The Market's View on the Probability of Banking Sector Failure: Cross-Country Comparisons

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Abstract

Considering the increasingly international banks of today, the health of a country's banking sector is crucial not only to the country's growth and prosperity but also to the rest of the international financial community. Early warning signals of a banking sector in trouble or a pending banking crisis would therefore be of great value to both banks, investors and banking regulators/supervisors world wide. Different warning signals exist and in this paper we investigate how the stock market can provide a market-based indicator of banking sector health. Hall and Miles (1990) suggests an approach of estimating default probabilities of individual banks using only their stock market valuations and volatilities. In this paper we apply an aggregated version of their approach to banking sectors around the world in both developed and emerging economies and study the market's assessment of the probability of systemic banking crises in these countries over the last decade, including the Asian Crisis 1997-98. In addition, we investigate whether there is a relationship between the probability of banking sector failure and institutional/structural features of the actual banking sector. The quality of governance and the degree of law and order in a country is found to be significantly negatively related to the market based failure probabilities as is an explicit deposit insurance during periods of crisis.

Keywords: banking sector; banking crisis; default probability; market discipline

JEL classification codes: G33; G14; G21; C32

1 Introduction

The health of the banking sector is of crucial importance to the functioning of a modern market economy and banks and other financial institutions are therefore closely monitored by governments, supervisors, and regulators. The government can influence the banking sector's susceptibility to problems (and potential crises) through the establishment of an efficient legal and institutional framework. It must implement adequate prudential supervision and regulation, and must further ensure appropriate accounting and auditing practices.

Although structural measures taken by the government to prevent crises from appearing in the banking sector are important, they are not always sufficient. If a crisis hits despite the government's attempts, standing ready and prepared to meet and minimize the negative effects of the crisis is equally important. This highlights the importance of finding ways to predict and identify an upcoming crisis as early as possible. What is needed are indicators or signals that early on can tell investors, financial institutions and regulators world wide where and when the probability of a crisis is high and where it is low. The structural and institutional features of a banking sector can usually be of some help but while such features might indicate *where* (in which country) a banking crisis eventually might hit, they are not always very good indicators of *when* the crisis will strike.

Information regarding the health of the banking system is usually available and the question is merely how to distill the information and create a reliable indicator that can be used as an *early warning signal*. Microeconomic indicators, like items from banks' balance sheets, that directly relate to the health of individual banks can be aggregated across the whole banking sector and can be useful as an indicator of the sector's health. If such bank-specific indicators are not available, or if they are not reliable, an alternative is to turn to macroeconomic indicators and market prices. Macroindicators like growth, consumption, investments, inflation and capital flows and priceindicators such as exchange rates, interest rates and stock prices can all be useful as indicators of a pending banking sector crisis.

The aggregated views of economic agents regarding risks and returns are efficiently reflected by the financial markets, and the discipline that the markets impose on financial entities can play a role in ensuring financial stability. An example of the increased emphasis by regulators on market forces as a tool to promote safety and soundness in the financial system is the approach to capital adequacy and banking supervision recently developed by the Basel Committee on Banking Supervision. Their new framework on banking supervision (The New Basel Capital Accord) rests on three pillars, and by including market discipline as one of the pillars, the committee recognizes the importance of the market as both an indicator and promotor of safety and soundness in different sectors of the economy.

In this paper we follow the market-based path and assume that investors' views on the health and prospects of the banking sector can be distilled from stock prices and that stock market information can help predict banking crises. In an efficient stock market, all relevant information that is related to the actual bank, macro- as well as micro-information, should be captured in the bank's market value and additional analysis of the bank, for instance by taking a closer look at the bank's balance sheet, or talking to its senior management, would be futile. If we expect markets to be efficient, then the variability in the bank's market value is an important piece of information that should be included in any indicator of the bank's performance and health.

Some attempts of using stock prices as indicators of banks' financial strength and credit-worthiness can be found in the literature. One such study is Shick and Sherman (1980) that investigates bank stock prices and their ability to function as early warning signals. Shick and Sherman (1980) finds that changes in the regulator rating of a certain bank are reflected in the behavior of the bank's stock price and that the stock price corrections lead the actual rating change by at least 15 months. An other study that examines the ability of stock prices, stock return volatilities as well as other market variables to predict rating changes is Curry, Elmer and Fissel (2001). Investigating a large number of banks that have faced changes in their regulator rating they find that stock prices keep falling and stock return volatilities keep rising for at least a year before an actual downgrade. The major drawback of these studies in the context of banks and their failure rates is their purely statistical nature and that they do not rest on theoretical grounds; there is no model underneath that motivates the choice of the particular market variables as default measures. In addition, there is no natural way of transforming these signals to actual default *probabilities*.

In order to avoid these problems, we have chosen to adopt an approach suggested by Hall and Miles (1990) that in a simple way gives us estimates of default probabilities. The approach relies solely on market data and can therefore be used on any bank (or group of banks) with traded stocks. It is also easily reproduced by anyone who has access to the history of stock prices of the bank(s) in question. The Hall and Miles (1990) approach is not without its own drawbacks and a major assumption is that of efficient markets. By relying on markets to be efficient, as well as the Capital Asset Pricing Model (CAPM) (Sharpe, 1964; Lintner, 1965), and a modelling of returns as Generalized Autoregressive Conditional Heteroscedastic in Mean (GARCH-M) processes, the Hall and Miles (1990) approach gives us a measure of the distance to default of a particular bank or banking sector at its current value and volatility. This distance to default measure can then easily be transformed to a default probability[1].

[1] In this paper we use the words default and failure as synonyms indicating a situation in which a bank, or the entire banking sector, might become unable to meet its contractual liabilities out of its own resources due to its

Hall and Miles (1990) applies their technique to four individual British banks over the period 1975 to 1987 and Clare and Priestly (2002) applies the same approach to Norwegian banks in the late 1980s when the Norwegian banking sector went through a serious banking crisis. Clare and Priestley (2002) shows that the market based approach of Hall and Miles (1990) captures much of this turmoil by indicating an increased probability of defaults in the banking sector during the crisis years compared to before or after the crisis. In a similar study Byström (2002) looks at the major Swedish banks during the Swedish banking crisis of the early 1990s. Byström (2002) compares market-based failure probabilities to rating implied probabilities by Moody's and Fitch, and extends the Hall and Miles (1990) approach using extreme value theory. Byström (2002) finds a close correspondence between actual credit health changes and the market-based default probabilities. The market is further found to react much faster than the rating agencies to the unfolding banking crisis.

While Hall and Miles (1990) applies their methodology to individual banks we apply an aggregated version of the approach to banking sectors in 34 countries around the world. As proxies for these banking sectors we use FTSE all-world banking sector stock indices. These indices include banks but no other financial firms and represent the aggregated valuation of the banking sector in a particular country. Compared to Hall and Miles (1990) and Clare and Priestley (2002) we present our results in a more informative way by transforming our estimated default measures to actual probabilities of default. These probabilities should probably not be interpreted literally but nonetheless they give an overall, albeit rather crude, indication of the health of the particular banking sector. In addition, the relative default risks in different countries, and the changes in the levels over time can provide useful information about how the market assesses the health of banking systems world wide. Considering the fact that most banks of today have significant parts of their credit exposures (to banks) abroad, this information can be used both by the banks themselves and by national bank supervisors in estimating the risks to their domestic financial system.

The time period we are looking at is 1994 to 2002, a time period containing the Asian crisis 1997-98. According to the market, failure probabilities in most banking sectors increased significantly during the crisis years, not only in the Asian countries directly involved in the turmoil. Considering most banks' considerable overseas exposures as well as the close links between banking systems in different countries this is not very surprising. The dot-com and technology boom in 1999 and 2000 and its bust in 2001 and 2002 are also covered by the data

negative net market-value. A failure is not always followed by a formal declaration of insolvency (and subsequent closure) by the chartering authority, but equity holders, and some debt holders, usually loose large parts of their invested capital.

but do not seem to be as critical to the credit health of the banking sectors as the Asian crisis.

We also investigate whether various structural features of a particular banking system are related to the market's view of the stability of the banking system and how likely it is to end up in distress. Factors we look at are the existence of an explicit deposit insurance scheme (whether the government will compensate depositors or not), regulatory environment (the way a bank is defined and what business the bank is allowed to engage in), ownership (proportion state-owned banks), the quality of government (law and order, lack of corruption), financial structure (if the financial system is "bank based" or "market based") and finally the efficiency of the banking sector (interest rate margin, overhead costs). The data comes from numerous studies at the World Bank and at the International Monetary Fund dealing with the stability of financial systems around the world (Barth, Caprio Jr. and Levine (1999); Barth, Caprio Jr. and Levine (2000); Beck, Demirgüç-Kunt and Levine (1999); Demirgüç-Kunt and Detragiache (1999), Demirgüç-Kunt and Levine (1999)). Using simple OLS regressions we find the quality of government (lack of corruption, law and order, small expropriation risk) as well as low degrees of state ownership in the banking sector to be negatively related to failure probabilities before the Asian crisis while during the Asian crisis an explicit deposit insurance scheme (as well as good governance) seems to reduce the conceived risk to the banking sector stability.

The paper is organized as follows. Section 2 discusses the Hall and Miles (1990) model and how we can assess the probability of bank failure using market prices. Section 3 describes the data and section 4 presents the empirical results. Section 5, finally, concludes the paper.

