Determining the probability of banking system’s weakness in developing countries: 
the case of Peruvian banking system

Michel Canta
Departamento de Investigación

DICIEMBRE 1998

Resumen

The paper develops a methodology for the creation of an index of banking system’s vulnerability that can be used, as an early warning system, to assess the soundness of banking systems in developing countries. This index is based on the weighted-by-assets probability of banks classified as unsound by the supervisory agency. Applying the index for the case of Peru, it is shown that the index provides more relevant information, in advance, about the fragility of the banking system than failure models. We found that the determinants of banks’ weaknesses are individual risks taken by financial institutions and external economic risks. The latter also help to determine the period of time before a bank is declared unsound. We also conclude that the banking system fragility’s index in the case of Peru has a feedback causality with the economic activity, and they are negatively correlated. This result makes a case for banking regulation.

CLASIFICACION JEL: C73, G21 L13

CLAVE: Probability of bank failure, early warning systems, banking system fragility.

E-Mail del Autor(es): mcanta@sbs.gob.pe
# Table of Contents

ABSTRACT ....................................................................................................................................................1  

I. INTRODUCTION ........................................................................................................................................3  

II. PREVIOUS RESEARCH ON EARLY WARNING SYSTEMS IN BANKING ................................................5  

III. BANKING SYSTEM’S FRAGILITY MEASURES: METHODOLOGY PROPOSED ..................................10  

IV. BANKING SYSTEM’S WEAKNESS: THE CASE OF PERU ................................................................14  
   PERUVIAN COMMERCIAL BANKING SYSTEM: STRUCTURE AND CHARACTERISTICS ..................15  
   THE DATA .................................................................................................................................................16  
   THE DEPENDENT VARIABLE ....................................................................................................................16  
   INDEPENDENT VARIABLES .....................................................................................................................18  

V. ESTIMATIONS ........................................................................................................................................23  
   THE SURVIVAL FUNCTIONS ...................................................................................................................27  
   BANKING SYSTEM FRAGILITY’S INDEX ..............................................................................................29  
   ALTERNATIVE INDICES OF BANKING SYSTEM’S FRAGILITY ..........................................................31  
   USES OF THE INDEX ...............................................................................................................................35  

VI. CONCLUSIONS .......................................................................................................................................39
I. Introduction

The banking crises in some countries, in the aftermath of the Mexican crisis, have raised the issue about the reliance on surveillance systems to measure the soundness of commercial banking systems. Supervisory authorities are keen on minimizing the losses incurred when banks fail, and on reducing the risk of banking crisis that can jeopardize economic stabilization programs that many developing countries have begun recently.

A attempt to measure banking system weakness has been made through the construction of early warning systems which express the probability of future failure as a function of a set of variables obtained from banks’ balance sheet and income statements 1/. Most of the efforts focused on explaining the factors that affect the probability of failure rather than the determinants of soundness.

Explanatory variables of such models, mainly financial ratios, have been considered as key variables to measure the weakness of the banking system and to detect in order to avoid banking failure. Nevertheless, it is important to illustrate that the event “failure” is not a good indicator of the banking system’s weakness. Banking failure is only the last stage that follows a series of persistent problems, negative shocks or bad performance. Therefore, if we consider the special characteristics of failed banks, as benchmarks for an early warning system, we actually may be considering factors different than those that cause banking weakness. The reason behind that is banks’ financial conditions can reflect policy actions taken before failure, once the bank has been defined as unsound, by the supervisory agency. Likewise, such conditions can reflect political factors that trigger supervisors to opt for closing troubled banks. The point to be maid here is that a banking system weakness index, built on such assumptions, can result in a “warning” too late to permit policy-makers take the necessary steps to strengthen the banking system soundness.

The purpose of the paper is to develop an index of banking system’s weakness that can be used, as an early warning system, to assess the soundness of banking systems in developing countries. The

1/ Starting from the paper of Santomero and Vinso (1977) and Martin (1977), many papers about the probability of banking failure have been written. See for example, Abrams and Huang (1987), Thomson (1991) and Hooks (1995). For a survey about the literature written in the eighties, see Demirgüc-Kunt (1989).
index will be based on the weighted-by-assets probability of banks classified as weak 2/ by the supervisory agencies. Unlike previous approaches, we will use the standard CAMEL analysis 3/ along with ratings used by supervisory agencies to measure of banks’ distress. Therefore, the index will reflect the probability of weakness of the banking institutions rather than their probability of failure. Accordingly, we can define main factors that cause the unsoundness in the banking system and its relation with economic events. The index is tested for the Peruvian banking system that has gone through several economic shocks, a stabilization program as well as banking failure and merger, during the period under consideration. The banking failure in this system involved the fourth largest banks. In general, failures and mergers accounted for near to 20% of total assets of the banking system at that time.

The main finding of the paper is that banks indices’ (built on banking weakness measures based on CAMEL ratings or ratios of threshold level of Non-performing loans over Loans, adjusted by provisioning for bad loans 4/) provide early and more relevant information about the weakness of the banking system than failure models. Another important finding is that the determinants of banks’ weakness are the risky behavior of financial institutions in addition to externalities caused by economic risks. The latter also help to explain the time before a bank is declared unsound. Furthermore, we found that the banking system weakness index has a feedback causality with the economic activity, and that they are negatively correlated. This fact makes a case for banking regulation.

The paper is structured as follows: the next section discuss the usefulness of failure models used by previous research, as indicator of banking system’s fragility. Section 3 presents the methodology to approach banking weakness and the use of non time-varying proportional hazards for the estimation of the index. Section 4 deal with constructing the data set and the explanatory variables. Section 5 presents the results of estimations and the index for the case of the Peruvian banking system and its correlation with the economic activity. The last section presents the conclusions.

2/ The terms weak and unsound will be used interchangeably throughout the text, because they simply refer to a bank’s condition. For instance, reduce in the bank’s soundness, is synonimous of increase in bank’s weakness. For a definition of banking weakness see Lindgren, et. al. (1996).

3/ The acronym CAMEL stands for Capital, Assets, Management, Earnings and Liquidity. The method consist in assign weights to financial ratios that represent each one of the above mentioned features of banks condition. The weighted financial ratios are added to constitute a final grade of the banking performance. According to the grade obtained, banks are classified in five groups.

4/ Provision for bad loans is the amount of resources that banks allocate to cover future losses caused by non-performing loans. The amount of these provisions depends on the portfolio.
II. Previous Research on Early Warning Systems in Banking

The development of an early warning system in banking is paramount to understanding the characteristics of troubled banks and their risky behavior (Demirguc-Kunt, 1989). The supervisory agency can take the necessary steps to maintain the soundness of the system, minimizing, at the same time, the potential costs of losses incurred by the insurance deposit fund or the Central Bank, which is beared by the tax payers.

The loss of monetary resources of shareholders are only short-term outcomes of banking failure, but the long-term likely effect on the economy is the loss of confidence in the banking intermediation on the part of depositors. This loss of confidence can cause a bank run and a contagion effect on other banks, placing risk on the whole banking system and causing devastating macroeconomic effects.

The challenge to avoid banking crisis has led several authors to come up with a set of variables that can anticipate, with enough time in advance, the unsoundness situation of the financial intermediaries. Their estimates are based on risk behavior reflected in financial data obtained from a sample of individual banks. The use of individual banking data provides enough evidence of the factors underlying banking failures. Although individual banks can fail for a variety of reasons 5/, a large number of failures, that occur in a period of time, could be a symptom of a systemic crisis.

Most of studies in literature pertinent to the probability of banking distress have focused on identifying measures of risk that predict banking failure rates. The measures have been tested using data for the US banking system, while few of them have been applied in a developing-countries context 6/. These studies have in common a forward-looking measure of banking system crisis, using models that estimate the one-step ahead probability of bank failure, based on identifying banks’ specific factors that affect this probability.

---

The general approach of these papers has been to use, as a dependent variable, the time of closure of banks. The dependent variable takes the value of one whenever banks are closed and zero otherwise. The closure time of banks is the more observable event to record in their life spell, whereas determining their insolvency or unsoundness depends more on the analysis of the information collected during on-site supervisions made by the supervisory agency, which are not necessarily available to all external researchers (Lindgren, et al, 1996). This problem, as explained below, affects the accuracy in the timing of the information that any early warning system, based on this approach, should have.

Banking failures have also been explained by a set of variables based on the information obtained in banks’ balance sheet and income statements. As Demirguc-Kunt (1989) explain, the independent variables set tries to mimic the evaluation process of the supervisory agency, using proxies of the different components of the CAMEL rating system 7/. Other authors 8/ have used variables such as the size of operations (measured by the share of an individual bank’s assets on the total assets of the banking system), the credit risk (i.e. portfolio concentration in a particular sector or client, etc.) and macroeconomic variables such as unemployment and economic activity index. These variables help to explain the effect of the business cycle in the bank’s probability of failure during the period under study.

The major shortcoming of estimating the probability of failure, as an early warning system, is that failure is a subsequent step after banks are defined as being in trouble by the supervisory agency. The closure option depends on different factors other than those applied to classify banks as unsound 9/. Consequently, probabilistic models used in the main stream of literature are not accurate to predict the right time in which banks are fragile.

