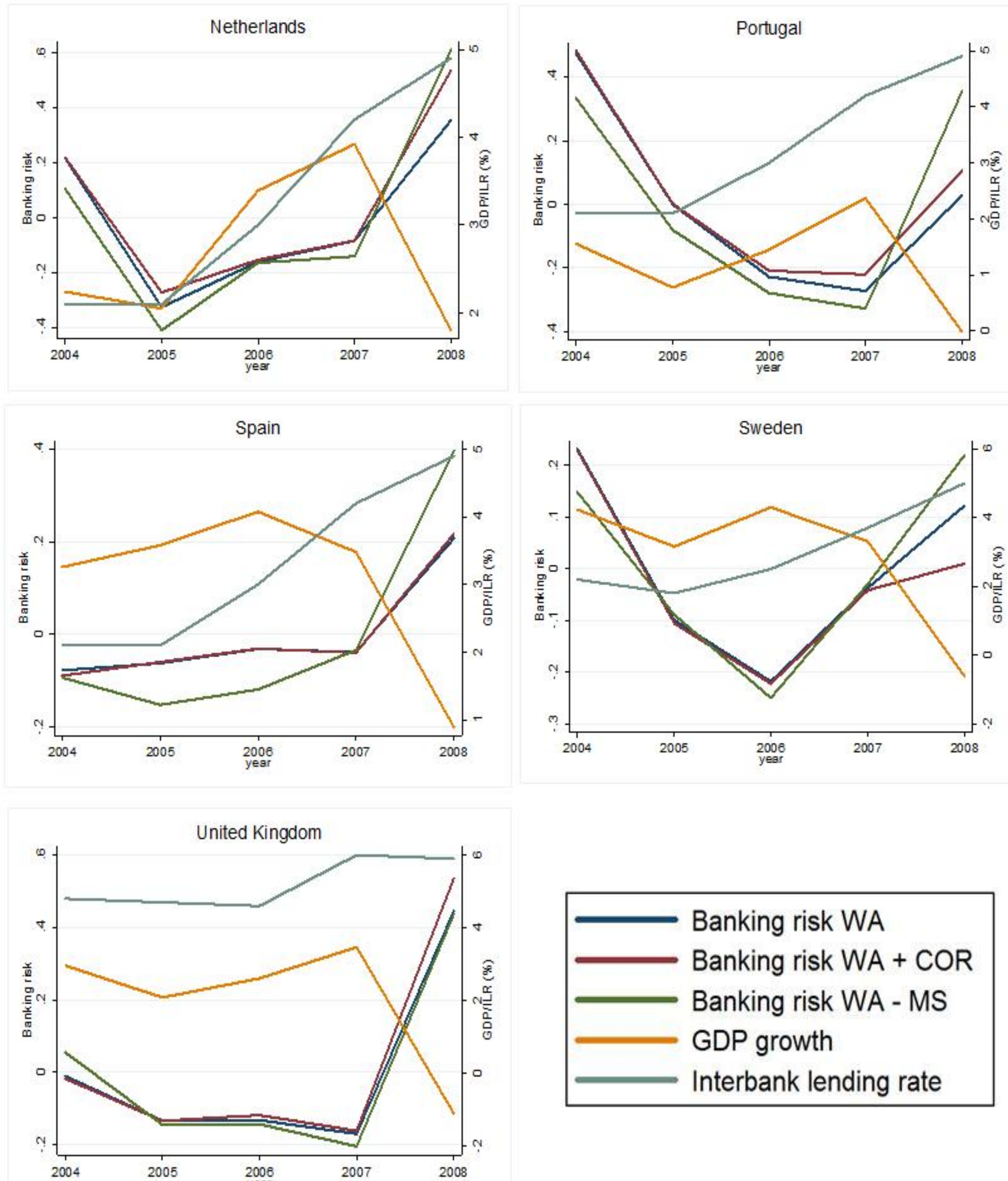
In section 5 we introduced the concept of a one-dimensional bank risk indicator. Using the two methods described in that section, we aim to construct one-dimensional risks over time. In order to project these risks on the economic environment over the sample period of 2004-2008, we use GDP growth as an indication for domestic economic development in general and interbank rates as an indication for the domestic bank sector in particular. In Graph 6.10, we present plots over time for each of the countries from Table 5.2. We use the asset-weighed approach from section 5 and obtain categorical indicators as we did in section 6.2. These indicators per category we aggregate in three different ways. First, we give proportional weight to each of the six CAMELS categories and aggregate as such (plotted as Banking risk WA). A second way is to weigh again all six risk categories proportionally, but to add a cross term including asset risk and earnings and profitability risk (plotted as 'Banking risk WA + COR'). Previously in this section we noticed that a correlation between these two types of risk may be relevant to include. We include the additional cross-term in a way similar to the extra correlation term in the FTK risk formula discussed in section 5. As a third way to aggregate, we again weigh categories proportionally, but we do so while only considering the four categories capital risk, asset risk, earning and profitability risk and liquidity risk. From the bank risk literature we have reason to at least doubt the correctness and completeness of balance-sheet based indicators for the categories management and sensitivity to market risk and therefore leave these two out (plotted as Banking risk WA – MS).

Our data period covers the pre-crisis period of 2004-2008, with the years 2007-2008 at the start of the global credit crisis (see Laeven and Valencia (2012)) as most interesting from an economic shock point of view. In all of the ten countries, we observe a decreasing and occasionally negative GDP growth and increasing interbank lending rates across the period 2007-2008. We find it plausible that any of our aggregated risk constructs, for each country, rises steeply from the start of the crisis in 2007. The three constructs also consistently assign average or low levels of risk in the domestic bank sector for the pre-crisis years of 2005, 2006 and 2007.

Under the condition that a bank at least holds ten per cent of the assets of the domestic bank sector, we determine the bank with the riskiest score on the asset risk indicator loan loss provision over total loans. The choice for a credit measure is based on the criteria that –from sections 6.1 and 6.2– it seems related to other risk measures and on the prominent role that credit risk played in the 2007 global financial crisis. For a complete overview of the results per country from this minimum-maximum approach, we refer to Appendix E. Mainly we find also for this method a steep increase for bank sector risk at the outbreak of the global crisis in every country. In the year before the crisis, almost half of the countries in the sample have a higher than average risk score. This is not the case for the weighted asset methods, which assign below average scores to all domestic banks sectors in the years 2006 and 2007.

Graph 6.10. Bank risk evolution per country





The graphs show the development of banking risk over the period 2004-2008 per country. Weighted for bank asset size, banking risk is constructed in three different ways: using proportional weights and all six CAMELS categories (Banking risk WA), similarly but including a cross term for asset and earnings risk (Banking risk WA + COR) and using proportional weights for only the CAEL categories (Banking risk WA – MS). Banking risk is plotted on the left y-axis; GDP growth and interbank rate on the right y-axis.

6.4 An assessment of one-dimensional bank risk indicators

In section 6.3 we presented one-dimensional bank risk constructs that we obtained using different methods. Here we provide a further analysis of the differences that appear between these one-dimensional constructs.

From as well the asset-weighed as the min-max method (see the compared results in Graph E.1) we obtained increasing risk patterns at the outbreak of the global financial crisis. Although we find this a plausible observation, both methods also reveal differences. Main difference is the range in which bank risk outcomes lie. Whereas for any country the high-low spread[15] is never larger than 0.8 in the case of using weighted aggregates, this outcome spread sometimes even exceeds three in the minimum-maximum approach (see results per country in Table E.1). Accordingly we calculate standard deviations and find that, for almost any country, the volatility of outcomes is more than a factor two higher in the minimum-maximum case than in the weighed asset case (see results per country in Table E.1). The larger spreads and deviations are not surprising from the point of view that the minimum-maximum method only uses one bank to construct a national indicator and that, as a consequence, it only takes one bank to change the national outcome. While this is a good explanation for the higher sensitivity, it also indicates that a large part of the information in the dataset is not regarded and evidently not used to obtain the result. It is questionable if this unused part of the data does not at all contain information that could be useful.

Another comparison to make is between the three weighted bank risk constructs in Graph 6.10. One measure uses data on all CAMELS categories, a second one uses all of these categories including a correlation term between asset and earnings risks and a third measure only uses the CAEL categories (not using management and sensitivity risk). From our results, we observe little difference between using all categories and adding a correlation term. For every country in all years, these two constructs are increasing or decreasing simultaneously and moreover below or above average (the zero line) consistently. This general consistency does not hold true for the two in comparison with the CAEL indicator. The CAEL indicator shows increasing risk in Greece (2005-2006), Hong Kong (2006-2007) and Spain (2006-2007) when the two other indicators show a decreasing risk pattern. At the time of these events, interbank lending rates are in all cases rising, which may occur at times of lower trust within the domestic banking system. We also looked at the cases in which interbank rates are increasing and GDP growth falls by more than one per cent. These events especially occur around the outbreak of the crisis –a negative shock that has been documented as a banking crisis for many of the countries in our sample (see also Laeven and Valencia (2012)). In almost all of these cases, the CAEL indicator shows a steeper risk increase than the other two weighted indicators, which suggests that it responds more sensitive to such an economic shock. This could be a desired property to detect bank crises of such an impact.

[15] With the high-low spread we mean, for every country, the highest bank risk value minus the lowest bank risk value during the time period 2004-2008.

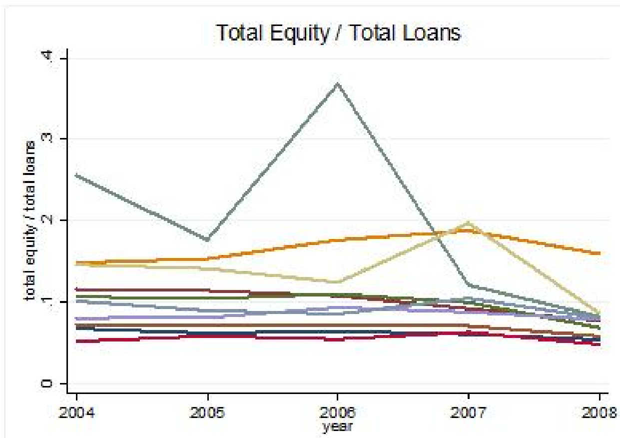
6.5 Non-standardized indicators

In the previous of this results section, we have looked at indicators that were standardized. In order not only to compare countries by the pattern of risks but moreover by the magnitude of risks, we use this part to look at non-standardized risks. A disadvantage of that approach is that indicators that are measured on different scales are not easily aggregated anymore. A practical approach then is to choose one indicator per category as a representative for the entire category. This is expressed by the World Bank (2012, p. 24) as: "to pick among competing variables." The World Bank (2012) emphasizes it is useful to pick one of the variables per category –which essentially means giving zero weight to all non-included variables and prevents one from choosing arbitrary weights. The World Bank (2012) suggests as a general approach to select indicators that are widely available and have a clearly documented economic link in the literature. We use this criterion to determine our selection of indicators –one per CAMELS category– displayed in Graphs 6.11 to 6.16. As before, assigning weights to banks based on their asset size is useful as a way to aggregate to a country level. Analysis per indicator then reveals a country's performance relative to others.