2 Assessing the Probability of Bank Failure Using Market Prices

In this section we will describe the Hall and Miles (1990) approach. The advantage of this method is that it relies solely on stock market data. While Hall and Miles (1990) apply their model to individual banks we instead apply it to the "diversified portfolio" of banks that makes up the banking sector in a particular country.

A typical bank[2] has both assets and liabilities and if we assume that all these claims are priced efficiently by the market then the stock price, S_t, of the bank in question could be calculated as

$$S_t = \frac{1}{N} \sum_{i=1}^{I} P_{it} X_{it}, \tag{1}$$

[2] We follow the derivation of Hall and Miles (1990) and use the word bank even though we apply the approach to entire banking sectors (portfolios of banks).

where N is the number of outstanding stocks, P_{it} is the price of the bank's asset or liability i at time t, and X_{it} is the amount of the asset/liability at time t (positive if an asset, negative if a liability). If we assume that (1) holds then the expected value of the stock in the future together with the variability of the value around this expectation can tell us something about the probability of the bank actually defaulting (the larger the number of standard deviations the stock capital represents at time t the smaller the probability of default)

As one of the most popular models of stock price formation, the CAPM expresses the expected return of a stock, $\mathrm{E}(R_t)$, at time t as the risk free return, RF_t, at time t (for instance a Treasury bill) plus a time varying risk premium, RP_t :

$$\mathrm{E}(R_t) = \frac{\mathrm{E}(S_t - S_{t-1})}{S_{t-1}} = RF_t + RP_t. \tag{2}$$

The expectations are formed at $t-1$ and the risk premium can be thought of as the amount of risk that an investor has to be compensated for multiplied by the market price of this risk, λ_t. According to the CAPM not all risk can be expected to be compensated for, and in equilibrium only non-diversifiable risk is priced. This means that only the risk that cannot be "diversified away" should be compensated in the market by a higher return than the risk free return. If we call the amount of expected non-diversifiable risk $\mathrm{E}(\mathrm{ND}_t)$ we can change (2) to

$$\mathrm{E}(R_t) = RF_t + \lambda_t \mathrm{E}(ND_t). \tag{3}$$

Since the market participants cannot be expected to be right all the time, (3) is only true on average. The actual return between $t-1$ and t is instead given by the expected return in (3) plus a stochastic error term, ε_t, that on average is equal to zero:

$$R_t = RF_t + \lambda_t \mathrm{E}(ND_t) + \varepsilon_t. \tag{4}$$

We can now express the *expected* value of bank capital, $\mathrm{E}(S_t N)$, as

$$\mathrm{E}(S_t N) = S_{t-1} N \left\{1 + RF_t + \lambda_t \mathrm{E}(ND_t)\right\}. \tag{5}$$

and *actual* value of bank capital as depending on the random term ε_t

$$S_t N = S_{t-1} N \left\{1 + RF_t + \lambda_t \mathrm{E}(ND_t) + \varepsilon_t\right\}. \tag{6}$$

Therefore, the actual value of bank capital at time t can be divided into a deterministic part and a stochastic part,

$$S_t N = \mathrm{E}(S_t N) + S_{t-1} N \varepsilon_t, \tag{7}$$

and the conditional variance, as measured at $t-1$, of the value of bank capital at time t can be written as

$$(S_{t-1}N)^2\sigma^2_{\varepsilon_t} \tag{8}$$

where $\sigma^2_{\varepsilon_t}$ is the variance of ε_t at time t. This is the variability in the market value of the bank (or its portfolio of assets and liabilities) around the market's expected value, and this is the variability measure that is of interest to the supervisor or regulator.

If the assumption of market efficiency holds, and if we divide the value of the bank, $S_{t-1}N$, by its standard deviation $S_{t-1}N\sigma_{\varepsilon_t}$, we get a simple measure of how probable a default by time t is:

$$\frac{S_{t-1}N}{S_{t-1}N\sigma_{\varepsilon_t}} = \frac{1}{\sigma_{\varepsilon_t}}.$$

This metric shows the number of standard deviations that the value of the bank (or banking sector) represents at time $t-1$ and it can easily be transformed to a default probability if we assume normality of the error term[3]. For instance, a value of $\frac{1}{\sigma_{\varepsilon_t}}$ equal to 2.33 would represent a 1 in 100 probability of default and a value of 3.09 would represent a 1 in 1000 probability of default between $t-1$ and t.

In order to get an estimate of σ_{ε_t}, the standard deviation of ε_t, we return to (2) which according to the CAPM can be rewritten as

$$\mathrm{E}(R_t) = \frac{\mathrm{E}(S_t - S_{t-1})}{S_{t-1}} = RF_t + \beta_t \mathrm{E}(RM_t - RF_t) \tag{9}$$

where RM_t is the return on the market portfolio and β_t is the expected conditional CAPM coefficient defined in its usual way as $\frac{\mathrm{E}(\sigma_{R_t,RM_t})}{\mathrm{E}(\sigma^2_{RM_t})}$. From the CAPM we also know that the risk premium on the market portfolio must be the market price of risk, λ_t, multiplied by the expected variance, $\mathrm{E}(\sigma^2_{RM_t})$, of the market portfolio returns (the expected non-diversifiable risk of the market portfolio). Thus

$$\mathrm{E}(RM_t) = RF_t + \lambda_t \mathrm{E}(\sigma^2_{RM_t}) \tag{10}$$

and, by definition, λ_t, the market price of risk is

$$\lambda_t = \frac{\mathrm{E}(RM_t - RF_t)}{\mathrm{E}(\sigma^2_{RM_t})}.$$

[3] We define default as the point in time when the value of the bank's capital (assets minus liabilities) is equal to zero. Of course, if some liabilities are not due at time t this measure should be modified to take this into consideration. The effect would be a reduction of the probability of default.

Rewriting (4) but for the market portfolio instead of the individual bank leaves us with

$$RM_t = RF_t + \lambda_t \mathrm{E}(\sigma^2_{RM_t}) + \upsilon_t = RF_t + \lambda_t \mathrm{E}(\sigma^2_{\upsilon_t}) + \upsilon_t \tag{11}$$

where υ_t is a random error term that on average is equal to zero just like ε_t. If we add the error term, ε_t, to (9) and substitute for the definition of β_t we also end up with an equation for the individual bank,

$$R_t = RF_t + \frac{\mathrm{E}(\sigma_{R_t,RM_t})\mathrm{E}(RM_t - RF_t)}{\mathrm{E}(\sigma^2_{RM_t})} + \varepsilon_t,$$

which, using the definition of the market price of risk finally can be written as

$$R_t = RF_t + \lambda_t E(\sigma_{R_t,RM_t}) + \varepsilon_t = RF_t + \lambda_t E(\sigma_{\varepsilon_t,\upsilon_t}) + \varepsilon_t. \tag{12}$$

The coupled equations (11) and (12) contain expectations of variances and covariances and in order to model these (and to get an estimate of the distance to default measure $\frac{1}{\sigma_{\varepsilon_t}}$) we use a bivariate GARCH-M framework. While Hall and Miles (1990) uses severely restricted non-standard versions of ARCH and GARCH, and Clare and Priestley (2002) makes a seemingly ad hoc choice of a non-standard AGARCH-M bivariate model we try to choose our model in a more systematic way. First of all, when estimating a multivariate GARCH-M system one easily ends up with tens (or hundreds) of parameters to estimate. In order to keep the number of parameters down, and hopefully get more reasonable parameter estimates, one should therefore favor parsimonious representations to more elaborated ones (particularly if one has rather short data series). Hall and Miles (1990) solves this problem by putting several restrictions on their equations and Clare and Priestley (2002) by choosing a non-standard covariance matrix representation.

In the spirit of transparency and parsimony we neglect possible asymmetries or seasonalities in the return series, and limit ourselves to a first order GARCH(1,1) representation. We also choose the parsimonious constant correlation representation for the covariance matrix. Finally, we assume the market price of risk, λ_t, to be constant, i.e. $\lambda_t = \lambda$, for all t. In this way we end up with a system (of excess returns) containing only 10 parameters to estimate using the maximum likelihood method (BHHH):

$$\begin{aligned} R_t - RF_t &= \alpha_{i,1} + \lambda E(\sigma_{\varepsilon_t,\upsilon_t}) + \varepsilon_t \\ RM_t - RF_t &= \alpha_{m,1} + \lambda E(\sigma^2_{\upsilon_t}) + \upsilon_t \end{aligned}$$

$$
\begin{aligned}
E(\sigma^2_{\varepsilon_t}) &= \phi_{i,1} + \phi_{i,2}\varepsilon^2_{t-1} + \phi_{i,3}\sigma^2_{\varepsilon_{t-1}} \\
E(\sigma^2_{\upsilon_t}) &= \phi_{m,1} + \phi_{m,2}\upsilon^2_{t-1} + \phi_{m,3}\sigma^2_{\upsilon_{t-1}} \\
E(\sigma_{\varepsilon_t,\upsilon_t}) &= \rho_{\varepsilon,\upsilon}\sqrt{E(\sigma^2_{\upsilon_t})E(\sigma^2_{\varepsilon_t})},
\end{aligned}
\tag{13}
$$

where $E(\sigma^2_{\varepsilon_t})$ and $E(\sigma^2_{\upsilon_t})$ are the expected conditional variances of ε_t and υ_t (as the market perceives it), $\rho_{\varepsilon,\upsilon}$ is the correlation coefficient, $E(\sigma_{\varepsilon_t,\upsilon_t})$ is the expected covariance between ε_t and υ_t, and $\varepsilon_t = \sigma_{\varepsilon_t}u_1$, and $\upsilon_t = \sigma_{\upsilon_t}u_2$ where $u_i \sim N(0,1)$. From (13) we obtain estimates of σ_{ε_t}, the conditional variance of the banking sector's excess return, at each point in time that we can plug into the metric for the probability of failure, $\frac{1}{\sigma_{\varepsilon_t}}$.