The closure option depends on supervisors’ decision and is constrained (or influenced) by political, social or credibility considerations. On the other hand, the unsoundness state could depend on the risk taken by banks in their investment and credit operations, as well as, the assets/liabilities

7/ See footnote No. 3 above.
9/ A previous attempt to separate the closure option from the banking insolvency situation has been made by Thomson (1990 and 1992). He approaches this two decisions by estimating a two-step model of probability of banking failure. In the first step, he estimates the factors that explain the causes of bank insolvency, whereas in the second step, he models the closure option of supervisors through an American call option, with strike price being a threshold level in fair-priced insurance deposit premium. The option is exercised any time that the price of the bank’s insurance deposit premium exceeds the threshold level.
management. In other words, it would appear that determining the time of banking unsoundness is very likely to measure the strength of the banking system, as opposed to detecting banking failure.

Notwithstanding the above-mentioned shortcoming, the estimation of banking failure determinants is important whenever the model compares sufficient cross-sectional data (such as in the case of US banking system) at a specific point in time. Using cross-sectional data is important to differentiate elements of troubled banks that fail from those of sound banks that manage to survive. Nevertheless, the importance and usefulness of banking failure models rely on the ultimate objective of the researchers or the supervisory agency. In small banking systems, in which data analysis is usually done through panel data, due to the small amount of observations, the case is different, because banks’ data use change over time and represent also changes in bank’s conditions.

Changes in banking conditions can be observed over time and, particularly, in transition process between the time in which banks have been found unsound and the closure time. Generally, when banks are closed, they have previously followed guidelines issued by the supervisory agency. Although the banks’ governance is not assumed necessarily by supervisors, it has been influenced by some “emergency measures”. Thus, balance sheets’ and financial statements’ data of troubled institutions that have been under intervention, could show, during the period of intervention, the results of policies’ measures that try to recover banks’ health. Moreover, the data at the time of failure, can represent a different picture of the banks’ financial position from the one at the beginning of their unsoundness.

Banking system’ weakness index, without considering the above mentioned factor, could send biased early warning signals. Financial ratios or other variables that are important in the recognition of the early stage of banking weakness, may not be statistically significant, and therefore, they can be excluded at the time of failure. As result, this index might send signals that are “too late” for the identification banking system’s vulnerability and for the need of some policy options by supervisors. When building a weighted-by-assets banking system’s weakness index 10/, assuming as a dependent variable the time of

---

10/ Weigthing by assets is useful to capture the size of each bank and the effect of its probability of failure on the composed banking system's weakness index. Although the index shows the average bank’s vulnerability, it also reflects the importance of larger banks. In the case of Peru, as five banks have almost 60% of the total assets in the system, the index approach the probability of weakness of the banking system, influenced by the vulnerability of larger banks. More weakness in the banking system could mean that larger banks are in trouble. This fact is important because larger banks failure can have deep impacts (through contagion effects or banks run caused by panics) on the rest of the system, and can represent higher cost of bail-outs.
failure and use a set of variables that mimic the supervisor’s closure option, the expected pattern could be similar to the one shown in Figure No. 1, for the Peruvian Banking system.

Following the pattern of the index, warning signals of banking system weakness will be emitted in a short period of time before the banks’ closure occurred. However, closed Peruvian banks showed insolvency and liquidity problems several months prior to the time of closure, as reported in Appendix No. 2. Therefore, signals emitted could be too late for taking the necessary steps to avoid the macroeconomic costs of banks’ bail-out.

Attempts to model the probability of banking weakness or insolvency have been made using CAMEL rating system (Whalen and Thomson, 1988). In these models, banks are considered in trouble if they have been graded level 3 to 5 in CAMEL rating system \(^\text{11/}\). Therefore, using a set of financial ratios that represents bank’s financial condition, these models estimate the probability of banks being graded as

\(^{11/}\) For an example about the methodology of this rating system, see Appendix No. 1.
troubled banks. Nevertheless, the probit models are estimated for one point in time, and the authors have not gone further to create an aggregated index that reflect fragility in the whole banking system.

Some studies have used split-survival models to identify not only factors that affect the probability of banking failure, but also the time to fail. Split-survival models are built in two steps. First, as previously, the probability of failure is determined. Compared to methodologies of previously-discussed models, this stage does not show significant difference. In the second step, the method identifies the factors that affect the time duration of a spell of survival, similar to proportional hazards models, used by other researchers. A spell of solvency is defined as the time elapsed, since the beginning of the operations, up to the time in which a bank failure occurs, or when a bank is censored (Lancaster, 1990). During the time in which the bank is censored, two events can happen: the bank survives throughout the whole period or it may fail during the period. In both cases, the hazard function is built as the probability of bank failure in the next period, given the bank was “alive” at the beginning of the spell. (Lane, et. al., 1986; and Whalen, 1991).

The main drawback of proportional hazards method is that all banks ultimately fail. However, there are banks that survive through the censored time and do not have similar characteristics to the ones that fail. Cole and Gunther (1995) have shown that this shortcoming could be avoided if the sample population is split in two groups: those that ultimately fail and those that do not. According to this split-population proportional hazard, it is clear that factors that affect the probability of failure are sometimes significantly different from those that affect the timing to fail. In spite of the usefulness of this methodology, this study still consider in their estimations the time of failure, rather the time in which banks are found unsound, a feature particularly important for the construction of a vulnerability index of the banking system.

As shown so far, the methodology used by previous studies might have overestimated the timing of the banking system unsoundness, because they used as proxy of unsoundness the time of bank closure. As pointed out by Lindgren, et. al (1996), the insolvency and timing of banking failure can be affected by factors other than those which trigger the authorities to opt for closure. The latter can be

14/ Gonzalez-Hermosillo, et. al. (1996) use a similar approach to Cole and Gunther (1995), but they define “failure” as the time in which banks have been intervened or have received
effected several months after a bank has been found insolvent by the supervisory agency, mainly due to political and other reasons.

Models that identify factors that affect weakness condition in the banking system are more suitable as early warning systems since they avoid unnecessary cost or delayed interventions by supervisory agency in keeping the soundness of the banking system. We consider that in this case, split survival models could help to estimate the factors that affect not only the probability of insolvency of the financial intermediary, but also, given the characteristics of the institution, the timing of survival in this category of solvency. These factors can be used as key variables to monitor in order to avoid severe banking crisis that could destabilize the economy.

III. Banking System’s Fragility Measures: Methodology Proposed

From the last section, it has been made clear that previous research methodologies have focused on the timing of bank closures. Although it is useful to find which banks’ characteristics are common in these events, it is more useful to anticipate them. One important requirement for an effective intervention is the ability to identify problems with enough time in advance to give the supervisory authority the opportunity to correct them. Late intervention does not help to avoid the cost that the closure implies. As Peek and Rosengren (1996) point out, it is “easy to identify a problem bank at the time of its failure. The challenge is to identify it in time to prevent its failure or at least in time to alter its behavior in order to limit the losses to the deposit insurance fund” (Peek and Rosengren, 1996: pp. 50)

As in the main stream of the above-mentioned literature, we will construct an weighted-by assets banking system’s fragility index, but based on the probability of “being weak” for each financial intermediary. That is essential in order to understand the key variables that can explain each bank’s condition, as well as the time that elapsed up to the change in its condition. An index built on this methodology, could send signals with enough time in advance for policy-makers (due to the fact that they identify troubled banks rather than closed banks) and estimate the timing in which, given certain characteristics, financial intermediaries become fragile.
Unlike previous approaches, in order to measure weakness, we rely on the CAMEL rating system. As explained in the appendix No. 1, the CAMEL rating method is an analysis of banks’ condition based on financial ratios. The reason behind choosing CAMEL is due to its common use by supervisory agencies and because it uses a widespread range of financial factors that can represent each component of the acronym CAMEL and explain banks’ financial position. According to an overall grade built on these financial ratios, each bank is classified in one of five different rating levels shown in Table No. 1.

<table>
<thead>
<tr>
<th>Rating</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>An institution that is basically sound in every respect.</td>
</tr>
<tr>
<td>2</td>
<td>An institution that is fundamentally sound, but with modest weaknesses.</td>
</tr>
<tr>
<td>3</td>
<td>An institution with financial, operational or compliance weaknesses that give cause for supervisory concern.</td>
</tr>
<tr>
<td>4</td>
<td>An institution with serious financial weaknesses that could impair future viability.</td>
</tr>
<tr>
<td>5</td>
<td>An institution with critical financial weaknesses that render the probability of failure extremely high in the near term.</td>
</tr>
</tbody>
</table>

Source: Cole, Cornyn and Gunther (1995)

It is worthy to notice that, there is criticism on the main aspect of the CAMEL rating construction: the weights assigned to each component to get the overall rating. These weights, which are fixed across estimation periods, have been determined subjectively rather than by rigorous statistical testing. Other limitation of CAMEL is the subjective manner in which financial ratios are selected. Regulators selected these ratios from a wider set of financial ratios that might be not statistically validated as being sufficiently important to produce accurate off-site assessment of risk. Even if the selected financial ratios contained all the information necessary for an accurate assessment of risk, improper weighting of those ratios would reduce the accuracy of estimation (Cole, Cornyn and Gunther, 1996).