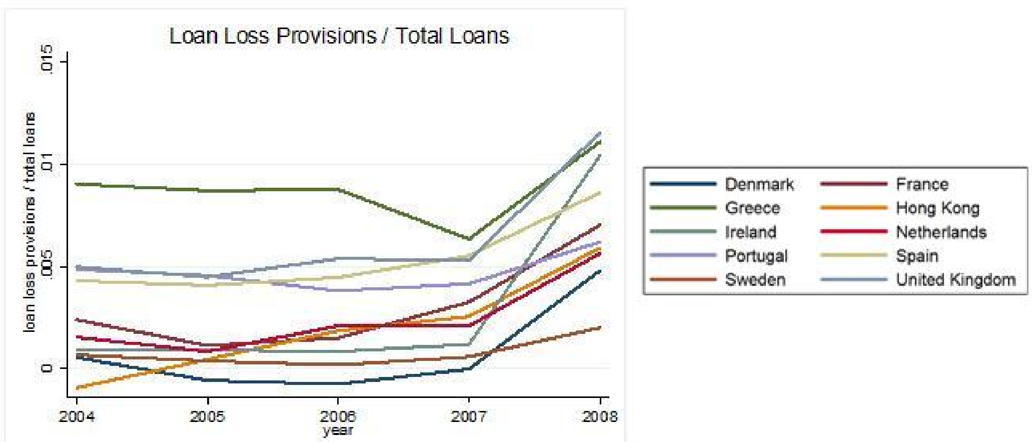
From Graph 6.11 we observe relatively flat solvency patterns over time for most countries with at most a slight decrease for all countries towards the end of the period. An exception is the only non-European country in the sample, Hong Kong, which seems to maintain a structurally higher solvency level than the others. Remarkable is also that The Netherlands have the lowest capital position of all countries, indicating a low capital position for Dutch banks across 2004-2008. The peak that occurs in the case of Ireland can be attributed to a peculiarity on the balance sheet of a single bank, which as a result of the low number of Irish banks in our dataset has a relatively large influence. An increase in equity in 2006 followed by an increase in total loans only in 2007 suggests the acquisition of extra capital but with a delay in the expansion of business. For all countries, Graph 6.12 shows increasing loan loss provision levels after the start of the global credit crisis. The Greek bank sector has the highest level of provisions compared to the magnitude of its total portfolio of loans outstanding. Worth noting is that Denmark and Hong Kong even have slightly negative provision shares some years before the crisis. The accounting background why this is theoretically possible is not in the scope of this thesis, but mostly the event is a signal that expected losses on both countries' credit portfolio are very low at those points in time.

Previously in this thesis we discussed whether or not issues may arise when aiming to capture management risk from balance sheet data. Regardless of that discussion, we generally observe rising cost levels for banks at the start of the crisis in Graph 6.13. In general we observe Hong Kong –the only non-European country in this research– to have the relatively most efficient bank sector. The Netherlands and France seem to be structurally high in costs. Graph 6.14 displays the income generating capacity per domestic bank sector. During the pre-crisis period until 2007, return on equity levels appear relatively constant. After that, these levels fall in a way that seems somewhat related to cost efficiency from Graph 6.13 as also here France, The Netherlands and the United Kingdom seem to be hurt most at the start of the crisis. Hong Kong maintains the highest return on equity levels also at the outbreak of the global crisis. A possible explanation for this could be that the Asian financial market was relatively less exposed to the initially hit North-American market at the outbreak of the crisis than the European market was. For all countries, we observe from Graph 6.15 highest domestic bank sector liquidity levels in the period 2004-2006. Structurally low are Spain, Portugal and Ireland, with Greek liquidity levels rapidly declining to similar levels. For the years preceding the crisis, Graph 6.16 shows lowest relative off-balance sheet item levels for The Netherlands, France and Greece. Highest exposures of non-balance sheet items are in the United Kingdom and Hong Kong.

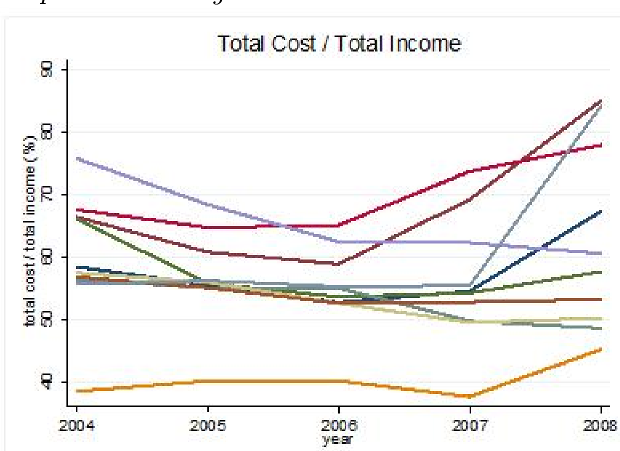
Graph 6.11. Capital risk – equity relative to loans



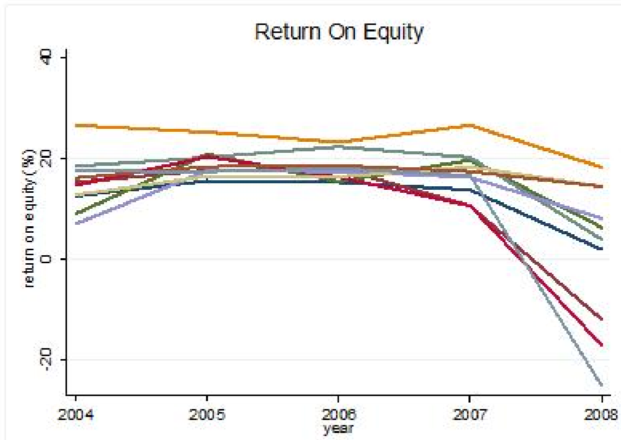
Graph 6.12. Asset risk – loan loss provisions relative to loans



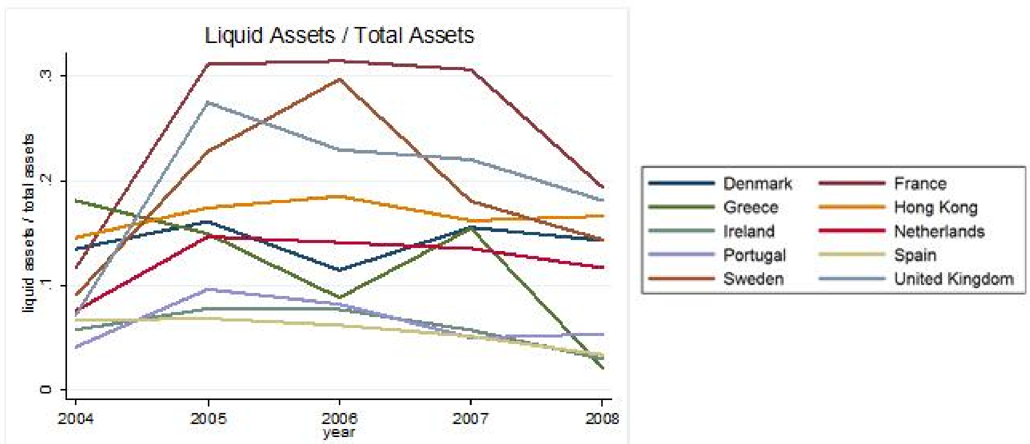
Graph 6.13. Management risk – costs relative to income



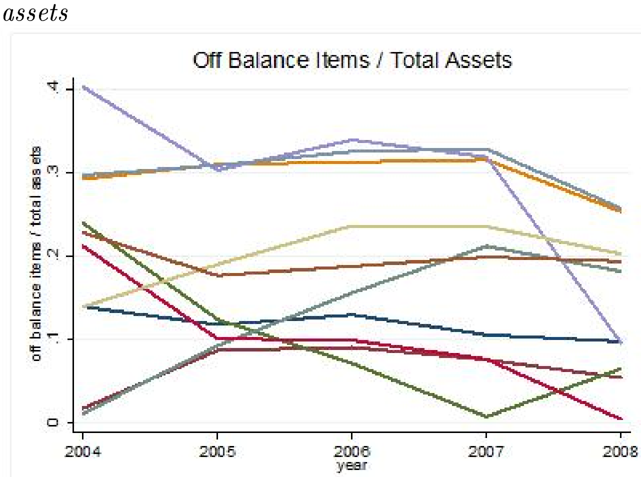
Graph 6.14. Earnings and profitability risk – returns relative to equity



Graph 6.15. Liquidity risk – liquid assets relative to total assets



Graph 6.16. Sensitivity to market risk – non-balance sheet items relative to assets



From the non-standardized plots in Graph 6.11 to 6.16 we looked at the development of ratios per country and compared these developments between countries. The observations give further insight into a country's relative position per risk category, but increasingly we would find it interesting to see whether a country's performance with respect to some ratio is also telling something about its performance on some other ratio (for the ones discussed in this paragraph). And if so, this may be the case for a certain moment in time but not for all years. To check for this, we compare indicator correlations for separate years in our sample. For a complete overview of the results, we refer to Appendix F.

From Graph 6.13 and Graph 6.14 we noticed to some extent similarities between management and earnings and profitability risk. Correlations between both risk indicators are in absolute value larger than 0.5 in every sample year. In addition to the discussion about the correctness of measuring management risk from balance sheet data, this is a suggestion that costs relative to income could probably as well be an earnings and profitability measure as a representation of management quality.[16] In all years we find a consistently negative correlation between the indicators for capital and management risk which may point at a similar issue. Also persistent over years is a positive correlation –in all cases larger than 0.4– between capital and earnings and profitability risk. From an economic view point, the interpretation for this could be that bank sectors with on average a better return also have better solvency positions, and vice versa. In other cases, yearly correlations do not appear consistent in sign or are small in magnitude. A remark we make is the fact that we have no more than ten countries available observed for only five years. An improvement on the analysis presented here would be a sample including more countries and more years observed.

[16]Efficiency may serve as a characteristic of management quality, however a case as e.g. the 2007 ABN Amro takeover (see as well section 2.1) provides a clear indication that cost efficiency is likely not the only determinant of a bank's management quality and that there can as well be important other indicators that reveal a bank management's grip on long term soundness.