The next issue to handle is the choice of time scale. Eq. (13) gives us a constantly updated metric as to the probability of failure of a particular banking sector within the next day, week, month or year depending on our choice of data. From a practical point of view, the most reasonable frequency for updating the default rate is probably monthly; daily or weekly estimates contain too much noise and are too frequent for our purpose, and quarterly or yearly estimates are unnecessarily infrequent considering the quality of data available. In order to use the relatively short data series as efficient as possible, however, we have chosen to estimate such a monthly (default within a month) $\frac{1}{\sigma_{\varepsilon_t}}$ measure using daily data. To create a monthly default measure from the daily σ_{ε_t} estimates we simply add up the 21 daily variances within the month (to get the monthly variance) and calculate a monthly default measure $\frac{1}{\sqrt{\sigma^2_{\varepsilon_1}+\sigma^2_{\varepsilon_2}+.....+\sigma^2_{\varepsilon_{21}}}}$[4].

Our next step is to calculate actual default probabilities associated with the default metric above. As mentioned earlier, in order to do so we draw on the assumption of normally distributed error terms and simply map the metric to a probability using the negative tail of the normal distribution function. Further, since the procedure outlined above gives us monthly default rates while common practice is to discuss yearly default rates, we choose to scale up the monthly probabilities using the square-root rule; the yearly failure probability is calculated using a yearly metric constructed from the monthly metric by dividing (scaling) the monthly metric by $\sqrt{12}$[5].

3 The Data

The purpose of this paper is to apply the technique described above to banking sectors around the world, focusing particularly on the Asian financial crisis period 1997-98. As proxies for the

[4] The procedure is an approximation since it assumes independent error terms, ε_t.

[5] Again, this procedure is an approximation since it assumes independent monthly metrics.

banking sectors we use FTSE All-World banking sector indices[6] and as market indices we use FTSE All-World country indices. As a proxy for the risk free interest rate we use the most liquid 3-month interest rate that is available in each country. All data is quoted daily (closing values) and all prices are measured in local currencies.

The FTSE All-World data base contains countries where financial markets and institutional frameworks are efficient enough for prices to reflect the actual values of the listed entities. The indices are weighted by market capitalization and are supposed to capture 90% of the total market capitalization in the corresponding sector or country (FTSE (2002)). The FTSE All-World data base (accessed using Datastream) contains 49 countries in total but 15 of these countries were removed from our sample because either the banking sector price series, the market price series, or the interest rate series was too short for our purpose (or contained periods of stale prices, zero prices or other price behavior not in accordance with market efficiency). The 34 remaining countries in our study are listed in Table 1. Most of the series cover the period January 1994 to June 2002 but for nine countries the data was only available from January 1996. In addition to these individual countries, we also look at the FTSE All-World global banking index divided into developed and emerging countries, respectively[7].

In addition to the stock market data used to calculate failure probabilities we also look at a range of structural parameters describing the financial institutional framework in each country. Our purpose is to investigate whether these structural factors are related to the market's assessment of failure probabilities. The factors we have chosen to look at are: the general financial structure, the amount of regulative restrictions to bank activities, the degree of state ownership in the banking sector, the quality of government, the efficiency of the banking sector, and the existence or not of an explicit deposit insurance scheme.

The first factor, *financial structure*, is simply a classification of a country as market-based or bank-based. Ratios of stock market development relative to banking sector development (based on measures of size, activity and efficiency) are used to calculate an overall index of financial structure. The larger this index is the more market-based the country's economy is. The index is calculated by Demirgüç-Kunt and Levine (1999) using data collected from up to 150 countries over the 1990s. As a measure of financial structure based on size they use the ratio of domestic stock market capitalization to domestic assets of deposit money banks, as a measure based on activity they use the ratio of the total value of stock transactions on domestic exchanges to

[6] In the case of Finland and New Zeeland there were no banking sector indicies available and broader financial indicies were used instead.

[7] The market index in this case is the global FTSE All-World index covering all 49 countries and 2300 stocks. The "world interest rate" is simply the average of the 3-month rates across all countries.

private credit by deposit money banks, and finally as a measure based on efficiency they use the product of the value of all stock market transactions as a share of GDP and banks average overhead costs. The financial structure index we use in this paper is simply the average of these ratios, after removing the means of each series, and the index is available for 32 of our 34 countries.

The second factor, *regulatory restrictions*, is represented by an index capturing how restrictive a country's bank regulation is. Barth, Caprio Jr. and Levine (2000), constructs such an index by looking at national regulatory authorities and their regulatory practices in 60 countries in 1997. They acknowledge the ability of commercial banks to engage in four different activities; (i) securities underwriting, brokerage and management of mutual funds, (ii) insurance underwriting and selling, (iii) real estate investment, development and management, and (iv) banks owning nonfinancial firms. They rate the degree of regulatory restrictiveness for each of these four activities from 1 to 4 (with larger numbers representing more restrictive regulations) and use the average as an index of restrictiveness. We use this index as a proxy for regulatory practices in 32 of our countries.

Barth, Caprio Jr. and Levine (2000) also studies the degree of *state ownership* of commercial banks in different countries in 1997. State ownership is defined as state-owned bank assets as a share of total commercial bank assets. We have data on state ownership in 30 of our countries.

An other important structural factor that we include in our study is the quality of government. Barth, Caprio Jr. and Levine (2000) defines *good government* as the sum of three variables from LaPorta, Lopez-de-Silanes, Schleifer, and Vishny (1998): (i) risk of expropriation by the government, (ii) degree of corruption, and (iii) tradition of law and order in the country. Each variable is based on a scale from 0 to 10 where higher values represent better government. We have good government indices (estimated using data from 1982 to 1995) for 29 of our countries.

Demirgüç-Kunt and Levine (1999) calculates measures of *banking sector efficiency.* In this paper we use an average of two such measures as an index of banking sector efficiency; low overhead costs as a share of total assets of banks is a sign of more efficient banks, and small bank net interest margins over total assets indicates greater competition between banks. The smaller the index the more efficient the sector, and it is calculated using data from the 1990s and for 32 of our countries.

The final structural factor we have chosen to include in our study is whether a country has an explicit *deposit insurance scheme* at place or not. Demirgüç-Kunt and Detragiache (1999) investigates the level of deposit protection in 61 countries and construct a zero-one dummy for the presence of an explicit deposit insurance scheme. The dummy reflects the situation in 1997 and is available for 28 of our countries.

In addition to the structural parameters above we have also constructed two dummies capturing whether a country experienced a banking crisis during one or more of the years 1996, 1997 and 1998 or whether it was one of the Asian crisis core countries in 1997-98. These dummies are used to assess the ability of our market-based default probability model to capture obvious credit deteriorations in a country's banks.

4 Empirical Results

In this section we apply the default probability model described above to banking sectors around the world and compare the probabilities assessed by the market cross-sectionally and over time. The relationship between the market's view on health and stability of banking sectors and different institutional and structural characteristics across countries are further studied.

All estimations and results regarding default probabilities are based on the daily data described in section 3 and the model described in section 2. The data shows quite typical characteristics for stock return series like heteroscedasticity and excess kurtosis. We fit the bivariate GARCH-M model in (13) to each of the 34 countries' banking sectors but in order to save space we only present parameter estimates for the world banking index modelled together with the world market index in Table 2. All GARCH parameters are positive but in the case of the developed world we cannot reject the possibility of IGARCH. The unconditional correlation between the world banking sector index and the world market index is very high, 0.85, for the developed world and much lower, 0.40, for the emerging world. The residuals are all fairly well behaved.

In Fig.s 1 to 4 we plot probabilities of default (the probability of a systemic domestic banking crisis hitting the country within one year) on a monthly basis for each of the countries from January 1994 (1996) to June 2002[8]. The two uppermost panels in Fig. 1 present "probabilities of default" for the developed world and the emerging world, respectively. Obviously, the market considers the probability of a world-wide collapse of the financial system to be very small. During the second half of 1998, at the height of the Asian crisis, the probability of default reached its peak at 0.3% in the developed world and at around 0.5%, in the emerging world. The probability of a collective bank failure is not only larger in the emerging world but is also kept at an elevated level for a longer period after the Asian crisis. However, while the market's assessment of the risk of a systemic bank failure in the emerging world steadily has decreased over the last two three years the risk in the developed world has in fact risen slightly. This is most probably caused by the IT/Telecom debacle that mostly affects banks in the developed world.

[8] The y-axis has a logarithmic scale and when looking at the graphs one should keep in mind that what seems like large fluctuations at low probabilities in the figures not are very large when compared to fluctuations at higher probabilities (i.e. a change in probability from 0.0000000001 to 0.000001, although a 10000-fold change in probability, would not be possibe to detect in a linear plot).