Supervisors apply the CAMEL method as part of the on-site examination, which facilitates in determining a grade on management, something that can not be observed on the basis of off-site examination. In the latter, they usually grade management based on some financial ratios that represent efficiency, such as operating expenses/assets, wages and salaries/total income and deposits or loans/number of personal, as a proxy for administrative cost.

---

15/ See footnote No. 3 above, for an explanation of the acronym CAMEL.
Each component of the CAMEL category uses a set of financial indicators. Since the benchmark for each financial ratio is determined subjectively and varies between banking systems, it is impossible to consider a bank operating in a certain environment in one country applying weights used in another country. Furthermore, the difference in accounting standards should be accounted for. In other words, applying the methodology to other banking systems requires the use of the own weights and rating system used by regulatory agencies.

In line with our methodology, a bank is considered in trouble whenever it is downgraded after CAMEL rating 2. A downgrade in the CAMEL rating system is considered as the increase in the bank’s weakness. Therefore, a binary dependent variable can be built assuming that banks that are downgraded take the value 1, and zero otherwise. The estimation of the probability of being in trouble could be done using standard probit or logit methods.

However, the time until the bank is downgraded (increase in the weakness or fragility) has to be approached using survival analysis that determines the time period up to the occurrence of the event provided that the bank has been sound during the previous period. We will use Non time-varying proportional hazards method to approach the factors that affect the time duration of a “soundness” spell of financial intermediaries.

The hazard rate in non time-varying proportional hazards will be used here as a measure of the conditional probability of unsoundness given that they have sound in the early time period. The dependent variable, therefore, is the time until a bank is being declared unsound. The probability distribution of time duration of the event “sound” can be specified by the distribution function:

\[ F(t) = \text{Prob} (t > T) \quad (1) \]

Which specifies the probability of time until unsoundness T is less than t periods. Differently, the survivor function or the probability of survival longer that t periods is:

\[ S(t) = 1 - F(t) = \text{Prob} (T < t) \quad (2) \]

As we can see, the probability density function of t is \( f(t) = -S'(t) \). The general form of the hazard function can then be written as:
The hazard function \( h(t) \) is assumed to have the simple form

\[
 h(t | X_t, \beta) = h_0(t) g(X_t, \beta) \tag{4}
\]

Where \( X \) is a collection of characteristic variables that affects the probability of weakness and \( \beta \) is the group of parameters to be estimated. The first part \( h(t) \) is called the baseline hazard probability, that can follow any distribution form. Cox and Oakes (1984) shows that Cox approach this hazard function to be exponential form:

\[
 h(t | X, \beta) = h_0(t) e^{X^\beta} \tag{5}
\]

The Cox approach is used to calculate the probability that a commercial bank, with a given set of characteristics, will survive longer than a given amount of time, as follows:

\[
 s(t | X, \beta) = S_0(t) e^{X^\beta} \tag{6}
\]

Our methodology is to estimate the coefficients \( \beta \) on a set of explanatory variables \( X \) and test if they are significantly different form zero. Cox and Oakes (1984) suggested that partial-likelihood approach can be used to estimate \( \beta \) in the proportional hazards models without specifying the form of the baseline hazard function \( h_0(t) \). As in Kiefer (1990), consider a sample of \( n \) institutions, of which \( x \) are downgraded during the observed period, with different downgrading times \( t_1 < t_2 < \ldots < t_x \). Suppose also that remaining \( n-x \) institutions exist that are right censored and do not fail during the period of time \( t_0 - t_r \). Then, we can build a variable \( \delta \) that has the value one if the institution has been downgraded during period \( t_0 - t_r \) and zero if it is right censored at time \( t_r \). If \( X_i \) is the set of characteristics of i-bank that fail at time \( i \) and \( X_{ij} \) is the set of characteristics of banks at risk during the period \( t_0 - t_r \), the partial likelihood function to be maximized is:
This partial likelihood function provides a mechanism to consider each institution that is downgraded and compare it with other institutions at risk and could have been downgraded during the same period of time. If the values of the explanatory variables of banks that are downgraded are significantly different from those that might have failed but have not, then the coefficient \( B \) will be significantly different from zero \((\text{Kiefer, 1990})\). \(^{16/}\)

As discussed above, the Cox proportional hazards model implicitly assumes that all banks fail at the end. However, in our sample, all banks have been degraded at least once, which means that the potential shortcoming of Cox proportional hazard is avoided.

IV. Banking System’s Weakness: The case of Peru.

Banking crises can occur anytime and anywhere, as long as the banking systems show the conditions mentioned by Lindgren, et. al (1996) and Rojas-Suarez and Weisbrod (1996). The importance of the methodology proposed above is based on the possibility of being tested in any banking system, regardless if it has had a banking crisis or not. We chose the Peruvian Banking System because it represent a typical case of a banking system in developing countries, facing several economic events including the money-based stabilization program in September 1990, the financial liberalization with new banking acts in 1991, four banking failures in 1992 and the external shock caused by the Mexican crisis in December 1994. We believe that an index built on this scenario should help to understand early warning signals about banking unsoundness.

It is worthy to point out that all methodological analysis in applying the same procedure for other banking systems should take into account the characteristics of accounting standards, banking regulation

\(^{16/}\) Here, It has to be taken in account that banks that are downgraded in more than one opportunity could be qualitative different of banks that fail once. In our approach, as we use non time varying proportional hazards, we are assuming that each bank’s downgrade has special characteristics that are independent across the time from others downgrading event for the same bank, as well as, from other banks’ downgrading.
and CAMEL rating system applied in the correspondent countries. Adapting rating systems of one country to another is not possible and can conduce to misinterpretations of banking soundness.


The Peruvian commercial banking system has faced a lot of changes since 1990. After the hyperinflation wave at the end of the eighties, the commercial banking system was comprised of private and state-owned commercial banks for a total of 25 institutions.

The hyperinflation wave and mismanagement eroded the solvency of most of state-owned commercial banks, which were merged or absorbed in 1991-92 for the two of the largest state-owned commercial banks, Banco Continental and Banco de la Nación. The latter can not be considered as a commercial bank, although it performs many services in this area, particularly those related with public services in rural areas. In 1992, four other commercial banks, accounting for almost 20% of total assets, were closed. Appendix 1 summarizes the main reasons for the closure of these banks.

Nowadays, the banking system is composed of only private commercial banks following the privatization of the two largest state-owned commercial banks (Banco Continental and Banco Internacional). A new banking act was put in place. As part of the whole process of financial reform, the reduction of barriers of entry in the system allowed the appearance of new commercial banks and other types of financial intermediaries that have replaced, to some extent, the task previously assigned to development banks. The entry of foreign banks has been improved competition mainly in the consumer loans segment.

Table No 2 shows the evolution of Peruvian banking system. Total assets, accounted for 9% of GDP in 1990, have grown to 35.5% in 1995. The loans and deposits show the same evolution. Although

---

17/ The hyperinflation process in Peru caused a loss of confidence in the domestic currency, that provoked, among other effects, the switch from domestic-currency deposits to foreign currency holdings outside of the banking system. This effect caused a significant reduction in the intermediation process and erode the solvency of many financial intermediaries.

18/ Although all these banks were commercial banks, they were partially owned by the state. The largest fourth bank, Banco Popular, was a candidate for privatization before its closure, but the lack of offers, because of its precarious financial condition, compel the government to take the decision of its closure.

19/ The new rural saving and loans system, created in 1993, has as a goal the intermediation of resources in rural areas, particularly the agriculture sector.
the competition in the market have been improved, the herfindal’s index, that measure the degree of concentration, shows that the market power of larger banks has remained practically unchanged.

Table No. 2
Peruvian Commercial Banking System

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Commercial Banks</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total No. of Banks</td>
<td>25</td>
<td>25</td>
<td>18</td>
<td>21</td>
<td>23</td>
<td>25</td>
</tr>
<tr>
<td>Cases of Failures</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>4</td>
</tr>
<tr>
<td>Mergers</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>New Entries</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td><strong>Assets (US$ Million)</strong></td>
<td>2,108</td>
<td>3,834</td>
<td>5,123</td>
<td>7,061</td>
<td>9,892</td>
<td>13,017</td>
</tr>
<tr>
<td>Non-Performing Loans (%)</td>
<td>9.0</td>
<td>7.1</td>
<td>13.0</td>
<td>9.8</td>
<td>6.9</td>
<td>4.8</td>
</tr>
<tr>
<td>Profitability (%)</td>
<td>10.6</td>
<td>9.3</td>
<td>8.8</td>
<td>8.9</td>
<td>11.6</td>
<td>18.8</td>
</tr>
<tr>
<td><strong>Competition</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Herfindal Index</td>
<td>6.51</td>
<td>6.38</td>
<td>5.99</td>
<td>6.26</td>
<td>6.66</td>
<td>6.58</td>
</tr>
<tr>
<td><strong>Intermediation (%) GDP</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Assets</td>
<td>9.0</td>
<td>15.1</td>
<td>20.3</td>
<td>25.6</td>
<td>31.0</td>
<td>35.5</td>
</tr>
<tr>
<td>Deposits</td>
<td>4.6</td>
<td>10.5</td>
<td>14.0</td>
<td>19.1</td>
<td>23.6</td>
<td>25.2</td>
</tr>
<tr>
<td>Loans</td>
<td>2.7</td>
<td>6.1</td>
<td>8.5</td>
<td>12.0</td>
<td>17.5</td>
<td>21.2</td>
</tr>
</tbody>
</table>

Source: Superintendency of Banks of Peru
1/ Percentage of total portfolio
2/ Return on Equity

The data

The majority of data for a sample of 21 banking institutions used in this study comes from bank’s balance sheet information submitted to the Superintendencia de Banca y Seguros, which is the government regulatory agency. We use quarterly data from 1990 to 1995. Right censoring is established at the end of the 24th quarter (December 1995), and is also supposed to be the maximum survival time. In this data set, we exclude some banks that appeared at the end of 1994, due to the lack of sampling data. The same applies to subsidiaries of international banks. Macroeconomic data have been obtained from the Banco Central de Reserva del Peru.