7 Conclusion and discussion

In this thesis we have reviewed the literature on balance sheet-based indicators for risk exposure of individual banks and analyzed a database consisting of such balance sheet information. We constructed a selected set of indicators and find that certain indicators rank individual banks similarly. Moreover we check which indicators explain the majority of variance in the data sample and use this criterion together with similarity in rankings to obtain a more narrow set of indicators. From here on, we increasingly take a country level perspective and decide whether our data –at the domestic bank sector level– is sufficiently representative compared to World Bank and European Central Bank statistics. For a selected set of ten countries on eleven standardized indicators we then apply two simple aggregation methods to obtain indicators at a national level. We compare the evolution of these aggregated measures over time and decide from correlation analysis to further reduce our analysis to eight indicators. Based on the two methods we obtain domestic bank sector risk evolutions over the period 2004-2008 and plot these in a simple framework of domestic macro-economic developments over time. For each country, all of our methods show an increase of bank sector risk from below average to above average after the outbreak of the global credit crisis in 2007. Depending on the exact method used, risk in the pre-crisis period until 2006 is moderately declining at levels that lie below average. In the last part of section 6, we observe non-standardized indicator results that –instead of a country's position in its own domestic macro-economic environment– indicate a country's relative position to others with respect to particular indicators. Globally, we observe increasing loan loss provision and cost levels, declining equity returns, solvency levels and liquid asset shares. As noticed earlier on in this thesis, we find the cost efficiency-measure used as an indicator for management risk to correlate strongly with earnings and profitability risk. Including cost efficiency risk does not necessarily spoil an aggregated risk analysis, but it might however raise the question whether cost efficiency is a correct indicator for the term management quality. An issue of this kind could also arise for sensitivity to market risk, which we proxy by means of the relative off-balance size share. Larger off-balance exposure (from guarantees, financial derivatives etc.) we associate with increasing sensitivity risk, however this does not mean that all kinds of financial market risks (e.g. exchange rate risk, interest rate risk) are covered this way. The observation of declining off-balance risks after the outbreak of the crisis could imply that banks decreased their off-balance shares, or that the measure at least not fully captures the term sensitivity to market risk.

The aggregation methods used in this thesis aim to aggregate individual observations into national indicators. Both methods described in section 5 are straightforward to use, yet different in their approach. A weighted average approach makes use of all observations whereas a minimum-maximum method only picks a specific, single observation to be used. Implicit to this second strategy is to throw part of the data away, which loss of information may be too extreme for a stand-alone method and therefore could support the idea to use this technique only as a complement to a weighted average approach. In addition, we use three different weighted asset approaches between which we observe slight differences. Its higher shock sensitivity and increasing risk patterns before the crisis can be interpreted as first reasons to prefer the indicator we construct without using the categories management and sensitivity risk over the other two approaches. This thesis provides a brief analysis of observations, but in a framework with a longer data horizon, more countries and using more sophisticated macro-economic indicators (e.g. the number of bank failures and bank mergers per country per year) the different bank risk constructs could more usefully be tested and compared. In such a –regression– model one could also think of including several domestic macro-economic indicators not specific to the bank sector such as inflation, GDP development and exchange rates as control variables.[17]

Regardless of which aggregation method is used, we perform our analysis conditional on the data that is available. Missing data does not only contrast with classic econometric assumptions, moreover it is a limitation to our research. A greater availability of data from Bankscope could as well lead to a better bank sector coverage per country as the incorporation of more countries in this analysis. A practical limitation is that the availability of data from a private institution as Bankscope is not costless. Another limitation is that we do not have complete insight in the decomposition of balance sheet indicators. Such a decomposition would allow to completely distinguish between national bank sectors and it can be useful to find explanatory backgrounds to specific indicator developments. Central banks have both complete national coverage and decomposition of bank balance sheets which they involve in their analysis. Another improvement to this research would be to reduce the time step between data points. Balance sheet data is static by nature, but the more continuous the monitoring (e.g. monthly) the more accurate and up-to-date the risk assessment of a bank sector. A more accurate assessment could also be achieved from additional –qualitative– analysis. Here one can think of a strategy or management assessment, which to a large extent determine the business environment in which a bank operates.

The results obtained in section 6 of this thesis show plausible patterns in relation to the time period and the economic environment with which they arise. As far as we know, this is one of the first researches that uses micro-level bank data to obtain macro-level indicators, which we then use for comparative analysis between domestic bank sectors. Such an approach especially continues upon IMF efforts as those made in "The Compilation Guide" (2006). Last, we add to this research discussion that an extension of the data horizon would greatly improve upon the short pre-crisis period setting here. Under a larger horizon, different time periods and different economic shocks[18] may be compared

[17]For an example of a research including control variables in a regression model, see Klomp and De Haan (2012).

and, not least important, it could enhance testability of the different balance-based aggregation methods. With a longer data period and the use of other, perhaps more sophisticated macro-economic indicators than the two presented here, one could frame a model setting under which the fit of one-dimensional risk representations with the domestic macro-economic environment could be tested. Such a model may be useful also for macro-economic predictions.

[18] In addition to observing economic shocks over time, one could also perform stress tests which "attempt to find exposures that are latent, i.e. not obvious from the analysis of financial soundness indicators" (from Čihák (2005, p. 420)). Such a stress testing procedure aims to do sensitivity and scenario analysis based on exceptional, but plausible, shocks to financial soundness indicators. A recent example of such a stress testing framework using bank balance sheet data is in the paper by Schmieder, Puhr and Hasan (2011).

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Appendix A

We know that for a pair of variables we can calculate the Pearson correlation r as

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{[\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2]^{0.5}} \tag{14}$$

where $x_i$and $y_i$are the actual variable values and $\bar{x}$ and $\bar{y}$ the sample means, respectively. We calculate the Spearman (1904) correlation coefficient r_s similarly, but now we replace actual values in (14) by ranks.

We calculate Kendall (1938) correlation coefficients τ as

$$\tau = \frac{n_c - n_d}{\frac{1}{2}n(n-1)} \tag{15}$$

where n_c denotes the number of concordant pairs, i.e. a pair is concordant when both on indicator A and B observation X is consistently ranked higher or lower than observation Y. n_d denotes the number of discordant pairs, where a discordant pair is characterized by non-consistence in ranking between X and Y on indicator A and B. n dedenotes the number of paired observations.

Table A.1. Spearman rank correlation coefficients between all measures defined in Table 3.2 using the mean per bank

	(1)	(2)	(3)	(4)	(5)	(6)	)7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
z-score (1)	1.000																	
NPLs (2)	-0.257	1.000																
net interest margin (3)	-0.048	0.268	1.000															
tot.equity/tot.assets (4)	0.295	0.010	**0.683***	1.000														
total capital ratio (5)	0.122	-0.085	0.469	**0.755***	1.000													
tot.equity/tot.loans (6)	0.052	0.065	**0.522***	**0.810***	**0.767***	1.000												
loan loss prov./tot.loans (7)	-0.242	0.451	**0.544***	0.187	0.064	0.162	1.000											
tot.loans/tot.equity (8)	-0.045	-0.077	**-0.517***	**-0.789***	**-0.757***	**-0.970***	-0.158	1.000										
tot.cost/tot.income (9)	-0.349	0.135	0.112	-0.001	0.047	0.111	0.082	-0.093	1.000									
overh.costs/tot.assets (10)	-0.159	0.284	**0.820***	**0.605***	0.422	**0.533***	0.473	**-0.517***	0.491	1.000								
return on equity (11)	-0.076	0.059	0.040	-0.230	-0.197	-0.142	-0.007	0.136	-0.389	-0.049	1.000							
return on assets (12)	0.217	0.071	**0.562***	**0.587***	0.451	**0.520***	0.107	**-0.531***	-0.360	0.382	**0.518***	1.000						
net int.margin/tot.income (13)	0.101	-0.001	**0.696***	**0.658***	**0.517***	**0.507***	0.231	-0.489	0.213	**0.634***	-0.199	0.378	1.000					
liq.assets/tot.assets (14)	-0.169	0.070	0.207	0.257	0.300	0.434	0.037	-0.417	0.166	0.280	0.015	0.213	0.196	1.000				
tot.loans/tot.deposits (15)	0.158	-0.015	0.004	-0.008	-0.248	-0.370	0.111	0.389	-0.132	-0.056	-0.071	-0.119	-0.053	-0.335	1.000			
fix.assets/tot.assets (16)	0.110	0.160	0.294	0.130	-0.058	0.008	0.339	-0.007	0.100	0.309	-0.027	0.046	0.153	-0.215	-0.020	1.000		
due to com.banks/tot.equity (17)	-0.382	0.054	-0.445	**-0.594***	**-0.522***	-0.411	-0.044	0.439	0.023	-0.346	0.105	-0.432	-0.472	0.011	-0.056	-0.117	1.000	
off-balance items/tot.assets (18)	0.287	-0.047	-0.185	-0.102	-0.111	-0.070	-0.064	0.068	-0.188	-0.192	0.139	0.042	-0.262	-0.065	-0.064	-0.015	0.002	1.000

Correlation coefficients larger than 0.5 in absolute value are in bold and marked with a (*).

Table A.2. Spearman rank correlation coefficients between all measures defined in Table 3.2 using the median per bank

	(1)	(2)	(3)	(4)	(5)	(6)	)7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
z-score (1)	1.000																	
NPLs (2)	-0.231	1.000																
net interest margin (3)	-0.081	0.245	1.000															
tot.equity/tot.assets (4)	0.298	0.012	**0.665***	1.000														
total capital ratio (5)	0.169	-0.087	0.453	**0.758***	1.000													
tot.equity/tot.loans (6)	0.072	0.035	0.492	**0.807***	**0.755***	1.000												
loan loss prov./tot.loans (7)	-0.257	0.434	**0.568***	0.175	0.057	0.143	1.000											
tot.loans/tot.equity (8)	-0.072	-0.036	-0.492	**-0.806***	**-0.755***	**-1.000***	-0.144	1.000										
tot.cost/tot.income (9)	-0.318	0.146	0.120	-0.014	0.020	0.077	0.074	-0.076	1.000									
overh.costs/tot.assets (10)	-0.198	0.271	**0.809***	**0.586***	0.406	**0.500***	0.471	-0.499	**0.502***	1.000								
return on equity (11)	-0.150	-0.032	-0.050	-0.317	-0.275	-0.209	0.044	0.212	-0.401	-0.117	1.000							
return on assets (12)	0.217	0.040	**0.542***	**0.625***	0.463	**0.560***	0.184	**-0.557***	-0.372	0.380	0.426	1.000						
net int.margin/tot.income (13)	0.049	0.054	**0.706***	**0.685***	**0.546***	**0.523***	0.223	**-0.519***	0.266	**0.665***	-0.338	0.360	1.000					
liq.assets/tot.assets (14)	-0.201	0.085	0.140	0.186	0.247	0.397	0.009	-0.396	0.168	0.229	0.046	0.197	0.129	1.000				
tot.loans/tot.deposits (15)	0.177	-0.005	-0.013	-0.033	-0.269	-0.416	0.073	0.418	-0.126	-0.064	-0.043	-0.125	-0.081	-0.355	1.000			
fix.assets/tot.assets (16)	0.117	0.148	0.280	0.090	-0.058	-0.033	0.328	0.033	0.129	0.273	-0.095	0.050	0.118	-0.209	-0.021	1.000		
due to com.banks/tot.equity (17)	-0.371	0.030	-0.475	**-0.630***	**-0.545***	-0.447	-0.101	0.447	-0.003	-0.386	0.195	-0.398	-0.487	0.037	-0.023	-0.144	1.000	
off-balance items/tot.assets (18)	0.297	-0.112	-0.219	-0.122	-0.081	-0.080	-0.040	0.080	-0.208	-0.227	0.133	0.024	-0.303	-0.060	-0.042	0.051	0.034	1.000

Correlation coefficients larger than 0.5 in absolute value are in bold and marked with a (*).