Continuing to the individual countries in Fig.s 1 to 4, we find a plethora of different patterns. The only feature common to more or less all the countries is the significant rise in default risk at the start of the Asian crisis 1997. Default probabilities in most countries remain high all through 1997, reach a peak at 1998, and slowly decrease during 1999. One of the more interesting patterns is that of Argentina's. With an economy in serious recession and with banks on the brink of ruin, its banking sector failure probability systematically has risen to the staggering average level of 10% in 2002. This is about five times the probability of the second-most fragile banking sector (i.e. Korea's). It is also about three times larger than Argentina's default probability in 1998 and at the same level as the most fragile banking sector in 1998 (i.e. Thailand's).

In Fig.s 5 and 6 we rank the banking sectors year by year according to their assumed probability of failure and it is obvious that probabilities overall increased after 1996. The probabilities peaked in 1998 and since then the levels have come down significantly. Not to the rather low levels of the pre-crisis years, however (notice the change of scale of the abscissa). It is also evident that the Asian crisis core countries, Malaysia, Korea and Thailand, all became much more risky (according to the market) 1997 and 1998 compared to before the crisis, both on absolute and on relative terms. In 1998 the three core countries occupied the worst three slots in Figure 5, and at least Korea and Thailand have remained risky relative to other countries even after the crisis. The other countries that suffered from banking crises during any of the three years 1996, 1997 or 1998 (Argentina, Brazil, Hong Kong, India, Japan and Mexico) were also considered much riskier than the average country in those years (but less so in other years)[9].

In the other end of the spectrum Australia positions itself as the country with the most stable banking sector according to the stock market. The reason for this believed stability might be the economy's (and banking sector's) relative isolation from world market events. It is also in line with the conception of Australia as being a safe haven in times of crisis.

There are many reasons why relative as well as absolute levels of banking sectors failure probability are interesting. However, it would also be interesting to know what structural and institutional factors the market focuses on when assessing the risk of the banking sector. By looking at correlations between the structural factors described in section 3 and the market's default probabilities we get an indication of possible such factors. However, it is of course important to remember the limitations of such a correlation study when it comes to determine whether these factors are the factors the market actually looks at. The structural factors might

[9] According to Barth, Caprio Jr. and Levine (2000), using data up until 1998, Argentina suffered from a systemic banking crisis from 1995 onwards, Brazil suffered from a systemic banking crisis from 1994 onwards, Hong Kong suffered from a non-systemic banking crisis in 1998, India suffered from a non-systemic banking crisis from 1993 onwards, Japan suffered from a systemic banking crisis all through the 1990s and Mexico suffered from a systemic banking crisis from 1995 onwards.

simply be correlated with other more fundamental factors.

Before we present these correlations we turn to Fig. 7 and how the different structural parameters are distributed across countries[10]. The most market-based countries are Malaysia followed by Hong Kong, Switzerland and the US. The least market-based is Austria. The most restrictive banking regulations are at place in Japan and Mexico, while Israel and the UK top the list of the least regulated banking sectors. In India the state owns a very large share (80%) of the banking sector, while in about half of the countries the banks are fully privately owned. European banking sectors tend to top the list of good government, while less developed countries like Pakistan and Peru occupy the other end of the list. The banking sectors in the Latin American countries are the least efficient, while the ones in the Netherlands, Singapore and Japan are the most efficient. Finally, up until 1997, explicit deposit insurance schemes have been put in place in about two thirds of the countries in our study.

In Table 3 we present correlations between the structural factors and the probabilities in 1996, 1997 and 1998[11]. The reason why we limit ourselves to these three years is that the structural factors change over time and that most of the estimates we have are from 1997[12]. Before the onset of the crisis both the amount of regulative restrictions and the degree of state ownership was positively correlated to banking sector fragility. Good government not surprisingly was negatively correlated with bank fragility.

During the crisis years, on the other hand, the perception of good government and the existence of an explicit deposit insurance scheme are the only structural factors that are significantly (negatively) correlated with the market's perception of how likely a systemic crisis is to occur. The (zero-one) dummies for countries experiencing a banking crisis or belonging to one of the Asian crisis countries are both highly correlated to default probabilities in 1997-98 but not in 1996. This confirms the results in Fig.s 1 to 4 and is in accordance with our expectations of the market considering crisis countries more prone to have a failing banking sector.

In addition to calculating simple correlations we also run OLS regressions of the default probabilities on the structural parameters. We regress the probabilities on the structural parameters both one at the time (including the banking crisis dummy and the Asian crisis dummy in each regression) and jointly in a multiple regression[13]. For the univariate regressions the results are

[10] There are rather few outliers. However, the banking sector in India stands out as the clearly most state-owned sector, and Malaysia's banking sector stands out as the most market-based one.

[11] We have structural parameters for a maximum of 32 of our 34 countries. Poland and Taiwan are not included in the correlation study.

[12] We believe that the factors change very little over the three years 1996, 1997 and 1998.

[13] All regressions have been rerun with GDP as a control variable. GDP has not been found to be significantly

presented in columns 1-6 in Table 4-6 and are fairly similar to those from the correlation study. Before the outbreak of the Asian crisis, most of the structural factors have significant regression parameters; more regulation and more state-owned banks are related to higher probabilities of default while good government is negatively related to banking sector weaknesses. The only new finding compared to the correlation study is that more market-based economies are expected, by the market, to have less fragile banking sectors. During the initial year of the crisis, 1997, there are some signs of the financial structure and the degree of state ownership being related to the perceived probability of default. Only good government and deposit insurance are significant both in 1997 and 1998, however. The crisis dummies overall behave as we expect them to; they are highly significant during the crisis years and barely significant prior to the crisis. During the crisis years the degree of explanation (R^2) in the univariate regressions is very high and we cannot reject the hypothesis that at least one of the regressors is different from zero (the F-test). This is not surprising considering the crisis dummies included in the univariate regressions. In the pre-crisis year 1996, however, only the degree of state ownership, the quality of government and the deposit insurance regressions have high R^2s and significant F-statistics.

In the univariate regressions above we have between 28 and 32 countries in each regression. The degrees of freedom are therefore between 24 and 28. If we regress all structural parameters jointly together with the two crisis dummies we end up with only 15 degrees of freedom[14]. In the multivariate regressions we have therefore chosen to exclude the crisis dummies[15]. To further reduce the number of regressors and to improve the quality of the regressions we have also chosen to reduce the number of explanatory variables. We base our choice of remaining regressors on three criteria; multicollinearity, significance of the individual regressors in the univariate regressions, and the R^2 and F-tests in the univariate regressions. The fact that good government and banking sector efficiency are the only factors that are significantly correlated (pair-wise correlations equal to -0.49) together with the non-significant univariate regressions on the banking sector efficiency (non-significant slope parameters, lowest R^2s, non-significant F-values) makes us choosing to remove banking sector efficiency from the regression. The resulting degrees of freedom is 18 and the multiple regression results are presented in column 7 in Table 4-6.

The results are very much in line with the univariate results and again the only structural parameter that is significant in all three years is the quality of government. The existence of

related to the default probability, however, and therefore it is left out of the regressions presented in the paper.

[14] The whole set of structural factors is available only in 24 countries. The number of parameters to estimate in the multiple regression is 9.

[15] We have already seen that the (exogenously defined) crises are captured very well by the dummies.

an explicit deposit insurance is again significantly negatively related to the probability of a banking failure during 1997 and 1998 but not in 1996. There is also some weak evidence of state ownership and restrictive regulation as being positively related to banking sector weaknesses. Finally, all regressions produce high R^2 values and in none of the regressions can we reject the hypothesis of at least one non-zero parameter.

One reason why banking sector efficiency does not seem to be related to banking sector fragility is that the index of banking sector efficiency is calculated using data from a ten-year period (the 1990s), not the single year of 1997. This could also be the reason for the relatively weak correlation between the financial structure and default probabilities. In addition, the effect of banking sector efficiency on default rates is expected to be rather ambiguous; as we define banking sector efficiency an efficient banking sector could be a signal of healthy banks producing services at low cost, but it could also signal tight competition in the banking sector with banks running tight margins and showing low profitability.

Good government is the only structural factor that is significantly related to default probabilities in all three years 1996, 1997 and 1998. Not surprisingly, corruption, lack of law and order and expropriation risk creates a lot of uncertainty regarding the future of banks (as well as other firms) both in tranquil and in volatile periods. The fact that the quality of government is estimated over a 15-year period preceding the period 1996 to 1998 should not necessarily be seen as a problem since the common perception of the quality of a particular country's government equally much is based on history and tradition as it is a product of the latest legal and political changes.

The degree of state ownership, in turn, is found to be significantly positively related to banking sector fragility before the crisis. During the crisis years this relationship partly disappears and a reason for this might be that the market learns that state owned banks receive support and subsidies making a collapse less likely.

An explicit deposit insurance scheme, on the other hand, does not affect the market's perception of banking sector stability in tranquil times while during the crisis years 1997 and 1998 the market seems to acknowledge the existence of such a scheme; even if equity holders are not captured by the depositors' guarantee they might value the guarantee's role in making bank runs, and resulting bank defaults, less likely.

Finally, regulations that limit the range of activities a bank is allowed to engage in are making the banking sector more fragile according to the market (at least before the crisis). These results are similar to those found by Barth, Caprio Jr., and Levine (2000) but relies on a different definition of banking distress. Greater diversification is probably considered to lower the risk of less restricted banks. Such banks, however, might also engage in riskier projects and particularly in times of crisis this might be considered a weakness. At the height of the Asian crisis there is no clear relationship between the level of regulation and the market's estimates of banking sector defaults.