The Dependent Variable
Unlike previous approaches, in this context we determine the factors that influence the weakness of Peruvian Banking system rather than factors behind the failure of financial intermediaries. Although both factors could be the same, the key aspect relies on the usefulness of the factors and their relevance to the early warning system. As we explain earlier, weakness precedes closure. Therefore, explaining factors behind the weakness of the Peruvian banking system is more useful to permit the regulatory agency to act promptly to avoid serious macroeconomic consequences of the banking crisis.

According to the above-mentioned methodology, we use the Peruvian CAMEL rating system. This particular CAMEL rating system avoids ad-hoc weights between each component of CAMEL, because it assigns weights to main financial ratios obtained by time-series estimations and uses all of them in terms of an overall rating.

Banks are classified into two major groups, troubled and non-troubled banks, in line with the work of Whalen and Thomson (1988). The group of non-troubled banks corresponds to CAMEL ratings 1 and 2, whereas the other group belongs to the other ratings. The classification of these two categories has not been ad-hoc. We can determine if substantial difference between the characteristics of each group exists using the Wilcoxon-Mann-Whitney rank test\(^{20}\), whose results are shown in Table No. 3. The test has been used to differentiate the characteristics between grade levels 2 and 3 in the CAMEL rating system, as well as between grade levels 3 and 4. Those banks classified as non-troubled banks, using CAMEL grades 1 and 2, have different and statistically significant characteristics than those classified as troubled. Unlike the above-mentioned result, there was not significant difference in the characteristics between banks with CAMEL grade levels 3 and 4.

From Table No. 3, we can also conclude that those banks, that were weak, have lower levels of liquidity; huge non-performing loans as percentage of loans in their portfolios (most of them not covered by provisions) and higher operative costs in comparison with non-troubled banks. In addition, these banks were found to charge higher interest rates for their loans as well as offer more profitability for their deposits\(^{21}\); and also to have higher risk concentration.

\(^{20}\) This test has been used previously by Dabós (1995), Cole and Gunther (1995) and Ledesma (1997).

\(^{21}\) It is expected that banks in trouble usually offer more returns on deposits than those that are not in trouble. The reason is based in try to capture more deposits to intermediate in loans, in
Table No. 3
Characteristics of Troubled Banks

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Means Non-Troubled Banks</th>
<th>Means Troubled Banks</th>
<th>P-value 1/</th>
</tr>
</thead>
<tbody>
<tr>
<td>Liquid Assets/Assets</td>
<td>32.26</td>
<td>29.38</td>
<td>0.002</td>
</tr>
<tr>
<td>Capital-Assets Risk ratio</td>
<td>10.35</td>
<td>10.91</td>
<td>0.089</td>
</tr>
<tr>
<td>Non-Performing Loans/Total Loans</td>
<td>5.32</td>
<td>14.68</td>
<td>0.000</td>
</tr>
<tr>
<td>FCD Loans/FCD Deposits 2/</td>
<td>81.37</td>
<td>93.04</td>
<td>0.152</td>
</tr>
<tr>
<td>Operative Expenses/Assets</td>
<td>6.99</td>
<td>9.71</td>
<td>0.000</td>
</tr>
<tr>
<td>Provisioning/Non-Performing Loans</td>
<td>101.42</td>
<td>53.39</td>
<td>0.000</td>
</tr>
<tr>
<td>Implicit Interest rate on FCD Loans</td>
<td>10.00</td>
<td>12.48</td>
<td>0.000</td>
</tr>
<tr>
<td>Implicit Interest rate on DCD Loans</td>
<td>78.35</td>
<td>64.20</td>
<td>0.425</td>
</tr>
<tr>
<td>Implicit Interest rate on FCD Deposits</td>
<td>3.85</td>
<td>4.49</td>
<td>0.000</td>
</tr>
<tr>
<td>Implicit Interest rate on DCD Deposits</td>
<td>23.45</td>
<td>30.67</td>
<td>0.000</td>
</tr>
<tr>
<td>FCD Spread</td>
<td>6.15</td>
<td>7.99</td>
<td>0.000</td>
</tr>
<tr>
<td>DCD Spread</td>
<td>54.90</td>
<td>33.53</td>
<td>0.000</td>
</tr>
<tr>
<td>Credit Risk Index</td>
<td>0.26</td>
<td>0.46</td>
<td>0.017</td>
</tr>
<tr>
<td>Herfindal Index of Concentration</td>
<td>4.16</td>
<td>4.32</td>
<td>0.062</td>
</tr>
</tbody>
</table>

1/ Significance value using Wilcoxon-Mann-Whitney Rank Test
2/ FCD and DCD stands for foreign and domestic currency denominated assets or liabilities

Unlike Peek and Rosengren (1996), who shows capital-assets weighted by risk ratio could be a leading indicator for banking problems, this ratio is not significantly different between troubled banks and non-troubled banks in the case of Peruvian banks. It can reflect the feature that both groups of banks do not need to be undercapitalized to be considered as weak.

Independent Variables

Explanatory variables, along with their expected impact on the probability of downgrading and survival time are identified in Table No. 4. A number of variables has been introduced mainly to identify risks inherent in the banking activity rather than bank’s financial conditions. The reason behind that is we would like to determine main factors causing the downgrading of banks, an event that imply an increase in the bank’s weakness and a deterioration of its financial position. In the same manner, we do not introduce order to finance, with higher interest rates on loans, their losses caused by non-performing portfolio.
variables that explicitly mimic CAMEL rating because we can end explaining the probability of downgrading (or fragility) with the same variables used to determine the downgrading event.

Table No. 4
Explanatory Variables

<table>
<thead>
<tr>
<th>Name</th>
<th>Definition</th>
<th>Impact</th>
</tr>
</thead>
<tbody>
<tr>
<td>LIQUID</td>
<td>Liquid Assets/Assets</td>
<td>-</td>
</tr>
<tr>
<td>BASLE</td>
<td>Capital-Assets weighted by risk ratio</td>
<td>+</td>
</tr>
<tr>
<td>RISK</td>
<td>Risky Assets/Capital</td>
<td>+</td>
</tr>
<tr>
<td>NPL</td>
<td>Non performing Loans/Total Loans</td>
<td>+</td>
</tr>
<tr>
<td>MISMATCH</td>
<td>FCD Loans/FCD deposits</td>
<td>+/-</td>
</tr>
<tr>
<td>EFFICIEN</td>
<td>Operating Expenses/Assets</td>
<td>+</td>
</tr>
<tr>
<td>PROVIS</td>
<td>Provisioning for Bad Loans/Non-Performing Loans</td>
<td>-</td>
</tr>
<tr>
<td>SPREADFC</td>
<td>FCD Implicit Interest Spread</td>
<td>+</td>
</tr>
<tr>
<td>SPREADDC</td>
<td>DCD Implicit interest Spread</td>
<td>+</td>
</tr>
<tr>
<td>IRRFC</td>
<td>Interest Rate Risk on Foreign Currency Assets</td>
<td>+</td>
</tr>
<tr>
<td>IRRDC</td>
<td>Interest Rate Risk on Domestic Currency Assets</td>
<td>+</td>
</tr>
<tr>
<td>AGRO</td>
<td>Loans to Agriculture Sector (% of total portfolio)</td>
<td>+/-</td>
</tr>
<tr>
<td>FISHING</td>
<td>Loans to Fishing Sector (% of total portfolio)</td>
<td>+/-</td>
</tr>
<tr>
<td>MINNING</td>
<td>Loans to Minning Sector (% of total portfolio)</td>
<td>+/-</td>
</tr>
<tr>
<td>INDUSTRY</td>
<td>Loans to Industry Sector (% of total portfolio)</td>
<td>+/-</td>
</tr>
<tr>
<td>CONSTRUC</td>
<td>Loans to Construction Sector (% of total portfolio)</td>
<td>+/-</td>
</tr>
<tr>
<td>CRI</td>
<td>Credit Risk Index</td>
<td>+</td>
</tr>
<tr>
<td>CONCEN</td>
<td>Herfindal Index of concentration</td>
<td>+</td>
</tr>
<tr>
<td>INTERM</td>
<td>Banking Assets/GDP (Intermediation)</td>
<td>-</td>
</tr>
<tr>
<td>EXCHR</td>
<td>Real Exchange Rate</td>
<td>+/-</td>
</tr>
<tr>
<td>DCTR</td>
<td>Real Depreciation</td>
<td>+/-</td>
</tr>
<tr>
<td>CONSUM</td>
<td>Private Consumption Annual Growth</td>
<td>+/-</td>
</tr>
<tr>
<td>WRATE</td>
<td>World Interest Rate (Libor)</td>
<td>+</td>
</tr>
<tr>
<td>INF</td>
<td>Anual Inflation</td>
<td>+</td>
</tr>
<tr>
<td>M2RIN</td>
<td>M2/International Reserves</td>
<td>+</td>
</tr>
<tr>
<td>GDPGROW</td>
<td>Economic Activity (Real GDP growth)</td>
<td>-</td>
</tr>
<tr>
<td>SPI</td>
<td>Stock Price Index</td>
<td>-</td>
</tr>
<tr>
<td>BSSPI</td>
<td>Banking System Stock Price Index</td>
<td>-</td>
</tr>
</tbody>
</table>