Table A.3. Kendall rank correlation coefficients between all measures defined in Table 3.2

	(1)	(2)	(3)	(4)	(5)	(6)	)7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
z-score (1)	1.000																	
NPLs (2)	-0.123	1.000																
net interest margin (3)	-0.109	0.232	1.000															
tot.equity/tot.assets (4)	0.125	0.053	**0.500***	1.000														
total capital ratio (5)	0.006	-0.023	0.268	**0.526***	1.000													
tot.equity/tot.loans (6)	0.000	0.056	0.375	**0.641***	**0.570***	1.000												
loan loss prov./tot.loans (7)	-0.131	0.319	0.362	0.124	0.059	0.081	1.000											
tot.loans/tot.equity (8)	0.000	-0.056	-0.375	**-0.641***	**-0.570***	**-1.000***	-0.081	1.000										
tot.cost/tot.income (9)	-0.182	0.093	0.049	-0.007	0.022	0.055	0.019	-0.055	1.000									
overh.costs/tot.assets (10)	-0.148	0.232	**0.639***	0.424	0.258	0.369	0.308	-0.369	0.346	1.000								
return on equity (11)	-0.043	0.012	0.046	-0.118	0.133	-0.067	-0.023	0.067	-0.282	-0.030	1.000							
return on assets (12)	0.105	0.054	0.391	0.424	0.242	0.360	0.048	-0.360	-0.263	0.246	0.449	1.000						
net int.margin/tot.income (13)	-0.041	0.094	0.486	0.469	0.313	0.357	0.134	-0.357	0.118	0.445	-0.094	0.297	1.000					
liq.assets/tot.assets (14)	-0.124	0.032	0.074	0.098	0.151	0.257	-0.009	-0.257	0.116	0.153	0.039	0.086	0.064	1.000				
tot.loans/tot.deposits (15)	0.082	-0.024	0.053	0.042	-0.121	-0.233	0.099	0.233	-0.068	0.009	-0.059	-0.034	-0.004	-0.238	1.000			
fix.assets/tot.assets (16)	0.137	0.051	0.135	0.088	-0.043	-0.030	0.108	0.030	0.057	0.141	-0.061	0.036	0.094	-0.166	0.029	1.000		
due to com.banks/tot.equity (17)	-0.143	-0.023	-0.302	-0.420	-0.322	-0.312	-0.091	0.312	0.038	-0.242	0.021	-0.280	-0.271	0.031	-0.106	-0.059	1.000	
off-balance items/tot.assets (18)	0.180	-0.104	-0.156	-0.083	-0.055	-0.055	-0.061	0.055	-0.126	-0.150	0.091	0.024	-0.163	0.015	-0.060	-0.028	0.010	1.000

Correlation coefficients larger than 0.5 in absolute value are in bold and marked with a (*).

Table A.4. Kendall rank correlation coefficients between all measures defined in Table 3.2 using the mean per bank

	(1)	(2)	(3)	(4)	(5)	(6)	)7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
z-score (1)	1.000																	
NPLs (2)	-0.176	1.000																
net interest margin (3)	-0.033	0.182	1.000															
tot.equity/tot.assets (4)	0.203	0.007	0.499	1.000														
total capital ratio (5)	0.081	-0.060	0.315	**0.583***	1.000													
tot.equity/tot.loans (6)	0.034	0.044	0.382	**0.656***	**0.588***	1.000												
loan loss prov./tot.loans (7)	-0.162	0.323	0.392	0.126	0.044	0.108	1.000											
tot.loans/tot.equity (8)	-0.030	-0.052	-0.377	**-0.643***	**-0.582***	**-0.925***	-0.108	1.000										
tot.cost/tot.income (9)	-0.231	0.094	0.074	-0.003	0.029	0.073	0.054	-0.061	1.000									
overh.costs/tot.assets (10)	-0.110	0.197	**0.644***	0.429	0.286	0.385	0.335	-0.372	0.348	1.000								
return on equity (11)	-0.063	0.045	0.023	-0.162	-0.143	-0.101	-0.003	0.096	-0.273	-0.040	1.000							
return on assets (12)	0.144	0.049	0.415	0.439	0.326	0.391	0.070	-0.396	-0.254	0.279	0.373	1.000						
net int.margin/tot.income (13)	0.066	-0.001	**0.501***	0.471	0.348	0.340	0.156	-0.327	0.142	0.445	-0.140	0.251	1.000					
liq.assets/tot.assets (14)	-0.118	0.051	0.142	0.174	0.204	0.300	0.024	-0.288	0.112	0.190	0.011	0.146	0.123	1.000				
tot.loans/tot.deposits (15)	0.104	-0.010	-0.007	-0.002	-0.162	-0.264	0.079	0.278	-0.094	-0.056	-0.044	-0.085	-0.034	-0.233	1.000			
fix.assets/tot.assets (16)	0.071	0.109	0.204	0.095	-0.035	0.012	0.242	-0.011	0.070	0.218	-0.016	0.031	0.105	-0.150	-0.016	1.000		
due to com.banks/tot.equity (17)	-0.269	0.036	-0.303	-0.429	-0.361	-0.285	-0.031	0.306	0.016	-0.230	0.072	-0.295	-0.322	0.010	-0.037	-0.081	1.000	
off-balance items/tot.assets (18)	0.188	-0.027	-0.135	-0.072	-0.081	-0.052	-0.044	0.050	-0.132	-0.142	0.104	0.024	-0.180	-0.047	-0.038	-0.017	0.002	1.000

Correlation coefficients larger than 0.5 in absolute value are in bold and marked with a (*).

Table A.5. *Kendall rank correlation coefficients between all measures defined in Table 3.2 using the median per bank*

	(1)	(2)	(3)	(4)	(5)	(6)	)7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
z-score (1)	1.000																	
NPLs (2)	-0.156	1.000																
net interest margin (3)	-0.056	0.169	1.000															
tot.equity/tot.assets (4)	0.204	0.007	0.485	1.000														
total capital ratio (5)	0.113	-0.061	0.301	**0.575***	1.000													
tot.equity/tot.loans (6)	0.052	0.027	0.363	**0.657***	**0.573***	1.000												
loan loss prov./tot.loans (7)	-0.172	0.306	0.413	0.123	0.039	0.103	1.000											
tot.loans/tot.equity (8)	-0.052	-0.028	-0.363	**-0.656***	**-0.573***	**-0.999***	-0.104	1.000										
tot.cost/tot.income (9)	-0.209	0.104	0.080	-0.012	0.010	0.051	0.046	-0.050	1.000									
overh.costs/tot.assets (10)	-0.135	0.191	**0.630***	0.413	0.270	0.362	0.334	-0.361	0.357	1.000								
return on equity (11)	-0.111	-0.022	-0.043	-0.217	-0.190	-0.138	0.031	0.140	-0.279	-0.082	1.000							
return on assets (12)	0.144	0.028	0.401	0.465	0.325	0.410	0.124	-0.409	-0.261	0.280	0.299	1.000						
net int.margin/tot.income (13)	0.033	0.034	**0.502***	0.489	0.369	0.348	0.157	-0.346	0.179	0.465	-0.238	0.244	1.000					
liq.assets/tot.assets (14)	-0.136	0.060	0.097	0.127	0.163	0.275	0.004	-0.274	0.112	0.156	0.030	0.134	0.080	1.000				
tot.loans/tot.deposits (15)	0.115	-0.006	-0.020	-0.020	-0.177	-0.297	0.052	0.298	-0.090	-0.058	-0.024	-0.089	-0.052	-0.249	1.000			
fix.assets/tot.assets (16)	0.076	0.101	0.198	0.071	-0.036	-0.013	0.239	0.013	0.092	0.197	-0.066	0.033	0.085	-0.146	-0.016	1.000		
due to com.banks/tot.equity (17)	-0.264	0.018	-0.328	-0.452	-0.381	-0.311	-0.071	0.312	-0.004	-0.255	0.138	-0.276	-0.338	0.032	-0.012	-0.101	1.000	
off-balance items/tot.assets (18)	0.195	-0.072	-0.154	-0.087	-0.059	-0.060	-0.026	0.060	-0.147	-0.161	0.102	0.014	-0.211	-0.041	-0.025	0.030	0.025	1.000

Correlation coefficients larger than 0.5 in absolute value are in bold and marked with a (*).

Appendix B

Table 3.5 presents the factor loadings for a four-factor model estimated on the basis of all data available in the sample (between 2002 and 2008). Additionally, in this section the estimated eigenvalues –key in the decision for a four-factor model– as well as the factor loadings for each model with a different time period are presented.

Table B.1. Eigenvalues for a factor model using all data between 2002 and 2008

Factor	Eigenvalue	Difference
Factor 1	2.626	0.834
Factor 2	1.191	0.543
Factor 3	1.248	0.114
Factor 4	1.134	0.633
Factor 5	0.500	0.212
Factor 6	0.288	0.150
Factor 7	0.138	0.020
Factor 8	0.117	0.041
Factor 9	0.077	0.060
Factor 10	0.017	0.026
Factor 11	-0.009	0.016
Factor 12	-0.025	0.019
Factor 13	-0.044	0.027
Factor 14	-0.071	0.045
Factor 15	-0.115	0.013
Factor 16	-0.128	0.053
Factor 17	-0.181	0.076
Factor 18	-0.257	

The larger the eigenvalue of a factor, the more variance in data is explained by that factor. See Table 3.5 for the factor loadings corresponding to the model estimated while using all data.

Table B.2. Eigenvalues for a factor model using data only for the year 2002

Factor	Eigenvalue	Difference
Factor 1	3.422	1.424
Factor 2	1.998	0.408
Factor 3	1.590	0.544
Factor 4	1.047	0.186
Factor 5	0.861	0.373
Factor 6	0.489	0.204
Factor 7	0.284	0.092
Factor 8	0.192	0.086
Factor 9	0.106	0.081
Factor 10	0.025	0.041
Factor 11	-0.016	0.001
Factor 12	-0.017	0.011
Factor 13	-0.028	0.036
Factor 14	-0.064	0.044
Factor 15	-0.108	0.033
Factor 16	-0.141	0.006
Factor 17	-0.147	0.050
Factor 18	-0.197	

The larger the eigenvalue of a factor, the more variance in data is explained by that factor.