5 Conclusions

In dealing with today's increasingly international banks it is important for regulators and supervisors to include the health of foreign banks and banking sectors when assessing their own domestic banking sector. It is not obvious how the health of (foreign) banks is to be revealed and in this paper we therefore suggest a simple approach based on stock market behavior. Using an aggregated version of a model by Hall and Miles (1990) that gives us estimates of time varying failure rates of banking sectors based only on quoted stock market index levels and their volatilities, we have studied the health of banking sectors world wide over the period 1994 to 2002. This period includes the Asian financial crisis of 1997-98 and we find the market's assessment of the probability of default to be significantly higher during the crisis than before it in almost all countries. After the crisis the probabilities have come down significantly but the fragility of banking sectors has nonetheless remained relatively high both in developed and in emerging countries. Some countries stand out as more prone to a systemic crisis than others; during the Asian crisis the most fragile banking sectors not surprisingly were found in the Asian crisis core countries Malaysia, Korea and Thailand, and from 2001 onwards the most troubled banking sector is Argentina's.

The relationship between institutional factors and the market's opinion on banking sectors' health is also studied. We find the quality of a country's government to be strongly negatively related to the market's assessment of the probability of failure of the banking sector. The existence of an explicit deposit insurance is also significantly negatively related to the probability of a systemic bank collapse, but only during the Asian crisis. As expected, we also find the probability of default to be systematically higher in countries suffering from some kind of (exogenously defined) banking crisis (at the time of the crisis).

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Table 1: Countries included in the study.

1994-2002			1996-2002
Argentina	Hong Kong	Singapore	Brazil
Australia	Italy	South Africa	Chile
Austria	Japan	Spain	India
Belgium	Korea	Switzerland	Israel
Canada	Malaysia	Taiwan	Mexico
Denmark	The Netherlands	United Kingdom	Norway
Finland	New Zeeland	United States	Pakistan
France	Peru		Sweden
Germany	Poland		Thailand

Table 2: GARCH-M parameter estimates and standardized residual statistics for the bank index modelled together with the market index (emerging countries and developed countries resp.).

	Emerging World		Developed World	
	Market Index	Bank Index	Market Index	Bank Index
α_1	$-6.45 \cdot 10^{-4}$ ($2.24 \cdot 10^{-4}$)	$-4.98 \cdot 10^{-4}$ ($2.48 \cdot 10^{-4}$)	$1.58 \cdot 10^{-4}$ ($1.79 \cdot 10^{-4}$)	$2.50 \cdot 10^{-4}$ ($2.22 \cdot 10^{-4}$)
ϕ_1	$4.08 \cdot 10^{-7}$ ($2.21 \cdot 10^{-7}$)	$3.91 \cdot 10^{-6}$ ($1.57 \cdot 10^{-6}$)	$5.21 \cdot 10^{-8}$ ($2.34 \cdot 10^{-8}$)	$2.35 \cdot 10^{-7}$ ($0.84 \cdot 10^{-7}$)
ϕ_2	0.0557 (0.00570)	0.120 (0.00839)	0.0485 (0.00337)	0.0597 (0.00300)
ϕ_3	0.938 (0.00640)	0.854 (0.0103)	0.954 (0.00324)	0.942 (0.00231)
λ	10.8 (4.45)		5.30 (3.75)	
ρ	0.407 (0.0166)		0.846 (0.00513)	
Mean	-0.0419	-0.0398	-0.0683	-0.0674
Standard Deviation	1.002	1.001	0.998	0.998
Skewness	-0.367	-0.097	-0.385	0.028
Excess Kurtosis	1.321	1.622	1.438	2.056

Small figures are standard deviations.

Table 3: Correlation between banking sector failure probabilities and structural factors in the 32 countries 1996, 1997, and 1998.

	prob 1996	prob 1997	prob 1998
financial structure	$-0,209$	$0,136$	$0,286$
	0,121	0,225	0,051*
regulative restrictions	$0,349$	$0,231$	$0,223$
	0,021**	0,096*	0,105
state ownership	$0,623$	$0,289$	$0,103$
	0,001***	0,054*	0,292
good government	$-0,655$	$-0,450$	$-0,531$
	0,001***	0,004***	0,001***
banking sector efficiency	$0,0862$	$-0,0130$	$-0,0216$
	0,318	0,472	0,453
deposit insurance dummy	$0,0292$	$-0,354$	$-0,341$
	0,441	0,027**	0,032**
banking crisis dummy	$0,165$	$0,616$	$0,717$
	0,188	0,001***	0,001***
Asian crisis dummy	$0,00202$	$0,686$	$0,835$
	0,496	0,001***	0.001***

Small figures are p-values and significance at the 10 percent, 5 percent, and 1 percent levels are denoted by *, **, and *** respectively.

Table 4: Regressions of banking sector failure probabilities 1996 (before the Asian crisis) on structural factors.

	1	2	3	4	5	6	7
constant	0,101	−0,221	−0,0346	1,247	0,0826	0,0281	0,151
	0,067*	0,162	0,304	0,001***	0,235	0,308	0,209
financial structure	−0,102						−0,0172
	0,071*						0,286
regulative restrictions		0,153					0,0859
		0,083*					0,0398**
state ownership			0,955				0,561
			0,001***				0,001***
good government				−0,0603			−0,0150
				0,001***			0,021**
banking sector efficiency					−0,198		
					0,473		
deposit insurance dummy						−0,0251	−0,0561
						0,344	0,190
banking crisis dummy	0,246	0,0994	0,0105	−0,0120	0,227	0,436	
	0,045**	0,279	0,470	0,468	0,079*	0,001***	
Asian crisis dummy	−0,0797	−0,0978	0,0259	−0,195	−0,180	−0,331	
	0,365	0,335	0,449	0,154	0,231	0,002***	
R^2	0,140	0,133	0,390	0,462	0,074	0,543	0,746
F(n, d.f.)	1,518	1,429	5,534	7,162	0,742	9,508	10,558
	0,231	0,255	0,004***	0,001***	0,536	0,000***	0,000***
no. of countries in regression	32	32	30	29	32	28	24

Small figures are p-values and significance at the 10 percent, 5 percent, and 1 percent levels are denoted by *, **, and *** respectively. R^2 is the degree of explanation and F(n, d.f) tests if at least one of the regression parameters of the independent variables is non-zero. n is the number of independent variables and d.f. is the degree of freedom.

Table 5: Regressions of banking sector failure probabilities 1997 (build-up of the Asian crisis) on structural factors.

	1	2	3	4	5	6	7
constant	$0,189$	$-0,0240$	$-0,0384$	$1,222$	$0,142$	$0,463$	$2,590$
	0,123	0,483	0,419	0,082*	0,302	0,078*	0,074*
financial structure	$-0,222$						$0,0141$
	0,092*						0,481
regulative restrictions		$0,082$					$0,269$
		0,383					0,284
state ownership			$1,343$				$1,475$
			0,030**				0,119
good government				$-0,0558$			$-0,0924$
				0,095*			0,096*
banking sector efficiency					$-0,227$		
					0,487		
deposit insurance dummy						$-0,491$	$-1,389$
						0,089*	0,012**
banking crisis dummy	$0,882$	$0,765$	$0,550$	$0,659$	$0,836$	$1,121$	
	0,001***	0,034**	0,075*	0,071*	0,015**	0,011**	
Asian crisis dummy	$2,125$	$1,960$	$2,201$	$1,851$	$1,913$	$1,465$	
	0,001***	0,001***	0,001***	0,001***	0,001***	0,016**	
R^2	$0,582$	$0,558$	$0,609$	$0,585$	$0,556$	$0,613$	$0,422$
F(n, d.f.)	$13,018$	$11,762$	$13,484$	$11,740$	$11,696$	$12,694$	$2,623$
	0,000***	0,000***	0,000***	0,000***	0,000***	0,000***	0,060*
no. of countries in regression	32	32	30	29	32	28	24

Small figures are p-values and significance at the 10 percent, 5 percent, and 1 percent levels are denoted by *, **, and *** respectively. R^2 is the degree of explanation and F(n, d.f) tests if at least one of the regression parameters of the independent variables is non-zero. n is the number of independent variables and d.f. is the degree of freedom.

Table 6: Regressions of banking sector failure probabilities 1998 (peak of the Asian crisis) on structural factors.

	1	2	3	4	5	6	7
constant	$1,220$ 0,001***	$0,565$ 0,297	$0,983$ 0,001***	$5,618$ 0,001***	$0,999$ 0,028**	$1,589$ 0,002***	$11,405$ 0,004***
financial structure	$-0,185$ 0,287						$0,851$ 0,113
regulative restrictions		$0,314$ 0,274					$-0,116$ 0,459
state ownership			$0,907$ 0,249				$0,847$ 0,389
good government				$-0,228$ 0,001***			$-0,416$ 0,007***
banking sector efficiency					$5,586$ 0,338		
deposit insurance dummy						$-0,743$ 0,095*	$-2,061$ 0,081*
banking crisis dummy	$1,686$ 0,007***	$1,391$ 0,041**	$1,529$ 0,016**	$0,539$ 0,238	$1,531$ 0,019**	$2,645$ 0,001***	
Asian crisis dummy	$6,871$ 0,001***	$6,856$ 0,001***	$6,889$ 0,001***	$6,812$ 0,001***	$6,857$ 0,001***	$5,532$ 0,001***	
R^2	$0,752$	$0,752$	$0,784$	$0,816$	$0,750$	$0,826$	$0,464$
F(n, d.f.)	$28,261$ 0,000***	$28,321$ 0,000***	$31,518$ 0,000***	$36,941$ 0,000***	$28,073$ 0,000***	$37,864$ 0,000***	$3,112$ 0,034**
no. of countries in regression	32	32	30	29	32	28	24

Small figures are p-values and significance at the 10 percent, 5 percent, and 1 percent levels are denoted by *, **, and *** respectively. R^2 is the degree of explanation and F(n, d.f) tests if at least one of the regression parameters of the independent variables is non-zero. n is the number of independent variables and d.f. is the degree of freedom.