1/ Implicit loan rate minus implicit deposit rate.
2/ Volatility risk (beta) of implicit interest rate against non-risk Central Bank's CD rate.
3/ Credit risk index calculated by expected risk in economic sector activity weighed by bank’s loan concentration to the same economic sector.
Variables can be grouped in five sets, the first of which represents interest rate risk and is composed by the volatility of implicit interest rate on loans and deposits classified by type of currency (IRR), the spread implicit (SPREAD) and the world interest rate, measured by the inter-bank Libor rate (WRATE). Interest rate volatility may reduce banking earnings. Also, the presence of derivatives in bank assets or liabilities entails a possibility of interest rate risk caused by the volatility in the price of the underlying asset. The interest rate risk can be measured through the stability of commercial banks’ net interest margins (the ratio of net interest income to average assets). In such a case, the risk is, however, partial, because margins do not reveal longer-term exposure that could cause losses if volatility of rates increased or if market rates change sharply. (Wright and Houpt, 1996).

We use an approach that resembles the mechanism in CAPM theory which allows determining if these assets are volatile or not with respect to a non-risk portfolio \(22/\). We expect that the interest risk explained above causes a positive impact on both the probability of weakness as well as on the reduction of the time for downgrading. High volatility of interest rates could affect banks’ interest income and reduce their profit margin. The effect is translated directly to the reduction of banks’ capital, converting them to undercapitalized banks. This renders the banks more vulnerable (or fragile) to external shocks, reducing their capacity to cope with such shocks.

The second group measures the credit risk, which is represented by variables accounting for banks’ portfolio concentration in specific main economic sectors, including agriculture (AGRO), fishing (FISHING), mining (MINING), manufacturing (INDUSTRY) and construction (CONSTRUC). Other variables in this group are the Herfindal’s index on portfolio concentration (CONCEN), and the credit risk index (CRI).

The credit risk index is calculated, for each individual bank, by weighting the bank’s portfolio share in each economic sector adjusted by the expected risk in the economic sector activity, measured through the volatility of its business cycle \(24/\). This index measures the possible impact of changes in the economic activity on a bank's profitability. The index is calculated using the volatility of the business cycle for each sector, which is a measure of the variability of economic activity in that sector.

---

\(22/\) The interest rate risk of each bank is approached by the value of “beta” obtained for the simple CAPM model. We consider the implicit return on portfolio for each bank and a risk-free interest rate, given by the return of Central Banks’ CD. The risk is calculated quarterly using sample data for twenty-four previous quarters.

\(23/\) Some other authors have studied if the market could identify banks in trouble or low-quality banks’ portfolios by using CAPM models. See, for instance, Randall (1989) and Simons and Cross (1991).

\(24/\) The expected risk in the economic activity is approached by the volatility of the business cycle. The volatility is measured through standard deviation of the cyclical component in the economic activity.
real sector on the banks’ portfolio quality. When a negative shock hits a particular economic sector, it could affect banks’ incomes for loan repayments, depending on the share of the loans in this sector in the banks’ portfolio. Therefore, the index measures if banks’ future incomes are threatened and the probability of increasing bad loan portfolio.

We expect that higher credit risk ratio and portfolio concentration will increase the probability of banks becoming unsound, and reduce the time to downgrading, because it could affect future income streams and could increase the share of bad debts in the banks’ total portfolio. Individually, higher loan concentration in a particular sector could have ambiguous effects on the probability of weakness or the time of downgrading because it will depend on the sector’s business cycle.

The third group of independent variables is composed of macroeconomic variables that measure the effects of external shocks on the banking activity or the increasing returns obtained for each bank due to economies of scale from the intermediation process. The variables in this group are the ratio of banking assets/GDP (INTERM) that represent the economies to scale in banking obtained by more intermediation in the economy, the level and changes in real exchange rate (EXCHR and DTCR), the annualized rate of inflation (INF), the ratio of M2 to international reserves (M2RIN), that represents the vulnerability of the financial sector to possible bank runs caused by external shocks in the economy, as defined in Calvo and Mendoza (1995) and Calvo (1996). This variable has a positive impact on the increase of probability of banking weakness and on the reduction of the time period to declare a troubled bank.

The group also encompasses the rate of growth of real GDP (GDPPGROW) and of the private consumption (CONSUM) which deals with the effects of the business cycle and consumption booms considered as factors underlying banking system fragility in other studies. We also include the stock price index (SPI) and the banking system stock price index (BSSPI) as proxies of assets’ price booms and market risk evaluation of banking activities. The latter variables have negative impact on the probability of weakness since an increase in the banks’ asset prices will show a positive market assessment of the banking activity.

---

Banking weakness is expected to be negatively related with the real activity. This is because the increase of bad portfolios in banking is correlated with recessions in the economic activity. On the other hand, an increase in the rate of growth of consumption is expected to increase the demand for banks' loans. It could have an ambiguous effect on the probability of weakness. Banks can have a positive shock caused by an expansionary phase in the business cycle, because they can intermediate more resources. However, some studies have considered that banking crises have been preceded by lending booms 26/ caused by excessive credit creation and poor monitoring of loans that increase the share of bad loans in the banks' portfolios. This argument makes the assumption that banks could take more risk in lending when there is an excess of loanable funds.

Exchange rate volatility causes troubles in banking system if there is a mismatch between foreign-currency-denominated banks' assets and liabilities. An abrupt change in exchange rate can cause an increase in the value of foreign currency banks' liabilities that could result in liquidity problems if the bank does not have enough provisions for exchange rate fluctuations. In such a case, there are lower levels of foreign currency assets and pressure to withdraw short term foreign currency liabilities arises. Another source of weakness could be the probability that borrowers could increase defaults on foreign currency loans, due to the fact that the said loans become more expensive as a result of a depreciation in the domestic currency. However, the mismatch between foreign assets and liabilities could also have positive effects on banking earnings when the value of foreign assets overcome the value of banks' foreign liabilities. This “positive mismatch” could drive banks to obtain more resources from the value of their assets. Then, in a system where foreign deposits or loans are permitted to be held by banks, the exchange rate volatility has an ambiguous effect regarding the probability of weakness or the time of downgrading.

The fourth group of independent variables represents liquidity risk that banks face in the business. The liquidity risk is a measure by the mismatch between foreign currency denominated assets and loans (MISMATCH) and the percentage of liquid assets out of total assets (LIQUID). The effect of a mismatch in foreign currency denominated assets and loans is ambiguous in terms of the probability of fragility, due to the same reasons that dominates the effect of exchange rate volatility, as explained above. Unlike the mismatch, a higher share of liquid assets permits the bank to have resources in order to meet short term requirements of liabilities. Therefore, the effect on the probability of weakness is negative and also increases the time to declare a bank fragile.

The last group is composed of a set of variables that capture solvency problems and inefficiency in the banking business. The variables in this group are the non-performing loan portfolio (NPL), the share of risky assets on banks’ capital (RISK), the weighted by risk Assets-Capital ratio (BASLE), the cover of provisioning for bad loans (PROVIS) and a measure of bank efficiency through the ratio of operating expenses/assets (EFFICIEN).

Higher provisioning for bad loans reduces the probability of weakness and increase the time of survival in the category of soundness since banks could afford any possible losses for a non-performing portfolio. However, the increase in the share of the non-performing portfolio or the increase in the share of risky assets could cause banks to become weak, reducing the time of survival in the category of non-troubled banks. The same impact has more inefficiency incurred through higher operating cost.

The variable BASLE is the inverse of Capital to risk-weighted assets ratio. This is a measure of solvency in banking system. Increase in the assets' risk taken by banks results in undercapitalized banks that are more vulnerable to shocks in the economy. Therefore, an increase in this ratio should cause higher probability of weakness and lower time before banks are being downgraded.

V. Estimations

Table No. 5 shows result of a split survival estimation on the probability of being downgraded according to the CAMEL rating system and the time elapsed till this event. The first column shows the coefficients of the variables that affect the probability of bank’s downgrading and its standard errors. These coefficients do not represent exactly the change in probability caused by the change in each explanatory variable, which is shown in the second column. Here, the numbers shown reflect the impact of a one-percent change in each variable on the probability of downgrading.