Table B.3. Factor loadings under a four-factor model, using data only for the year 2002

indicator (risk category)	factor 1	factor 2	factor 3	factor 4	uniqueness
z-score (e)	-0.056	-0.052	-0.063	0.059	0.987
NPLs (a)	0.977**	0.006	0.030	-0.034	0.044
net interest margin (e)	0.017	0.394	-0.027	0.381	0.699
tot.equity/tot.assets (c)	0.485	0.607**	-0.071	0.206	0.350
total capital ratio (c)	0.979**	-0.032	-0.154	-0.065	0.013
tot.equity/tot.loans (c)	0.765**	0.113	0.489	-0.023	0.162
loan loss prov./tot.loans (a)	-0.004	0.011	0.922**	-0.012	0.150
tot.loans/tot.equity (a)	-0.052	-0.709**	-0.058	-0.031	0.491
tot.cost/tot.income (m)	0.491	0.124	-0.027	-0.526	0.466
overh.costs/tot.assets (m)	0.194	0.409	0.007	-0.127	0.779
return on equity (e)	-0.127	0.125	0.009	0.404	0.805
return on assets (e)	-0.165	0.096	-0.031	0.760**	0.386
net.int.margin/tot.income (e)	0.094	-0.031	0.018	0.109	0.978
liq.assets/tot.assets (l)	-0.062	-0.544	-0.025	0.083	0.692
tot.loans/tot.deposits (l)	-0.016	0.019	-0.002	0.054	0.997
fix.assets/tot.assets (l)	0.150	0.239	-0.103	-0.142	0.890
due to com.banks/tot.equity (l)	0.345	-0.574	-0.136	-0.005	0.533
off-balance items/tot.assets (s)	0.014	0.030	0.691**	0.002	0.521

Correlation coefficients per associated factor and indicator. In column 1, we use (c) for capital risk, (a) for asset risk, (m) for management risk, (e) for earnings and profitability risk, (l) for liquidity risk and (s) for sensitivity to market risk. The degree of uniqueness classifies how much of a measure's variance it has in common with the other measures, where (1 – uniqueness) defines the degree of commonality. Factor loadings larger than 0.6 in absolute value are marked as (**).

Table B.4. Eigenvalues for a factor model using data only for the year 2003

Factor	Eigenvalue	Difference
Factor 1	2.484	0.474
Factor 2	2.010	0.298
Factor 3	1.712	0.377
Factor 4	1.335	0.458
Factor 5	0.877	0.075
Factor 6	0.802	0.192
Factor 7	0.610	0.219
Factor 8	0.391	0.204
Factor 9	0.187	0.098
Factor 10	0.089	0.061
Factor 11	0.028	0.006
Factor 12	0.022	0.054
Factor 13	-0.032	0.047
Factor 14	-0.079	0.020
Factor 15	-0.099	0.065
Factor 16	-0.164	0.029
Factor 17	-0.194	0.034
Factor 18	-0.228	

The larger the eigenvalue of a factor, the more variance in data is explained by that factor.

Table B.5. Factor loadings under a four-factor model, using data only for the year 2003

indicator (risk category)	factor 1	factor 2	factor 3	factor 4	uniqueness
z-score (e)	0.025	-0.026	-0.015	-0.019	0.998
NPLs (a)	0.832**	0.055	-0.133	-0.013	0.286
net interest margin (e)	0.067	-0.057	0.285	-0.282	0.832
tot.equity/tot.assets (c)	0.632**	-0.233	0.225	-0.227	0.444
total capital ratio (c)	0.458	-0.769**	0.074	0.347	0.073
tot.equity/tot.loans (c)	0.646**	0.466	0.043	-0.079	0.358
loan loss prov./tot.loans (a)	0.227	0.908**	0.012	0.078	0.118
tot.loans/tot.equity (a)	-0.213	-0.008	-0.063	0.607**	0.582
tot.cost/tot.income (m)	0.189	-0.117	-0.562	-0.006	0.634
overh.costs/tot.assets (m)	0.536	0.015	-0.073	-0.066	0.703
return on equity (e)	-0.108	0.004	0.735**	0.203	0.408
return on assets (e)	0.101	-0.056	0.817**	-0.105	0.308
net.int.margin/tot.income (e)	0.073	-0.176	-0.037	-0.113	0.949
liq.assets/tot.assets (l)	-0.224	-0.024	-0.049	0.301	0.856
tot.loans/tot.deposits (l)	-0.026	0.003	0.079	-0.035	0.992
fix.assets/tot.assets (l)	0.199	-0.120	-0.016	-0.069	0.841
due to com.banks/tot.equity (l)	-0.045	-0.110	0.052	0.846**	0.268
off-balance items/tot.assets (s)	0.156	0.503	0.081	0.072	0.711

Correlation coefficients per associated factor and indicator. In column 1, we use (c) for capital risk, (a) for asset risk, (m) for management risk, (e) for earnings and profitability risk, (l) for liquidity risk and (s) for sensitivity to market risk. The degree of uniqueness classifies how much of a measure's variance it has in common with the other measures, where (1 – uniqueness) defines the degree of commonality. Factor loadings larger than 0.6 in absolute value are marked as (**).

Table B.6. Eigenvalues for a factor model using data only for the year 2004

Factor	Eigenvalue	Difference
Factor 1	2.964	0.160
Factor 2	2.803	1.216
Factor 3	1.587	0.274
Factor 4	1.313	0.220
Factor 5	1.093	0.534
Factor 6	0.559	0.236
Factor 7	0.323	0.161
Factor 8	0.162	0.050
Factor 9	0.112	0.056
Factor 10	0.056	0.015
Factor 11	0.041	0.040
Factor 12	0.001	0.018
Factor 13	-0.017	0.014
Factor 14	-0.031	0.056
Factor 15	-0.087	0.065
Factor 16	-0.152	0.023
Factor 17	-0.176	0.020
Factor 18	-0.196	

The larger the eigenvalue of a factor, the more variance in data is explained by that factor.

Table B.7. Factor loadings under a four-factor model, using data only for the year 2004

indicator (risk category)	factor 1	factor 2	factor 3	factor 4	uniqueness
z-score (e)	0.030	-0.066	0.007	0.064	0.991
NPLs (a)	0.100	0.928**	-0.027	0.052	0.126
net interest margin (e)	-0.027	0.088	0.102	0.419	0.806
tot.equity/tot.assets (c)	-0.148	0.251	0.074	0.678**	0.450
total capital ratio (c)	-0.966**	-0.093	0.002	0.060	0.055
tot.equity/tot.loans (c)	-0.051	0.775**	0.012	0.201	0.356
loan loss prov./tot.loans (a)	0.022	0.961**	-0.001	-0.066	0.072
tot.loans/tot.equity (a)	0.882**	-0.041	-0.118	-0.053	0.203
tot.cost/tot.income (m)	-0.060	0.037	-0.571	0.074	0.663
overh.costs/tot.assets (m)	-0.100	0.360	-0.096	0.494	0.608
return on equity (e)	-0.268	-0.071	0.796**	-0.118	0.276
return on assets (e)	-0.017	0.042	0.810**	0.161	0.317
net.int.margin/tot.income (e)	0.051	-0.116	-0.021	0.497	0.737
liq.assets/tot.assets (l)	0.134	-0.073	-0.092	-0.125	0.953
tot.loans/tot.deposits (l)	-0.004	-0.010	0.070	-0.010	0.995
fix.assets/tot.assets (l)	-0.120	0.070	-0.080	0.232	0.921
due to com.banks/tot.equity (l)	0.985**	0.014	-0.039	0.040	0.027
off-balance items/tot.assets (s)	-0.034	0.158	0.062	-0.439	0.778

Correlation coefficients per associated factor and indicator. In column 1, we use (c) for capital risk, (a) for asset risk, (m) for management risk, (e) for earnings and profitability risk, (l) for liquidity risk and (s) for sensitivity to market risk. The degree of uniqueness classifies how much of a measure's variance it has in common with the other measures, where (1 − uniqueness) defines the degree of commonality. Factor loadings larger than 0.6 in absolute value are marked as (**).

Table B.8. Eigenvalues for a factor model using data only for the year 2005

Factor	Eigenvalue	Difference
Factor 1	2.646	0.553
Factor 2	2.093	0.677
Factor 3	1.416	0.407
Factor 4	1.009	0.360
Factor 5	0.649	0.209
Factor 6	0.440	0.167
Factor 7	0.273	0.127
Factor 8	0.146	0.023
Factor 9	0.123	0.022
Factor 10	0.101	0.070
Factor 11	0.031	0.033
Factor 12	-0.002	0.079
Factor 13	-0.081	0.034
Factor 14	-0.0115	0.012
Factor 15	-0.127	0.042
Factor 16	-0.169	0.038
Factor 17	-0.207	0.065
Factor 18	-0.273	

The larger the eigenvalue of a factor, the more variance in data is explained by that factor.

Table B.9. Factor loadings under a four-factor model, using data only for the year 2005

indicator (risk category)	factor 1	factor 2	factor 3	factor 4	uniqueness
z-score (e)	-0.061	0.084	-0.181	-0.054	0.954
NPLs (a)	-0.012	0.121	0.669**	0.072	0.533
net interest margin (e)	0.193	0.202	0.363	-0.143	0.770
tot.equity/tot.assets (c)	0.091	0.738**	0.329	0.103	0.328
total capital ratio (c)	-0.066	0.632**	0.080	0.710**	0.086
tot.equity/tot.loans (c)	0.351	0.027	0.102	0.076	0.860
loan loss prov./tot.loans (a)	0.208	0.086	0.713**	0.016	0.440
tot.loans/tot.equity (a)	-0.121	-0.722**	0.019	0.250	0.401
tot.cost/tot.income (m)	-0.628**	0.087	0.295	0.034	0.510
overh.costs/tot.assets (m)	-0.239	0.353	0.588	-0.092	0.464
return on equity (e)	0.788**	-0.053	-0.041	-0.056	0.371
return on assets (e)	0.836**	0.184	0.195	-0.072	0.224
net.int.margin/tot.income (e)	-0.041	0.081	0.096	0.001	0.983
liq.assets/tot.assets (l)	0.012	-0.264	0.022	0.070	0.925
tot.loans/tot.deposits (l)	0.026	0.038	-0.031	-0.017	0.997
fix.assets/tot.assets (l)	-0.064	0.292	0.080	0.015	0.904
due to com.banks/tot.equity (l)	-0.059	-0.117	-0.026	0.938**	0.103
off-balance items/tot.assets (s)	0.083	0.081	0.038	-0.018	0.985

Correlation coefficients per associated factor and indicator. In column 1, we use (c) for capital risk, (a) for asset risk, (m) for management risk, (e) for earnings and profitability risk, (l) for liquidity risk and (s) for sensitivity to market risk. The degree of uniqueness classifies how much of a measure's variance it has in common with the other measures, where (1 – uniqueness) defines the degree of commonality. Factor loadings larger than 0.6 in absolute value are marked as (**).

Table B.10. Eigenvalues for a factor model using data only for the year 2006

Factor	Eigenvalue	Difference
Factor 1	2.456	0.359
Factor 2	2.097	0.871
Factor 3	1.225	0.317
Factor 4	0.909	0.099
Factor 5	0.810	0.368
Factor 6	0.442	0.116
Factor 7	0.325	0.160
Factor 8	0.165	0.040
Factor 9	0.124	0.054
Factor 10	0.070	0.062
Factor 11	0.008	0.056
Factor 12	-0.047	0.026
Factor 13	-0.073	0.014
Factor 14	-0.087	0.061
Factor 15	-0.148	0.051
Factor 16	-0.199	0.012
Factor 17	-0.212	0.020
Factor 18	-0.232	

The larger the eigenvalue of a factor, the more variance in data is explained by that factor.