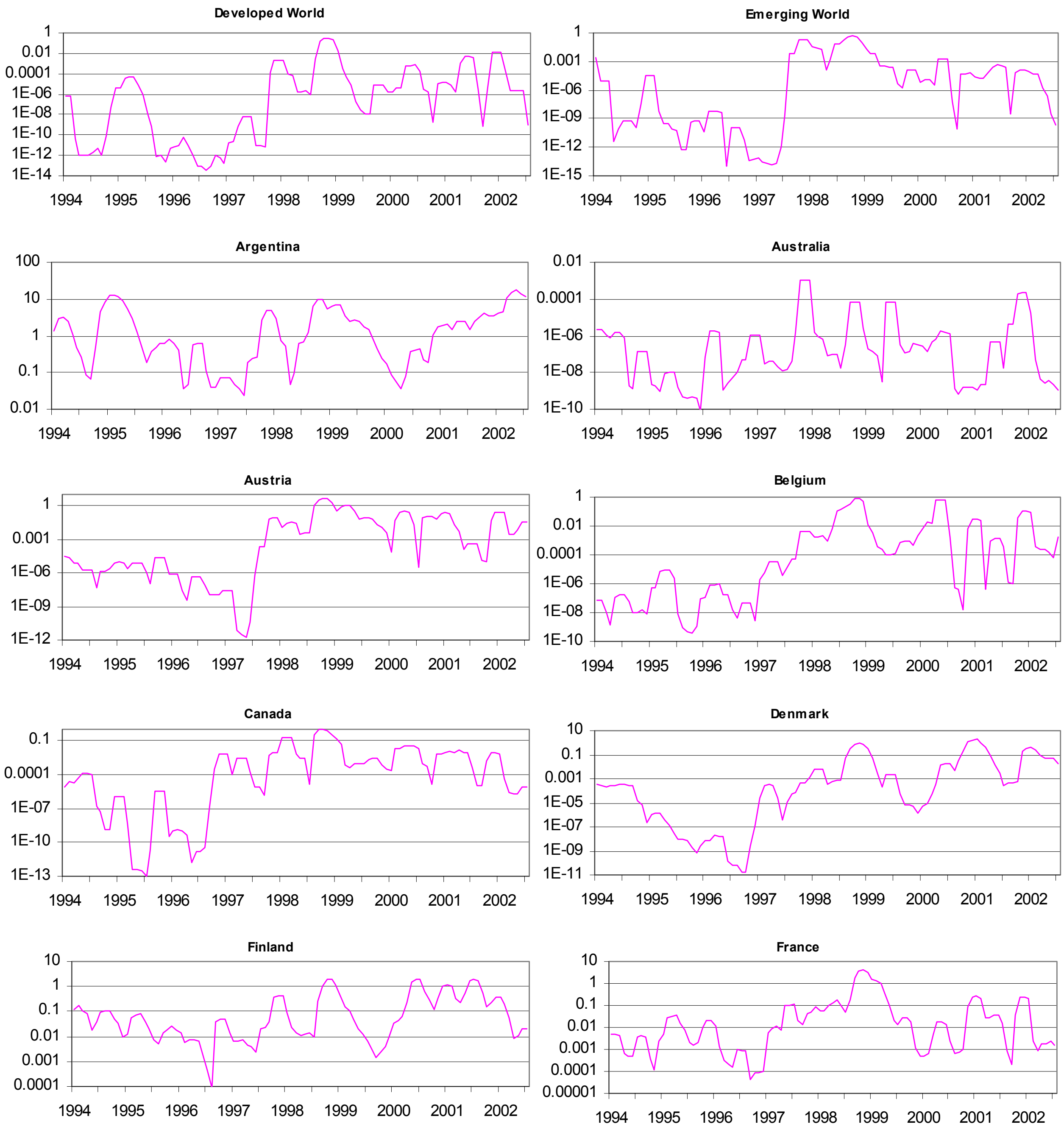

Figure 1: Probability of default within one year (%). 1994, 1995 and so on means January 1994, January 1995 etc.

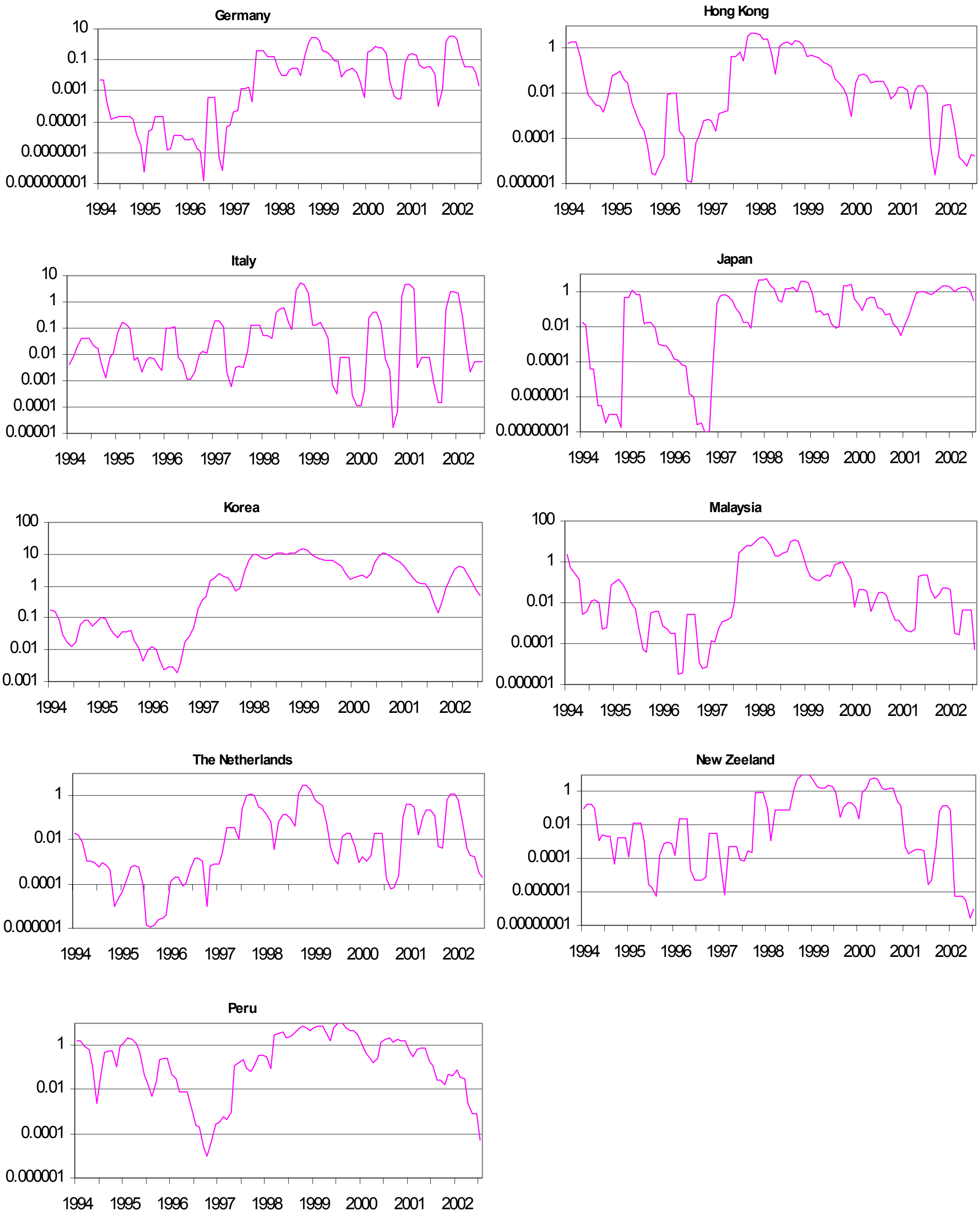

Figure 2: Probability of default within one year (%). 1994, 1995 and so on means January 1994, January 1995 etc.