The third column presents the coefficient of the survivor function. Variables that are positively associated with an increase in the probability of survival, such as banking intermediation (INTERM), will have negative signs, whereas, variables that decrease the probability of survival, such as the share of non-performing loans in total loan portfolio (NPL), will exhibit positive values. It can also be reflected in the hazard or risk ratio, shown in the fourth column. The hazard ratio is the exponential of the coefficient
shown in the third column and how much the baseline hazard is shifted when the independent variable changes (Helwege, 1996). Risk ratios greater than one indicate that the survival time is reduced. Therefore, variables that increase the probability of downgrading and reduce the survival time have higher risk ratios, compared to those related with a lower probability of downgrading and higher time of survival (Helwege, 1996).

Shown in the table, in explaining the probability of an increase in weakness (downgrade in CAMEL rating system), all variables have the expected sign and most of them are significant, with the exception of the currency mismatch between assets and liabilities (MISMATCH). However, explaining the survivor function, the risk ratio for this variable is bigger than one, meaning that the currency mismatch between assets and liabilities is an important factor that explains the cause of bank’s fragility and the reduction in its time in which it is classified as a non-troubled bank.

Higher credit risk is greatly associated with higher probability of fragility. From the results in table No. 5, we can see that a one-percent increase in this risk causes a 0.12% increase in the probability of classifying a troubled bank. This result captures the importance of a complete portfolio evaluation at the time of determining if banks are facing risk for concentrated loans in a particular sector. However, this variable is not significant in terms of explaining the time during which the bank will survive without problems. Nevertheless, higher concentration in construction sector causes a reduction in the time till a bank is being declared weak, because this sector is highly volatile. The impact of this variable also has the highest risk ratio in the hazard function.

Macroeconomic variables also have impacts on banking fragility. Banking system fragility is explained positively by M2RIN ratio, as implied by Calvo (1996). The more volatility in this ratio implies high vulnerability of the economy to a currency crisis. This will affect the banking system liabilities, causing a run on deposits in domestic currency in favor of deposits in foreign currency. It could increase a currency mismatch between banks’ assets and liabilities. The variable M2RIN coupled with the variable MISMATCH are the key factor in determining the effect of a change in the real exchange rate on banks’ health. Volatility of the exchange rate, accompanied by a mismatch between assets and liabilities, is a cause of serious problems in the banking system as the estimation shows.
Banking variables that capture solvency and efficiency problems are also important in the determination of the probability of weakness. Unlike other studies\(^{27/}\), these variables also affect the timing related to unsoundness, along with the macroeconomic variables. For instance, cost inefficiency, bad quality of portfolio and higher risk in assets cause increase in the hazard function and higher probability of weakness. On the other hand, better provisioning coverage protects banks from losing income and reduces the probability of weakness.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Downgrading Bank</th>
<th>NPL</th>
<th>NPL Adjusted 2/</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Prob</td>
<td>dF/dx</td>
<td>Time</td>
</tr>
<tr>
<td>Cons</td>
<td>-2.47909</td>
<td>(0.4068)</td>
<td>-0.3238</td>
</tr>
<tr>
<td>Mismatch</td>
<td>0.0003a/</td>
<td>(0.0003)</td>
<td>0.0001</td>
</tr>
<tr>
<td>Efficien</td>
<td>0.0831</td>
<td>(0.0186)</td>
<td>0.0325</td>
</tr>
<tr>
<td>Provis</td>
<td>-0.0038</td>
<td>(0.0010)</td>
<td>-0.0015</td>
</tr>
<tr>
<td>NPL</td>
<td>0.1229</td>
<td>(0.0178)</td>
<td>0.0482</td>
</tr>
<tr>
<td>Risk</td>
<td>0.0187</td>
<td>(0.0026)</td>
<td>0.0073</td>
</tr>
<tr>
<td>IRR</td>
<td>0.3129</td>
<td>(0.1180)</td>
<td>0.1227</td>
</tr>
<tr>
<td>Fishing</td>
<td>18.1533</td>
<td>(3.1858)</td>
<td>7.2399</td>
</tr>
<tr>
<td>Industry</td>
<td>-0.6503a/</td>
<td>(0.5924)</td>
<td>-0.2593</td>
</tr>
<tr>
<td>Construct</td>
<td>17.1658</td>
<td>(7.0009)</td>
<td>2.8507</td>
</tr>
<tr>
<td>Dtcr</td>
<td>0.0002</td>
<td>(0.0001)</td>
<td>0.0001</td>
</tr>
<tr>
<td>Interm</td>
<td>-0.0564</td>
<td>(0.0223)</td>
<td>-0.0221</td>
</tr>
<tr>
<td>M2RIN</td>
<td>0.5745</td>
<td>(0.2401)</td>
<td>0.2253</td>
</tr>
<tr>
<td>GDPgrow</td>
<td>-0.0631</td>
<td>(0.0168)</td>
<td>-0.0243</td>
</tr>
<tr>
<td>TCR</td>
<td>0.1954</td>
<td>(0.0302)</td>
<td>0.0753</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-155.12</td>
<td></td>
<td>-90.37</td>
</tr>
<tr>
<td>Type 1 Error b/</td>
<td>7.14</td>
<td></td>
<td>14.88</td>
</tr>
<tr>
<td>Type 2 Error c/</td>
<td>7.94</td>
<td></td>
<td>9.92</td>
</tr>
</tbody>
</table>

1/ Standard errors in brackets, all coefficients are significant at 5%, at least the contrary is mentioned
2/ Non-performing loans accounting for provisioning on bad loans
a/ No significant at 5%
b/ Type 1 Error is defined as the percentage of banks estimated to be solvent when they are not
c/ Type 2 Error is defined as the percentage of banks estimated to be insolvent when they are solvent

It is important to notice that interest rate risk affects significantly the timing of survival in the category of non-troubled banks. Volatility of interest incomes makes banks more vulnerable to be
undercapitalized and therefore, more vulnerable to external shocks. Then, higher interest rate risk could conduce to faster downgrades in the evaluation of the banks.

The accuracy of the estimated models is measured by the errors in estimation. Type I error is defined as the misclassification of a bank as a non-troubled bank when it is already in trouble. Type II error happens when a bank is classified as a troubled bank, when it has not been in trouble during the period of estimation. From the point of view of accuracy of prediction of weakness, type I error is the most important. However, from the point of view of cost of supervision, type II error is the most important, given that supervisors can allocate scarce resources in non-fragile banks when they can be used to monitoring troubled banks (Whalen, 1991).

For our purposes, type I error is the most relevant because it signifies the inability to identify troubled banks. A weighted-by-assets index, built on a model that have a large type I error, could not be helpful to identify banking system’s fragility with enough time to permit policy makers to put in place measures to strengthen the system. Our estimates show a very low level of type I error (7.14%), meaning that more than 92% of the troubled banks have been correctly identified. Therefore, we can rely on these estimates to construct a weighted-by-assets fragility index for the whole Peruvian banking system.

The Survival Functions

A Kaplan-Meier survival function 28/, shown in Figure No. 2, is built based on our data. It is worthy to notice that almost 50% of banks are downgraded during the first four quarters, given the initial conditions at the beginning of the soundness spell. Most of them, as we will see below, are small banks. Therefore, the weakness in the system could reach a higher level, if no policy actions are taken before the first year. Also the survival estimates show that in eighteen quarters (four years and a half), at least 20% of banks have not been downgraded.

Survival estimates are also calculated according to bank size, measured by the share of bank’s assets in total assets of the system. Here we split the population into small and large banks in order to find

---

28/ The Kaplan-Meier survival function is an unbiased estimate of the hazard rate, interpreting in percentage, the number of downgrading at time t, divided by the number of institutions at risk. This function has not explanatory variables and it is only a representation of the time to downgrading, giving initial conditions of the banks. See Lancaster (1990) and Helwege (1996).
out if the size is an important factor in the survival of the banks. Here, we refer survival time to the time elapsed until a bank is downgraded, as before. Banks are defined as large if their share in total assets is higher than 5%. In the Peruvian banking system, it corresponds to 5 banks, accounting for 57% of the total assets in the banking system, on average.

When the survival function is split into these two populations, we can see in Figure No. 3 that large banks spend more time before they are downgraded. Using log-rank test for equality of two survival functions, we reject the hypothesis of equality in survival functions. Put simply, given the characteristics at the beginning of the soundness spell, small banks tend to be downgraded faster than large banks. Therefore, Peruvian small banks are weaker and could also be taking higher risk than large banks.

Figure No. 2
Kaplan-Meier survival estimate

When the survival function is split into these two populations, we can see in Figure No. 3 that large banks spend more time before they are downgraded. Using log-rank test for equality of two survival functions, we reject the hypothesis of equality in survival functions. Put simply, given the characteristics at the beginning of the soundness spell, small banks tend to be downgraded faster than large banks. Therefore, Peruvian small banks are weaker and could also be taking higher risk than large banks.