Table B.11. Factor loadings under a four-factor model, using data only for the year 2006

indicator (risk category)	factor 1	factor 2	factor 3	factor 4	uniqueness
z-score (e)	-0.049	0.031	-0.121	-0.076	0.976
NPLs (a)	0.089	0.237	-0.141	0.045	0.914
net interest margin (e)	-0.032	0.387	0.153	-0.064	0.822
tot.equity/tot.assets (c)	0.099	0.828**	-0.025	-0.066	0.300
total capital ratio (c)	0.933**	0.122	-0.072	0.291	0.025
tot.equity/tot.loans (c)	0.002	0.103	0.034	0.130	0.971
loan loss prov./tot.loans (a)	0.952**	-0.041	0.034	-0.139	0.073
tot.loans/tot.equity (a)	-0.018	-0.344	-0.074	0.504	0.622
tot.cost/tot.income (m)	-0.035	0.195	-0.535	0.070	0.670
overh.costs/tot.assets (m)	0.053	0.607**	0.167	-0.178	0.569
return on equity (e)	-0.052	0.043	0.778**	-0.064	0.386
return on assets (e)	-0.018	0.602**	0.666**	-0.075	0.189
net.int.margin/tot.income (e)	0.041	0.185	-0.079	0.048	0.956
liq.assets/tot.assets (l)	-0.454	-0.024	-0.051	0.283	0.711
tot.loans/tot.deposits (l)	0.017	0.018	0.016	0.014	0.998
fix.assets/tot.assets (l)	0.032	0.291	-0.156	-0.112	0.878
due to com.banks/tot.equity (l)	0.164	-0.143	-0.097	0.807**	0.293
off-balance items/tot.assets (s)	0.146	-0.030	0.089	-0.088	0.962

Correlation coefficients per associated factor and indicator. In column 1, we use (c) for capital risk, (a) for asset risk, (m) for management risk, (e) for earnings and profitability risk, (l) for liquidity risk and (s) for sensitivity to market risk. The degree of uniqueness classifies how much of a measure's variance it has in common with the other measures, where (1 – uniqueness) defines the degree of commonality. Factor loadings larger than 0.6 in absolute value are marked as (**).

Table B.12. Eigenvalues for a factor model using data only for the year 2007

Factor	Eigenvalue	Difference
Factor 1	2.765	0.549
Factor 2	2.216	0.723
Factor 3	1.493	0.234
Factor 4	1.258	0.362
Factor 5	0.896	0.234
Factor 6	0.662	0.208
Factor 7	0.454	0.297
Factor 8	0.157	0.048
Factor 9	0.109	0.045
Factor 10	0.064	0.034
Factor 11	0.030	0.023
Factor 12	0.007	0.043
Factor 13	-0.036	0.050
Factor 14	-0.086	0.031
Factor 15	-0.117	0.046
Factor 16	-0.162	0.035
Factor 17	-0.197	0.024
Factor 18	-0.222	

The larger the eigenvalue of a factor, the more variance in data is explained by that factor.

Table B.13. Factor loadings under a four-factor model, using data only for the year 2007

indicator (risk category)	factor 1	factor 2	factor 3	factor 4	uniqueness
z-score (e)	0.060	-0.129	0.383	-0.076	0.827
NPLs (a)	0.026	0.898**	0.074	-0.079	0.182
net interest margin (e)	0.495	0.034	-0.001	0.136	0.735
tot.equity/tot.assets (c)	0.628**	0.077	0.470	0.171	0.349
total capital ratio (c)	-0.006	0.498	0.844**	-0.001	0.040
tot.equity/tot.loans (c)	0.062	-0.031	0.165	0.056	0.965
loan loss prov./tot.loans (a)	0.043	0.930**	0.109	0.043	0.120
tot.loans/tot.equity (a)	-0.558	-0.042	0.114	-0.190	0.638
tot.cost/tot.income (m)	0.274	0.016	0.003	-0.533	0.640
overh.costs/tot.assets (m)	0.726**	0.087	0.120	0.077	0.446
return on equity (e)	0.031	-0.040	-0.101	0.808**	0.334
return on assets (e)	0.376	0.001	0.074	0.762**	0.272
net.int.margin/tot.income (e)	0.134	-0.136	0.779**	-0.067	0.352
liq.assets/tot.assets (l)	-0.202	-0.111	0.045	-0.118	0.931
tot.loans/tot.deposits (l)	-0.002	0.030	0.040	0.041	0.996
fix.assets/tot.assets (l)	0.327	0.126	0.021	-0.093	0.868
due to com.banks/tot.equity (l)	-0.484	0.151	0.346	-0.011	0.623
off-balance items/tot.assets (s)	0.052	0.175	-0.026	0.124	0.951

Correlation coefficients per associated factor and indicator. In column 1, we use (c) for capital risk, (a) for asset risk, (m) for management risk, (e) for earnings and profitability risk, (l) for liquidity risk and (s) for sensitivity to market risk. The degree of uniqueness classifies how much of a measure's variance it has in common with the other measures, where (1 – uniqueness) defines the degree of commonality. Factor loadings larger than 0.6 in absolute value are marked as (**).

Table B.14. Eigenvalues for a factor model using data only for the year 2008

Factor	Eigenvalue	Difference
Factor 1	2.843	0.991
Factor 2	1.852	0.474
Factor 3	1.378	0.443
Factor 4	0.935	0.209
Factor 5	0.726	0.074
Factor 6	0.652	0.365
Factor 7	0.287	0.116
Factor 8	0.171	0.077
Factor 9	0.094	0.029
Factor 10	0.065	0.063
Factor 11	0.002	0.024
Factor 12	-0.022	0.031
Factor 13	-0.053	0.064
Factor 14	-0.117	0.039
Factor 15	-0.156	0.043
Factor 16	-0.198	0.065
Factor 17	-0.264	0.036
Factor 18	-0.299	

The larger the eigenvalue of a factor, the more variance in data is explained by that factor.

Table B.15. Factor loadings under a four-factor model, using data only for the year 2008

indicator (risk category)	factor 1	factor 2	factor 3	factor 4	uniqueness
z-score (e)	-0.007	-0.110	0.093	0.113	0.967
NPLs (a)	0.134	0.444	0.060	-0.249	0.720
net interest margin (e)	0.355	0.516	0.347	-0.030	0.486
tot.equity/tot.assets (c)	0.488	0.383	0.159	0.584	0.249
total capital ratio (c)	0.915**	-0.031	-0.081	0.086	0.148
tot.equity/tot.loans (c)	0.181	-0.041	0.059	0.675**	0.506
loan loss prov./tot.loans (a)	-0.171	0.479	0.145	-0.169	0.692
tot.loans/tot.equity (a)	-0.164	-0.669**	0.135	-0.187	0.472
tot.cost/tot.income (m)	0.374	0.002	-0.564	-0.057	0.540
overh.costs/tot.assets (m)	0.939**	0.070	-0.003	0.015	0.112
return on equity (e)	-0.039	-0.162	0.648**	0.008	0.552
return on assets (e)	0.008	0.300	0.574	0.180	0.548
net.int.margin/tot.income (e)	0.016	0.083	0.048	0.264	0.921
liq.assets/tot.assets (l)	0.228	-0.489	0.225	0.091	0.651
tot.loans/tot.deposits (l)	0.094	0.092	0.064	-0.414	0.807
fix.assets/tot.assets (l)	0.150	0.091	0.010	-0.045	0.967
due to com.banks/tot.equity (l)	-0.049	-0.496	-0.042	-0.160	0.725
off-balance items/tot.assets (s)	-0.051	0.247	0.069	-0.046	0.930

Correlation coefficients per associated factor and indicator. In column 1, we use (c) for capital risk, (a) for asset risk, (m) for management risk, (e) for earnings and profitability risk, (l) for liquidity risk and (s) for sensitivity to market risk. The degree of uniqueness classifies how much of a measure's variance it has in common with the other measures, where (1 – uniqueness) defines the degree of commonality. Factor loadings larger than 0.6 in absolute value are marked as (**).

Appendix C

In Table 4.1 to 4.3, comparative results regarding domestic credit size and bank sector distribution are displayed. Additionally, here the non-compared results are provided.

Table C.1. Share of the five largest banks in the total bank sector assets per country from the data

Country name	Year				
	2004	2005	2006	2007	2008
Argentina	0.991	0.990	0.992	0.993	0.998
Belgium	1.000	1.000	1.000	1.000	1.000
Bosnia-Herzegovina	0.971	0.966	0.963	0.963	-
Brazil	0.830	0.825	0.831	0.799	0.787
Bulgaria	1.000	1.000	1.000	1.000	-
Canada	0.975	0.975	0.976	0.966	0.994
China	0.921	0.919	0.914	0.900	0.957
Denmark	0.946	0.946	0.939	0.936	0.937
France	0.893	0.899	0.908	0.902	0.913
Germany	0.792	0.783	0.757	0.754	0.891
Greece	0.796	0.808	0.806	0.809	0.817
Hong Kong	0.824	0.820	0.825	0.828	0.838
Hungary	0.999	0.999	0.999	0.999	-
India	0.899	0.896	0.894	0.891	-
Indonesia	0.913	0.920	0.930	0.908	1.000
Ireland	0.993	0.994	0.995	0.996	1.000
Italy	0.810	0.887	0.875	0.885	0.891
Japan	0.998	0.998	0.998	0.998	1.000
Latvia	0.978	0.987	0.991	0.992	0.990
Luxembourg	0.979	0.982	0.982	0.983	1.000
Netherlands	0.990	0.990	0.990	0.990	0.990
Norway	0.775	0.785	0.787	0.788	0.825
Portugal	0.983	0.979	0.979	0.977	0.984
Romania	0.951	0.935	0.930	0.920	-
Russia	0.403	0.388	0.399	0.382	0.635
Spain	0.699	0.696	0.667	0.665	0.680
Sweden	0.975	0.977	0.976	0.976	0.998
Switzerland	0.949	0.956	0.955	0.955	0.962
Taiwan	1.000	1.000	1.000	1.000	1.000
Thailand	0.992	0.992	0.992	0.991	1.000
Ukraine	0.554	0.561	0.555	0.567	1.000
United Kingdom	0.838	0.822	0.822	0.827	0.859
United States	0.914	0.901	0.949	0.954	0.995

In the cases of Bosnia-Herzegovina, Bulgaria, Hungary, India and Romania in 2008 we did not have individual bank data available.