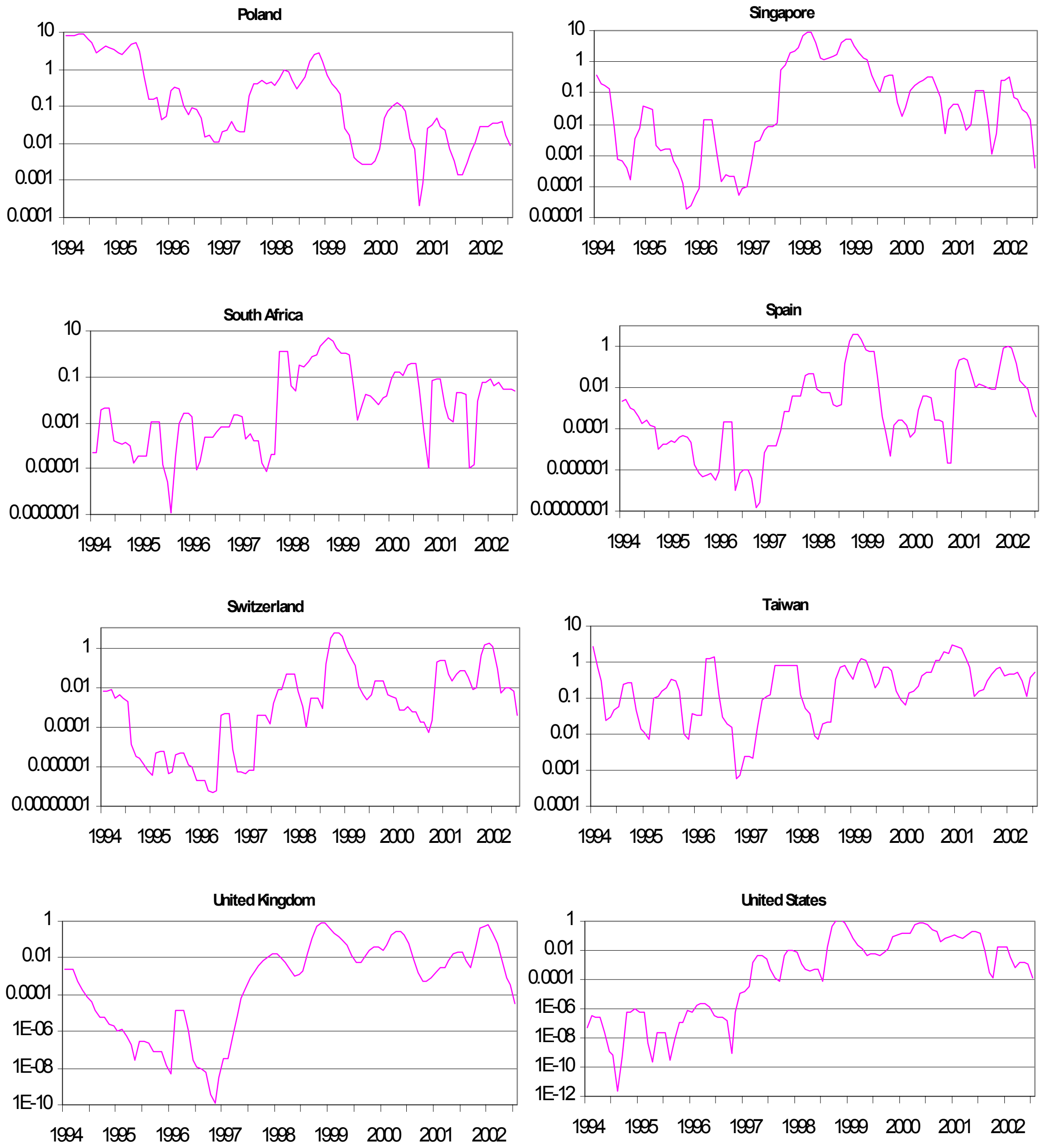

Figure 3: Probability of default within one year (%). 1994, 1995 and so on means January 1994, January 1995 etc.

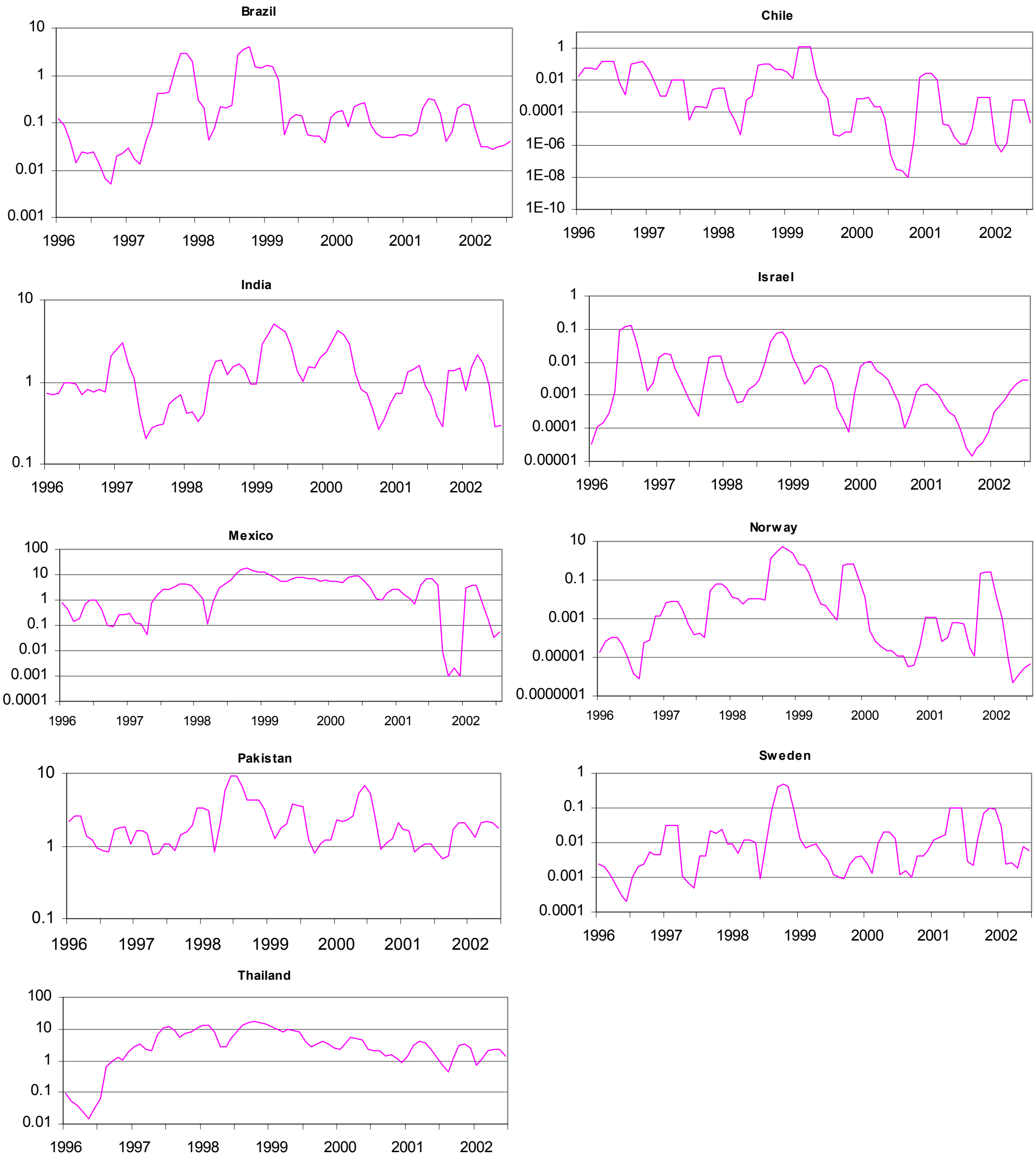

Figure 4: Probability of default within one year (%). 1996, 1997 and so on means January 1996, January 1997 etc.