See Stata version 5.0 manual
Thus, in the case of small banks, the risks taken have a greater impact on the probability of being downgraded than in the case of large banks. It also coincide with the results of Buchinsky and Yosha (1995) that found that small banks take more risks than large banks. Unlike the results obtained by Cole and Gunther (1996), weakness in large failing banks is delayed with respect to small banks. However, 50% of small and large banks are weak in the first four to six quarters, given their characteristics at the beginning of the soundness spell. This is an important finding, because it implies that supervisors should take policy action to achieve the soundness of banks as quickly as possible, in order to avoid a deterioration of the soundness in the banking system.

![Figure No. 3](image)

Kaplan-Meier survival estimates, by big

Banking System Fragility's Index

Weighting by assets, we can calculate an aggregate fragility index based on the probability of being downgraded (increase in weakness) for each bank in the system. The index can be seen in Figure No. 4. The figure shows a volatile pattern that has an upward trend until December 1993. Also, it can be seen that the fragility in the Peruvian Banking system has been a marked peak in September 1990. This peak could reflect the shock caused by the money-based stabilization program. With 45% on average probability of weakness, the index shows that the Peruvian Banking system was in a fragile position.
between 1990 and 1992. The peaks in these two years represents mergers in the banking system and the failure of the fourth larger bank in 1992. Despite the peaks are clear warning signals of fragility in the system, the index has been giving strong similar signals, on average, during the first three years. The index shows a more clear leading information of fragility in the system than an index based on banking failure.

Another important aspect is the effect of banking regulation on the fragility of the system. In 1991, Peruvian banking act was changed and prudential regulation was established in a two-year period. The increase in fragility of the system could show the first impact of strengthening banking regulation in banks’ balance sheets. New provisioning requirements have had impact on profitability, credit risks and liquidity of banks. This process came to a hault in December 1993 at a time when the second banking act was issued to amended and clarified previous regulatory policies in the banking system. As of this year, the Peruvian banking system became more sound, with prudential regulations in place, reflecting a steady fall in the fragility index to levels as low as 10% of probability of unsoundness in the system.

Figure No. 4
Banking System Fragility Index
(Probability of Unsoundness according CAMEL Classification)
It can be noticed also that, with strong prudential regulation in place, the weakness of the Peruvian banking system has not been affected by a contagion effect caused by the Mexican crisis in December 1994. In order to see the accuracy of the index under currency crisis or contagion effects, the index should be tested in countries with fixed exchange rate system, such as Argentina.

Alternative indices of Banking System’s Fragility

An alternative banking system’s fragility index can be built using another measures of banking weakness. For instance, a common measure of identification of troubled banks is the level of non-performing loans level, expressed in terms of the percentage of total bank’s portfolio. Gonzalez-Hermosillo, et al (1996) use a threshold level of non-performing loans as indicator of banking fragility. They proved in the Mexican case that this indicator issues warning signals about banking weakness with enough time in advance, before a banking crisis is declared. The threshold level used in the above-mentioned paper is set in a range of 6% to 8%, and represents the level of non-performing loans (as percentage of total loans) that banks had on average at before the first wave of failure occurred. In the same fashion, we identify a non-performing threshold level for the Peruvian banking system as 8% of the total portfolio. This level is consistent with a weighted-by-assets observation of each bank’s non-performing loans level at the time of its downgrading.

In other words, in the quarter during which a bank is downgraded from a non-troubled group to a troubled group, we consider its non-performing level. As banks can be downgraded many times, each time a different level is considered as well as the amount of assets that the bank had at the time of downgrading. Thus, we add all the values of assets for all banks that has been downgraded, and use the result to construct a weighted-by-assets non-performing loans to loans ratio. The threshold level was found to be 8%. Next, every bank that passes the level of 8% is considered as weak, whereas the rest are not.

The estimated coefficients of the possible variables that affect the probability of a bank exceed the threshold level in non-performing loans to loans ratio and their impact in the density function, is shown in table No. 5, columns 5 and 6. Non-performing loans level is explained particularly for variables representing credit risk and macroeconomic conditions, rather than variables representing other banking decisions. The only variable that represents bank’s financial position used here is EFFICIEN that shows
that higher and inefficiently used monitoring cost does not avoid banks from accumulating non-performing loans.  

In the Peruvian case, the concentration of credit in fishing and construction sectors increases the probability of banks’ weakness, given that both sectors are highly volatile. The production and the business cycle of the fishing industry is seasonal and also depends on weather conditions. The Niño Phenomenon in the Pacific Ocean, adversely affects the development of this industry. In the case of construction, the sector reacts more sensitively than the economy’s business cycle and can cause serious banks’ portfolio problems at the time of recessions. Unlike the above-mentioned sectors, in the Peruvian case, the concentration of loans in manufacturing industry works as a cushion for economic shocks, before banks can diversify their risk in different sub-sectors of manufacturing industry. The agricultural sector loans does not have a significant impact in explaining banks’ non-performing loans, due to its small share in the Peruvian banks’ portfolio. This contrast with the findings of some authors, that consider these loans as one of the likely causes of the Saving and Loans crisis in United States.

Another factor that may raise the non-performing loan portfolio is the exchange rate risk, represented in our estimates as changes in the real exchange rate. It has a positive and significant impact on the probability of increasing weakness. This result is consistent with Kaminsky and Reinhart (1996) findings that severe devaluation of the domestic currency could precede banking crisis. Furthermore, as before, the M2RIN ratio increases the weakness in the case of Peruvian banking system.

Although the explanatory variables are significant and have the effect expected on the probability of weakness, the accuracy of this indicator is less than the one obtained by classifying banks according to a wider range of financial ratios, as the CAMEL rating system does. The type I error in this estimation is 14.8%, meaning that more than 85% of banks are accurately identified as unsound when they already are.

Figure No. 5, panel A, shows the results of the weighted-by-asset probability of banking fragility index. The figure shows that the volatility of this index is greater than the one built on downgrades in the CAMEL rating system. A particularly interesting aspect is the fact that the probability of surpassing the

---

30/ Berger and De Young (1997) have suggested that cost inefficiency may be an important indicator of future non-performing loans and other banking problems. In their study for the US Banking system, they found that measures to improve cost efficiency precede the reduction in non-performing portfolio, whereas increases in inefficiency are causes for more accumulation of problem loans.
threshold level on non-performing loans increased at the beginning of 1995. If we compare this result with the index built on downgrades in the CAMEL system, the latter shows a steady downward trend since 1993. It can imply that banks' portfolio in this period is reflecting the recession period in the Peruvian business cycle, rather than an increase in the fragility.

This argument is sustained by the fact that the index based on downgrades in the CAMEL rating system represents an evaluation of different aspects in the banking business. Every downgrade is made on the basis of a comparison of a wider range of financial variables that not only represent the risk of the business, but also the governance and risk behavior of banks. In this manner, CAMEL rating-based index of weakness is more accurate in its classification of troubled banks and hence it performs better as an early warning system of banking system's weakness, when compared to other indices.

We think that considering the ratio of non-performing loans to loans as an indicator of fragility, does not show accurately if the bank has problems in recovering the arrears or not. In the screening process of providing credit, banks usually consider the value of collateral. Collateral, however, might be guaranteed by liquid assets, like cash or deposits, or not liquid, such as real estate. In the latter case, whenever a crisis occurs, the value of collateral could decline since in the market, in which it is negotiated, a banking crisis may cause a serious economic recession. Therefore, prudential regulations require the use of provisioning, in order to cover any possible losses incurred for the inability of recovering loans or selling collateral. Therefore, when a bank constitutes the necessary provisions on bad loans, it reduces the risk of being insolvent.

For the above-mentioned reasons, we adjust the non-performing loans by the amount of provisions. In this particular case, we consider that banks in troubled are those which have levels of non-performing loans ratio discounting the amount of provision higher than 4%. Using this indicator, we test different key variables that could explain the probability of weakness, whose results are shown in Table No. 5 (columns 7 and 8). The estimated model depends in general on macroeconomic variables as in the case of previous index. In terms of accuracy, this last index does not perform very well, because the type I error is near to more 23% (less than 77% of accuracy).

31/ See, for instance, Helwege (1996).
Figure No. 5
Banking System's Fragility Indices

Panel A

Panel B

Prob of Insolvency NPL>NPL*

Prob of Insolvency NPLadj 1/
Applying a similar methodology as before, we construct a weighted-by-assets index of banking fragility (shown in Figure No. 5, panel B). The pattern of this index shows a very similar behavior to the index based on CAMEL system rating, obtained previously. The break-point of December 1993, in which new prudential regulation was issued, continues to show a decrease in the probability of weakness in the Peruvian banking system. Similar to the threshold NPL indicator, the index also shows that increases in the levels of non-performing loans in the banking system (represented by the increase of the probability of surpassing the threshold level) do not necessarily force banks to be classified as troubled (represented by the probability of unsoundness according CAMEL ratings, which is decreasing).

Uses of the Index

The index of banking vulnerability is not only important as an early warning system for supervisors, but can be used to detect how the fragility of the system is affected by movements in the economic activity or facing external shocks, as well. Since banking system’s portfolio has a strong relation with the business cycle, the quality of the portfolio could be affected by any shock in the economy.