Table C.2. Concentration indexes based on applying the Herfindahl method to the data

Country name	Year				
	2004	2005	2006	2007	2008
Argentina	0.579	0.649	0.540	0.524	0.598
Belgium	0.972	0.975	0.976	0.977	0.978
Bosnia-Herzegovina	0.480	0.392	0.398	0.367	-
Brazil	0.198	0.207	0.243	0.232	0.237
Bulgaria	0.470	0.380	0.364	0.430	-
Canada	0.601	0.641	0.627	0.537	0.580
China	0.211	0.212	0.208	0.200	0.239
Denmark	0.346	0.351	0.353	0.367	0.354
France	0.213	0.221	0.224	0.225	0.234
Germany	0.193	0.183	0.172	0.152	0.196
Greece	0.160	0.159	0.160	0.157	0.160
Hong Kong	0.261	0.262	0.268	0.280	0.284
Hungary	0.579	0.507	0.503	0.481	-
India	0.337	0.306	0.288	0.287	-
Indonesia	0.223	0.220	0.231	0.207	0.319
Ireland	0.319	0.334	0.320	0.322	0.325
Italy	0.271	0.500	0.484	0.525	0.490
Japan	0.429	0.431	0.435	0.436	1.000
Latvia	0.376	0.480	0.513	0.511	0.526
Luxembourg	0.278	0.358	0.336	0.295	0.969
Netherlands	0.396	0.407	0.409	0.410	0.412
Norway	0.239	0.240	0.244	0.247	0.276
Portugal	0.294	0.288	0.284	0.281	0.287
Romania	0.328	0.300	0.267	0.227	-
Russia	0.042	0.038	0.040	0.039	0.091
Spain	0.172	0.172	0.151	0.146	0.156
Sweden	0.310	0.313	0.307	0.309	0.336
Switzerland	0.724	0.725	0.721	0.715	0.789
Taiwan	0.722	0.699	0.655	0.565	1.000
Thailand	0.747	0.688	0.658	0.676	0.979
Ukraine	0.096	0.100	0.088	0.091	1.000
United Kingdom	0.171	0.170	0.167	0.169	0.189
United States	0.438	0.434	0.530	0.555	0.663

In the cases of Bosnia-Herzegovina, Bulgaria, Hungary, India and Romania in 2008 we did not have individual bank data available.

Appendix D

In section 6, a factor analysis on the separate indicators (at a national level) for the categories asset risk, earnings and profitability risk and liquidity risk is performed. Additionally, Table D.1. displays the estimated eigenvalues part of that analysis.

Table D.1. Eigenvalues for a factor model using national level asset, earnings/profitability and liquidity indicators

Factor	Eigenvalue	Difference
Factor 1	2.370	1.323
Factor 2	1.047	0.794
Factor 3	0.253	0.113
Factor 4	0.140	0.083
Factor 5	0.057	0.123
Factor 6	-0.066	0.050
Factor 7	-0.117	0.207
Factor 8	-0.324	

The larger the eigenvalue of a factor, the more variance in data is explained by that factor.

In Table 6.1, a weighted aggregate approach was used for constructing national indicators and these aggregates are used for correlation analysis. To check for the robustness of these correlations when using another way to derive national risk indicators, aggregates resulting from the minimum-maximum method are used to obtain the correlations displayed here. In each case here, the minimum required asset size for a bank to be considered was taken to be ten per cent of the country total, i.e. $T = 0.10$ in (9) and (10).

Table D.2. Pearson correlation coefficients between asset, earnings and liquidity risk indicators from using a minimum capital criterion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) loan loss prov./tot.loans (a)	1.000							
(2) NPLs (a)	0.419	1.000						
(3) return on equity (e)	0.567	0.236	1.000					
(4) z-score (e)	0.159	-0.059	-0.064	1.000				
(5) liq.assets/tot.assets (l)	-0.027	-0.213	0.066	0.020	1.000			
(6) tot.loans/tot.deposits (l)	-0.027	-0.273	0.226	-0.168	0.400	1.000		
(7) fix.assets/tot.assets (l)	-0.305	-0.046	0.055	-0.119	-0.062	-0.024	1.000	
(8) due to com.banks/tot.equity (l)	-0.341	-0.010	-0.307	0.176	-0.072	-0.452	-0.062	1.000

National level indicators are obtained from choosing per country and per year the bank with the lowest total equity relative to total loans. In column 1, we use (a) for asset risk, (e) for earnings and profitability risk and (l) for liquidity risk.

Table D.3. Pearson correlation coefficients between asset, earnings and liquidity risk indicators from using a maximum credit provision criterion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) loan loss prov./tot.loans (a)	1.000							
(2) NPLs (a)	0.351	1.000						
(3) return on equity (e)	0.637	0.210	1.000					
(4) z-score (e)	0.301	-0.062	0.056	1.000				
(5) liq.assets/tot.assets (l)	0.268	-0.044	0.398	0.110	1.000			
(6) tot.loans/tot.deposits (l)	0.014	-0.241	0.100	0.099	0.238	1.000		
(7) fix.assets/tot.assets (l)	-0.409	-0.065	0.104	-0.481	0.255	-0.145	1.000	
(8) due to com.banks/tot.equity (l)	-0.099	0.376	-0.285	0.011	-0.261	-0.574	-0.108	1.000

National level indicators are obtained from choosing per country and per year the bank with the highest share of loan loss provisions relative to total loans outstanding. In column 1, we use (a) for asset risk, (e) for earnings and profitability risk and (l) for liquidity risk.

Table D.4. Pearson correlation coefficients between asset, earnings and liquidity risk indicators from using a maximum cost inefficiency (management) criterion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) loan loss prov./tot.loans (a)	1.000							
(2) NPLs (a)	0.203	1.000						
(3) return on equity (e)	0.347	-0.094	1.000					
(4) z-score (e)	0.134	-0.039	0.062	1.000				
(5) liq.assets/tot.assets (l)	-0.058	-0.214	0.150	0.056	1.000			
(6) tot.loans/tot.deposits (l)	-0.219	-0.224	0.216	-0.059	0.297	1.000		
(7) fix.assets/tot.assets (l)	-0.315	0.110	0.009	-0.296	0.183	-0.086	1.000	
(8) due to com.banks/tot.equity (l)	-0.126	0.074	-0.448	0.262	-0.084	-0.420	-0.076	1.000

National level indicators are obtained from choosing per country and per year the bank with the highest ratio of costs over income. In column 1, we use (a) for asset risk, (e) for earnings and profitability risk and (l) for liquidity risk.

Table D.5. Pearson correlation coefficients between asset, earnings and liquidity risk indicators from using a minimum earnings/profitability criterion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) loan loss prov./tot.loans (a)	1.000							
(2) NPLs (a)	0.373	1.000						
(3) return on equity (e)	0.468	0.119	1.000					
(4) z-score (e)	0.235	0.027	0.141	1.000				
(5) liq.assets/tot.assets (l)	0.335	-0.097	0.514	0.218	1.000			
(6) tot.loans/tot.deposits (l)	-0.186	-0.374	0.266	-0.234	0.271	1.000		
(7) fix.assets/tot.assets (l)	-0.290	0.065	0.063	-0.072	0.218	-0.063	1.000	
(8) due to com.banks/tot.equity (l)	0.014	0.164	-0.434	0.012	-0.372	-0.611	-0.173	1.000

National level indicators are obtained from choosing per country and per year the bank with the lowest z-score. In column 1, we use (a) for asset risk, (e) for earnings and profitability risk and (l) for liquidity risk.

Table D.6. Pearson correlation coefficients between asset, earnings and liquidity risk indicators from using a minimum liquidity criterion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) loan loss prov./tot.loans (a)	1.000							
(2) NPLs (a)	0.453	1.000						
(3) return on equity (e)	0.414	0.001	1.000					
(4) z-score (e)	-0.194	-0.114	-0.300	1.000				
(5) liq.assets/tot.assets (l)	0.106	-0.081	0.151	-0.062	1.000			
(6) tot.loans/tot.deposits (l)	-0.097	-0.221	0.205	-0.283	0.303	1.000		
(7) fix.assets/tot.assets (l)	-0.066	0.004	0.106	-0.108	0.284	0.141	1.000	
(8) due to com.banks/tot.equity (l)	-0.373	0.039	-0.123	0.197	0.013	-0.185	-0.055	1.000

National level indicators are obtained from choosing per country and per year the bank with the highest share of its own debt that is due to commercial banks. In column 1, we use (a) for asset risk, (e) for earnings and profitability risk and (l) for liquidity risk.

Table D.7. Pearson correlation coefficients between asset, earnings and liquidity risk indicators from using a high sensitivity to market risk criterion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) loan loss prov./tot.loans (a)	1.000							
(2) NPLs (a)	-0.208	1.000						
(3) return on equity (e)	0.128	0.018	1.000					
(4) z-score (e)	0.111	-0.031	0.022	1.000				
(5) liq.assets/tot.assets (l)	0.203	-0.250	0.228	-0.056	1.000			
(6) tot.loans/tot.deposits (l)	-0.175	-0.074	0.155	-0.075	0.121	1.000		
(7) fix.assets/tot.assets (l)	-0.185	-0.188	0.119	-0.075	0.149	-0.162	1.000	
(8) due to com.banks/tot.equity (l)	0.567	0.172	-0.130	0.377	-0.294	-0.290	-0.093	1.000

National level indicators are obtained from choosing per country and per year the bank with the highest ratio between off-balance sheet items and total assets. In column 1, we use (a) for asset risk, (e) for earnings and profitability risk and (l) for liquidity risk.