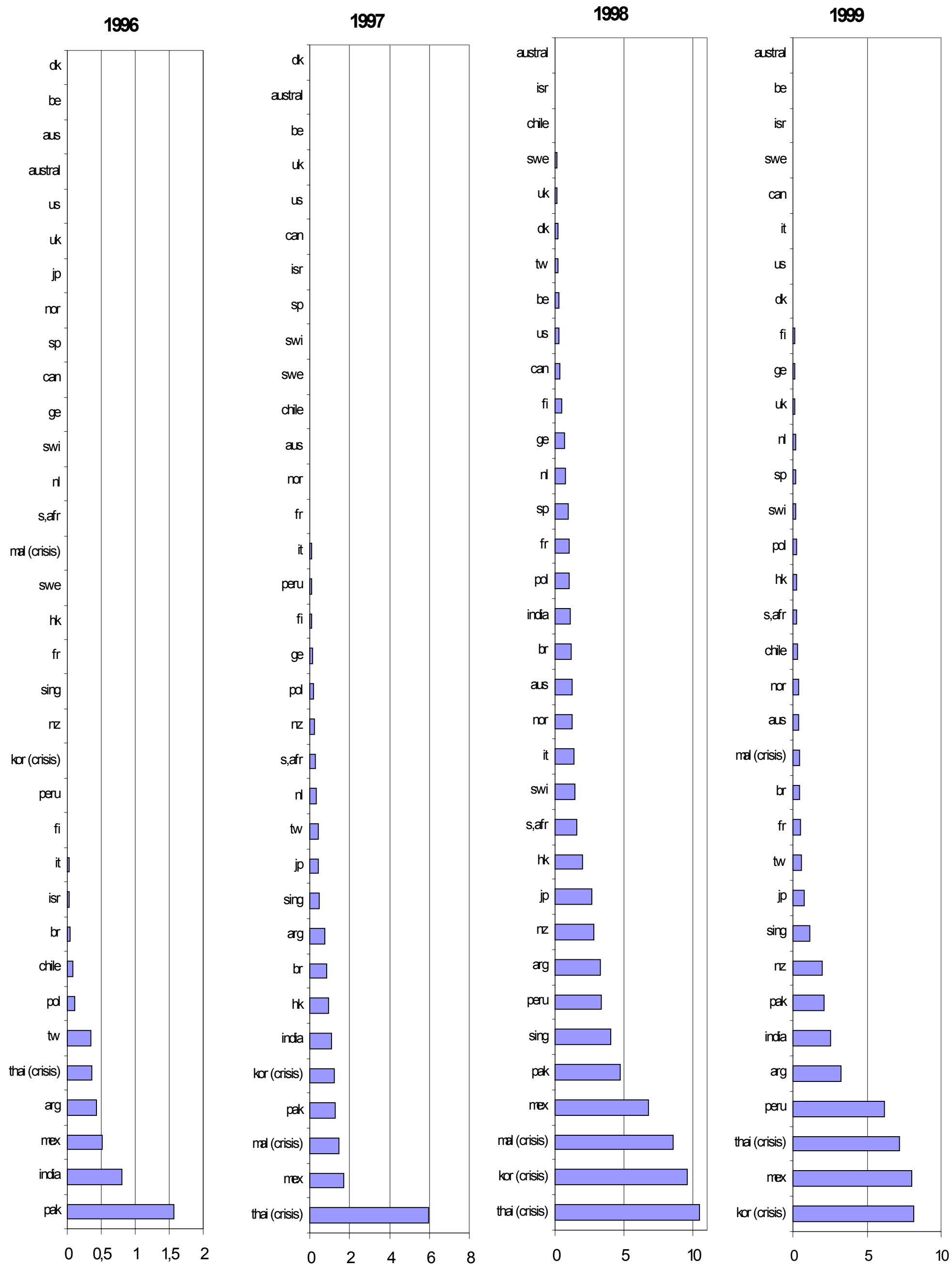

Figure 5: Ranking of probability of default (annual average) within one year (%).

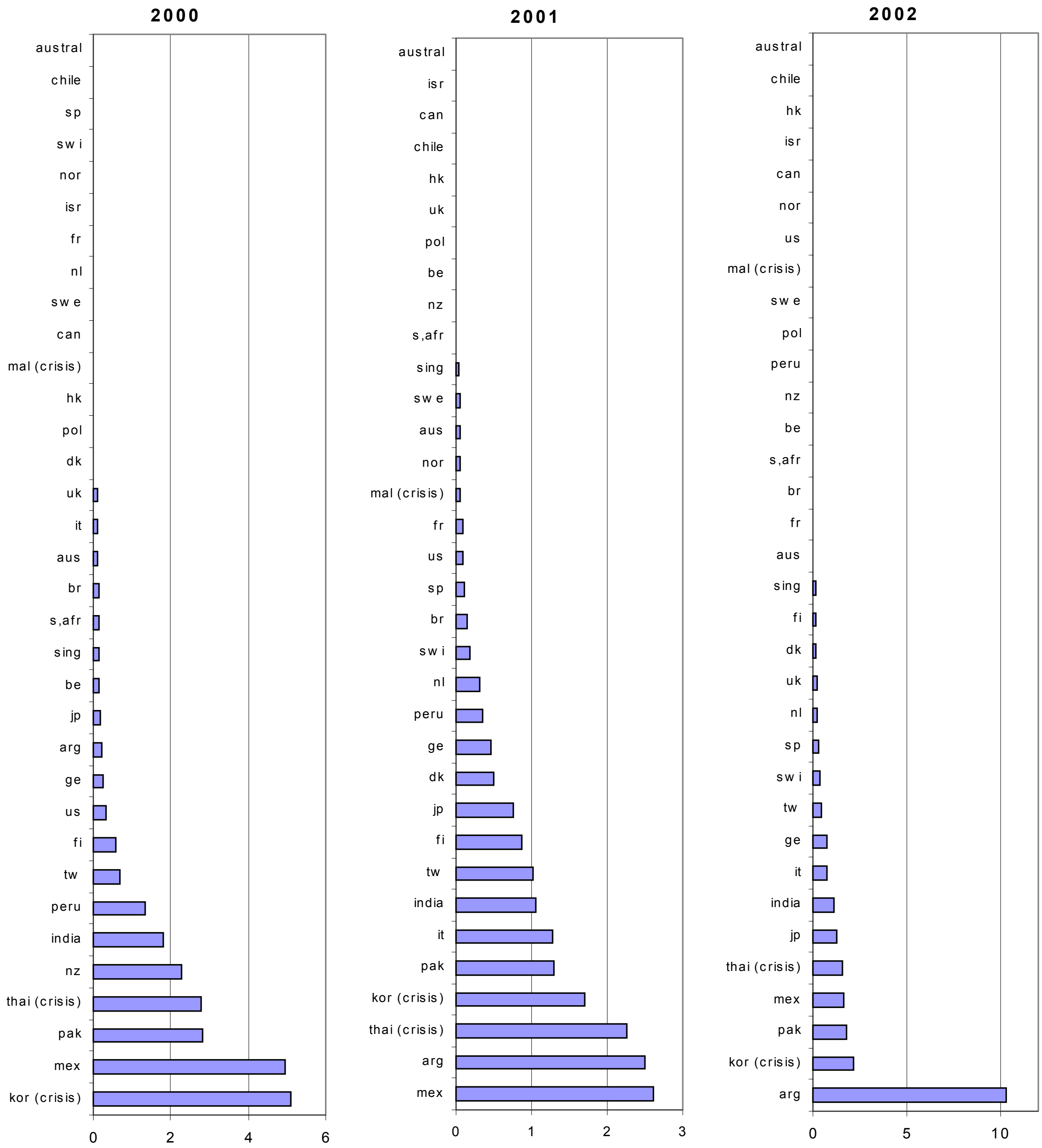

Figure 6: Ranking of probability of default (annual average) within one year (%).

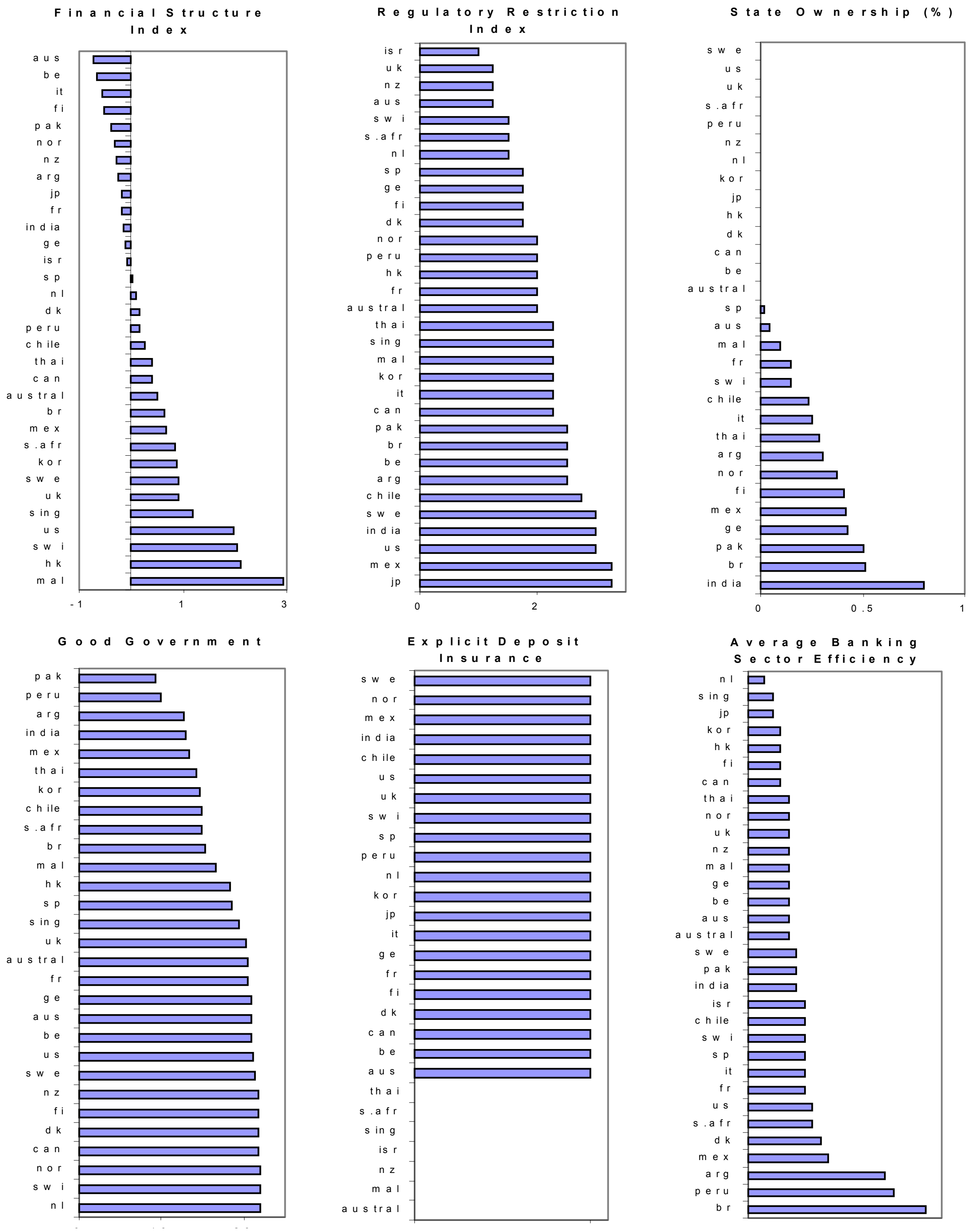

Figure 7: Cross-country distribution of structural parameters.