Several authors mention that shocks are the cause of banking system fragility 32/. For instance, such as in the case of Argentina, the external shock caused by the Mexican crisis had an important effect on banking system liquidity, magnified by the limitation of its currency board system to act as a lender of last resort. In general, the nature of the banking business makes them vulnerable to economic shocks. Banks operate with high levels of leverage and most of their liabilities are liquid which have to be matched in structure and timing with liquid assets. Any increase in the volatility of assets’ prices, caused by an economic shock, could affect the relationship between bank assets and liabilities, making them more vulnerable.

Balance of payment crises or contagion effects could cause banking unsoundness, as well as, domestic productivity shocks, like droughts, because domestic shocks can increase the risks in banks’ portfolio, if the latter is concentrated in the sector in which the shock happens.

Serious problems in banking systems also generate difficulties in the monetary policy. Troubled banks cause inefficiencies in the allocation of resources in the rest of economy. Moreover, they can affect the goals of intermediate targets in the monetary policy. For instance, non-liquid insolvent banks can cause increases in interest rates, in order to obtain the necessary resources to finance bad portfolio problems or to finance higher operating cost and other inefficiencies.

The causality between the fragility of the banking system and the business cycle could also be reversed. Credit cycles or credit rationing are also factors that affect the performance of real sector and might also be the cause of booms and downturns in the business cycle. Increase in fragility in the banking system might lead to more volatile business cycle that, in turn, might generate a deterioration in banks' portfolios as feedback effects.

We test the relationship between our fragility index, based on CAMEL rating, and the business cycle in the Peruvian economy. Using a simple VAR model, shown in Table No. 6, we found that positive shocks in the GDP are translated in reductions of the banking system fragility, whereas increases in the risk taken by banks (changes in the fragility index), could be translated into higher real GDP growth. Changes in real exchange rate as well as in the world interest rate are causes for an increase in the banking system fragility, a fact well established in the case of the Mexican crisis by several authors.

33/ Kiyotaki and Moore (1997) shows the generation of credit cycles due to external shocks, through the price of the loan collateral. Other studies show a credit channel of the monetary policy as influential factor of the economic business cycle. See to this respect Bernanke and Gertler (1995). On the effects on business cycle of credit rationing and asymmetric information, see Greenwald and Stiglitz (1993).

34/ The amount of lags in the explanatory variables was chosen using the Akaike Information Criteria.

Table No. 6
Vector Autoregression Estimates

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficients</th>
<th>Rate of Growth of Real GDP (GDPgrow)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fragility Index (FI)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>11.5983</td>
<td>-5.7212</td>
</tr>
<tr>
<td></td>
<td>(8.1829)</td>
<td>(3.1751)</td>
</tr>
<tr>
<td>FI (-1)</td>
<td>0.8456</td>
<td>0.1448</td>
</tr>
<tr>
<td></td>
<td>(0.1591)</td>
<td>(0.0617)</td>
</tr>
<tr>
<td>GDPgrow (-1)</td>
<td>-0.3526</td>
<td>0.8714</td>
</tr>
<tr>
<td></td>
<td>(0.1255)</td>
<td>(0.1651)</td>
</tr>
<tr>
<td>Real Exchange Rate</td>
<td>0.1612</td>
<td>-0.0492</td>
</tr>
<tr>
<td></td>
<td>(0.2847)</td>
<td>(0.1104)</td>
</tr>
<tr>
<td>World Interest Rate</td>
<td>0.7994</td>
<td>-0.0616</td>
</tr>
<tr>
<td></td>
<td>(0.6818)</td>
<td>(0.2645)</td>
</tr>
<tr>
<td>R-Square</td>
<td>0.7546</td>
<td>0.7694</td>
</tr>
</tbody>
</table>

1/ Standard errors are shown in brackets

This finding shows an interesting transmission mechanism between the banking system fragility and the real sector. At time 0, a positive shock in the financial sector, such as a financial or current account liberalization, that increases loanable funds held by banks, is translated in higher loans to the real sector, and therefore, in an increases of the economic activity in further periods. At the same time, this lending boom, as other authors have pointed out 36/, could also imply that banks take more risk. This factor will increase the fragility of the banking system.

Once the rate of growth of real GDP has increased, it will contribute to posterior reduction of the vulnerability of the banking system, ceteris paribus, through the repayments of the loans and through the banks' portfolio diversification in other assets like real estate or financial assets that are also boosted for the expansion of the economic activity. The adjustment continues till the time in which banks allocate more resources to alternative investments that become more profitable than lending activities. It will reduce the amount of resources available to the real sector and, hence, reduce the growth of the economic activity.

The above-mentioned transmission mechanism makes a case for prudential banking supervision and regulation. Although the lending boom will increase the rate of growth of the economic activity, due to the fact that higher risks are taken by the intermediaries increase the banking system fragility in the short term, the financial institutions are more vulnerable to other shocks in the economy. Shocks, such as increases in international interest rates or crisis contagion from other countries in the region, not only could bring the economy to a recession, but also have devastating effects on the banking system when it is more vulnerable. For that reason, prudential regulation and adequate supervision of banks in trouble, could be the solution to smooth the increase in fragility of the banking system, as result of a positive shock in the financial sector.

Even though the GDP could grow faster in a banking system without prudential banking regulation, an overheating of the economy, caused by lending booms, will magnify the impact of shocks on banking vulnerability, causing banking crises, with their devastating side effects. Prudential banking regulation, used to mitigate financial sector shocks, avoids an overheating of the economy, and contributes to reducing the impact of a fall in economic activity (due to unexpected shocks) on the banking soundness. Therefore, prudential regulation is a powerful tool that policy makers use to keep the solvency of the financial intermediaries, as well as, to reduce the volatility of the business cycle in the economy.

Figure No. 6 confirms the dynamic response of the banking system fragility index and the rate of growth of GDP, to shocks in both, the financial system and in the real sector. A positive shock that increase the banking system's fragility cause a very short term fall in output. After the initial adjustment, as long as the fragility of the banking system is reduced, the shock is translated in an expansion of the economic activity. However, this expansionary phase will stop when there is a further decrease in the fragility of banking system. This could represent the effects of conservative lending policies that constraint or ration credit to the firms.

Figure No. 6
In the same manner, a positive shock to the economic activity will reduce the banking system fragility due to the effect of increasing the intermediation business. However, the banking system weakness will increase when the rate of growth of the economy is falling. This finding is consistent with Kaminsky and Reinhart (1996) insight, that at the time the banking crises begin, the growth in economic activity is significantly lower than the growth rates in “tranquil” times.

VI. Conclusions

This paper has presented a methodology to approach the probability of banking system's weakness using standard CAMEL rating system. An index of banking system vulnerability is built in order
to estimate warning signals at the right time in which banks are unsound. The index, applied for the case of Peru, also helps to understand the role of prudential regulation in managing internal and external shocks to the financial system, and its feedback effects on the economic activity.

Other insights that should be taken into account in the construction and employment of warning systems about the soundness of the banking system are that early warning system built on the probability of downgrading in the supervisors’ rating system, helps to measure the time in which banks are declared unsound. This system is more efficient in giving relevant information about the right time of banking system vulnerability than those based on the probability of banking failure. Early warning signals of weaknesses provide policy makers with enough time in advance to intervene and correct any problem, in order to avoid bank failures and crises.

Issuing warnings about the unsoundness of the banking system is important to recognize the factors behind this situation. Credit and interest risks, quality of portfolio, bank management of assets-liabilities mismatch and macroeconomic variables such as the vulnerability of the economy to currency crisis and the risk of the economic activity are the key factors that determine the probability of weakness in banking systems, such as in the case of Peru.

Finally, in the case of Peru, the banking system’s fragility has a feedback effect with the business cycle. Factors like financial liberalization that increase, the banking intermediation could also affect positively the vulnerability of banks, because they entail more risks. These lending booms temporarily increase the growth rate of GDP. In this stage, however, banks are more vulnerable to external shocks and downturns in the economic activity. This event provides a case for prudential banking regulation that has the particularity of smoothing the effects of external shocks in the banking soundness as well as reducing the volatility of the business cycle.
References


Superintendencia de Banca y Seguros del Peru. Información Financiera Mensual. Various Issues.


APPENDIX 1
Peruvian Banking Failure and Mergers Between 1990 and 1995

Failed Banks


b) Banco Central Hipotecario del Peru. Date of Closure: August 1992. The bank was liquidated after several years of recurrence of capital insufficiency associated with continuous losses. Bad performance and weak maturity matching cause a liquidity crisis. At the liquidation time, this institution run a 20-month long reserve requirement deficit. Other cause: That institution was concentrated its loans in mortgage loans. This business was in contraction between 1987 and 1991 in which cause its portfolio to be in default and without possibility to recover. High accumulation of non-performing loans.

c) Banco Popular del Peru. Date of Closure: December 1992. The institution used to be one of the most important commercial bank in Peru for many decades (It was founded in 1895). The bank started to have deep problems after the government took its governance. The bank was liquidated in the middle of a solvency crisis basically due to its very weak portfolio and its non-technical management.

d) Caja de Ahorros de Lima. Date of Closure: May 1992 This saving and loan institution was the only one in its gender in Peru. For the size of its operations was always considered as a hybrid commercial bank. The bank went into liquidation due to an extreme solvency crisis related with a huge portfolio hidden losses. Also, at the time of liquidation, the bank faced a four-month long personnel strike.

Merged Banks