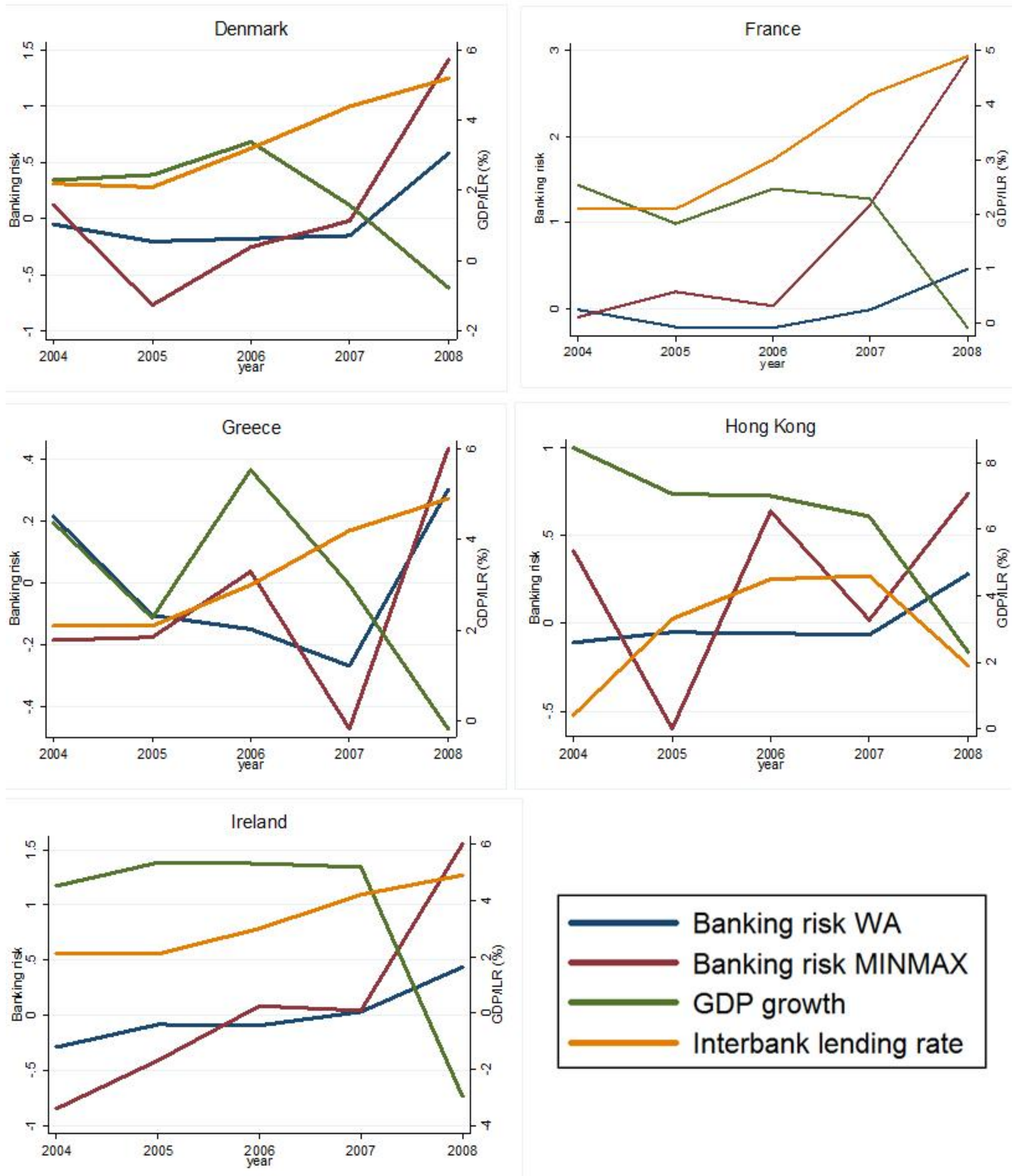
Table D.8. Pearson correlation coefficients between asset, earnings and liquidity risk indicators from using a combined criterion

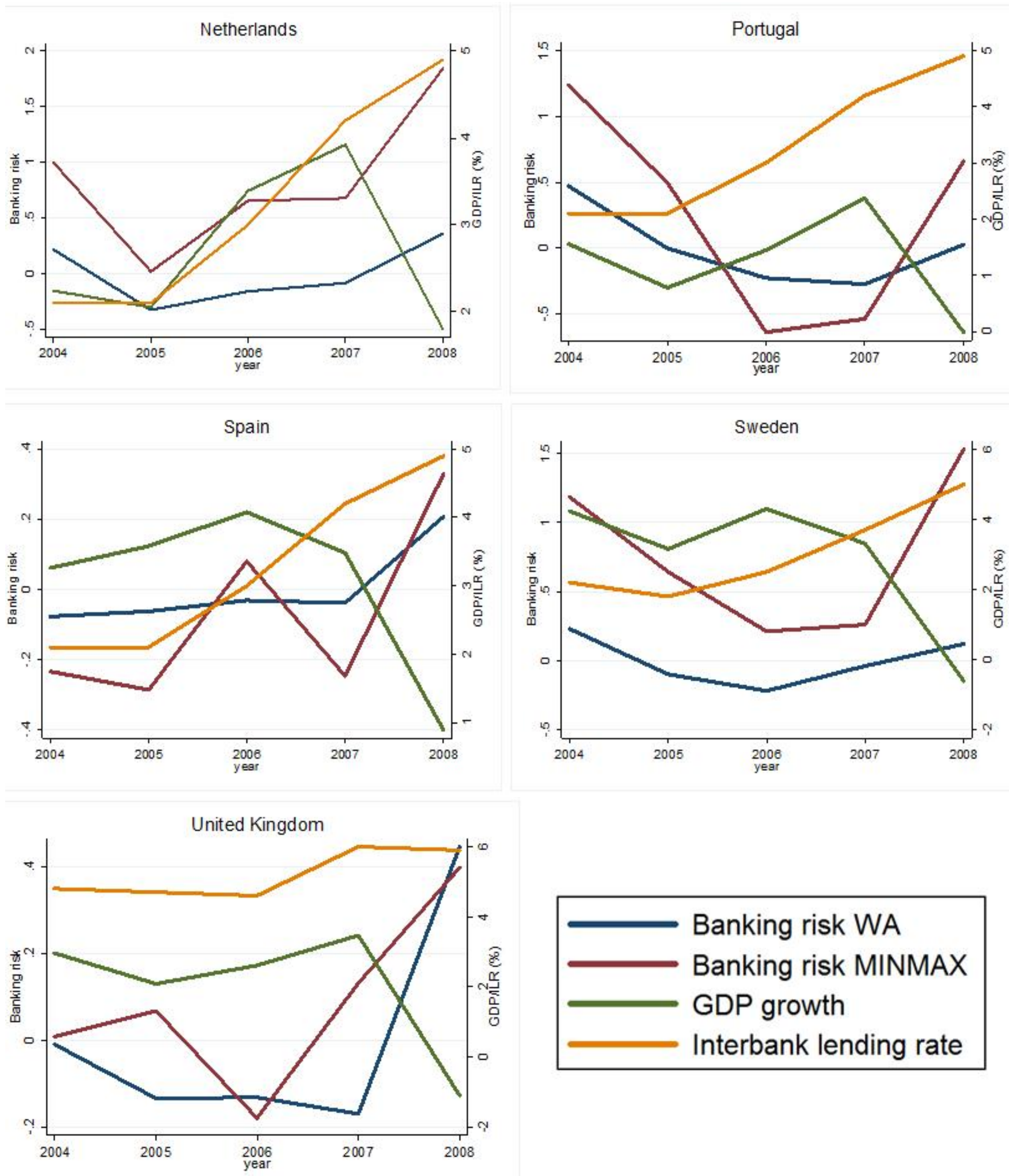
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) loan loss prov./tot.loans (a)	1.000							
(2) NPLs (a)	0.358	1.000						
(3) return on equity (e)	0.180	0.630	1.000					
(4) z-score (e)	-0.118	-0.008	-0.148	1.000				
(5) liq.assets/tot.assets (l)	-0.246	0.252	0.409	-0.027	1.000			
(6) tot.loans/tot.deposits (l)	-0.186	-0.057	0.132	-0.188	0.403	1.000		
(7) fix.assets/tot.assets (l)	-0.061	-0.343	-0.007	-0.020	0.021	-0.170	1.000	
(8) due to com.banks/tot.equity (l)	0.161	-0.240	-0.317	0.237	-0.307	-0.466	0.098	1.000

National level indicators are obtained from choosing per country and per year the bank four different observations. These are the bank with the lowest equity to loans ratio, the bank with the highest loan loss provisions relative to its total loans, the bank with the lowest z-score and the bank with the highest ratio of loans due to commercial banks over the size of its own debt. In column 1, we use (a) for asset risk, (e) for earnings and profitability risk and (l) for liquidity risk.

Appendix E

Graph E.1. Bank risk evolution per country using both methods from section 5





We compare risk evolutions at the domestic bank sector level, derived from both methods in section 5. The blue lines for 'Banking risk WA' are copies of the blue lines in Graph 6.10, i.e. constructing a bank risk indicator using proportional weights and all six CAMELS categories. The red lines are risk constructs obtained with the minimum-maximum criterion (plotted as 'Banking risk MINMAX').

Table E.1. Spreads and standard deviations for one-dimensional bank risk per country

Country	**High-low spread WA**	**High-low spread Min-Max**	**Standard deviation WA**	**Standard deviation Min-Max**
Denmark	0.79	2.19	0.33	0.81
France	0.68	3.01	0.28	1.26
Greece	0.57	0.91	0.25	0.34
Hong Kong	0.39	1.34	0.16	0.54
Ireland	0.72	2.40	0.27	0.90
The Netherlands	0.68	1.82	0.28	0.66
Portugal	0.74	1.87	0.30	0.81
Spain	0.29	0.61	0.12	0.27
Sweden	0.45	1.31	0.18	0.58
United Kingdom	0.61	0.58	0.26	0.21

This table presents additional information regarding the one-dimensional bank indicators constructed when weighing all CAMELS categories proportionally (WA) and when using the min-max criterion (Min-Max). The high-low spread represents the maximum bank risk value (in 2004-2008) minus the minimum bank risk value (in 2004-2008), for both different indicators (column two and three). Standard deviations of risk lines are presented in column four and five.

Appendix F

Table F.1. Pearson correlations between non-standardized indicators in separate years

	year	(1)	(2)	(3)	(4)	(5)	(6)
tot.equity/tot.loans (1)	**2004**	1.000	-0.140	-0.395	0.411	-0.147	-0.508
	2005	1.000	0.029	-0.532	0.438	-0.303	0.035
	2006	1.000	-0.137	-0.266	0.726	-0.309	0.019
	2007	1.000	0.398	-0.682	0.703	-0.299	0.468
	2008	1.000	0.116	-0.455	0.411	0.156	0.608
loan loss prov./tot.loans (2)	**2004**	-0.140	1.000	0.535	-0.677	0.122	0.281
	2005	0.029	1.000	0.210	-0.017	-0.164	0.209
	2006	-0.137	1.000	0.071	-0.327	-0.309	0.089
	2007	0.398	1.000	0.013	0.145	-0.038	0.082
	2008	0.116	1.000	0.112	-0.337	-0.375	0.160
tot.cost/tot.income (3)	**2004**	-0.395	0.535	1.000	-0.884	-0.286	0.070
	2005	-0.532	0.210	1.000	-0.017	-0.164	0.209
	2006	-0.266	0.071	1.000	-0.522	-0.075	-0.285
	2007	-0.682	0.013	1.000	-0.921	0.266	-0.474
	2008	-0.455	0.112	1.000	-0.921	0.553	-0.428
return on equity (4)	**2004**	0.411	-0.677	-0.884	1.000	0.132	-0.153
	2005	0.438	-0.017	-0.585	1.000	-0.073	0.181
	2006	0.726	-0.327	-0.522	1.000	0.182	0.380
	2007	0.703	0.145	-0.921	1.000	-0.332	0.488
	2008	0.411	-0.337	-0.921	1.000	-0.423	0.292
liq.assets/tot.assets (5)	**2004**	-0.147	0.122	-0.286	0.132	1.000	-0.061
	2005	-0.303	-0.164	-0.080	-0.073	1.000	0.033
	2006	-0.309	-0.309	-0.075	0.182	1.000	-0.040
	2007	-0.299	-0.038	0.266	-0.332	1.000	-0.301
	2008	0.156	-0.375	0.553	-0.423	1.000	0.151
off bal.items/tot.assets (6)	**2004**	-0.508	0.281	0.070	-0.153	-0.061	1.000
	2005	0.035	0.209	-0.246	0.181	0.033	1.000
	2006	0.019	0.089	-0.285	0.380	-0.040	1.000
	2007	0.468	0.082	-0.474	0.488	-0.301	1.000
	2008	0.608	0.160	-0.428	0.292	0.151	1.000