Early Warning System for Systemic Banking Crisis in India: Parametric and Non-parametric approaches

1: Introduction

Episodes of banking and currency crises have generated large costs for both national and international financial systems. To avert these costs, the crucial issue of crisis prediction has come to the fore and has led to the development of a vibrant area of research known as Early Warning System (EWS). Early warning models which exploit systematic relationships apparent in historical data between variables associated with the build-up to crises and the actual incidence of crisis aim to forewarn the policy makers about the future financial crisis and help them to take pre-emptive measures. In the light of the ongoing global economic and financial crisis, the urgency to build such models and avert financial disasters has amplified.

Individual researchers have basically relied on the parametric approach of using qualitative choice models such as the Developing Countries Studies Division (DCSD) model of the IMF and the non-parametric 'signals' approach developed by Kaminsky, Lizondo and Reinhart (KLR, 1998) for devising country-specific and multi-country early warning models for predicting currency and banking crises. Studies involving early warning models for banking crisis aim at predicting either individual bank failure or the collapse of the entire banking system of a country. With large scale occurrence of systemic banking crisis in recent years, there is an increasing awareness of focusing on the banking system as a whole and in this context, the role underplayed by the domestic macroeconomic and global financial environment has assumed great significance.

Quite a few cross-country empirical studies have used discrete choice models and annual data for a section of countries experiencing banking crisis including India. However there is no study that focuses on identifying banking crisis on a monthly basis and developing an early warning model using both the 'signals' approach and the DCSD model exclusively for the Indian banking sector. This paper makes an attempt to fill this lacuna in literature and proposes an early warning model based on macroeconomic and global indicators for forecasting banking crisis in India.[1]

[1] With each method having their relative advantages and disadvantages, this paper thought it best to integrate both the approaches in an attempt to develop a EWS for forecasting banking crisis in India.

The paper is divided into the following sections. Section 2 deals with the existing literature on the identification of banking crises dates and the use of signal extraction approach and discrete choice models for banking and currency crises. Section 3 states the methodology and data sources. Section 4 gives the empirical results and their interpretation. Section 5 states the concluding observations and policy implications. Finally Section 6 briefly states the limitations of the present study and mentions the relevant areas for future research.

2: State-of–the-Art

An important precondition for using 'signals' approach and the discrete choice models is that a crisis must have occurred in the "recent past" (Ahec-Sonje, 1996-99 p 274). Empirical literature on currency and banking crises have thus identified crises dates based on a specific definition of crisis as the foremost step while attempting to devise an EWS for crisis prediction. Two common methods usually deployed to identify the period of banking crisis are: event-based method (based on annual data) and the index method (based on monthly or quarterly data). The event-based or 'qualitative method' of crisis identification recognizes a systemic banking crisis only after the occurrence of certain events like bank runs, closures, mergers , holidays, recapitalization and huge Non-Performing Assets (Demirguc Kunt and Detragiache, 1998a, p 91; Kaminsky & Reinhart 1999, p 476; Caprio Klingebiel, 2003, p1 and IMF 1998, p 74-75). This method however has several limitations. Identification of crisis only when it becomes severe enough to trigger certain events can lead to delayed recognition of a crisis (Hagen & Ho, 2003a, p 2-3).[2] Moreover, there is also certain amount of randomness inherent in the definitions.[3] According to Ahmed (1998, p 15) the event-based method follows an approach that does not consider any explicit threshold level and therefore all financial market turmoil events are termed as crises. This method thus does not identify the different degrees of crisis severity. Also there is no reliable data on 'events' like NPAs, as such data are often manipulated. Further the event-based method does not clearly identify the beginning and end of a crisis. Finally, event-based studies which use annual data usually label an entire year as crisis even though the crisis may have occurred in just a few months of that year.

The index method used for the identification of banking crisis is built on the lines of the Exchange Market Pressure (EMP) index of for dating currency crisis, has several advantages

[2]For instance, banks may be nationalized or bank holidays may occur only when the crisis has spread to the whole. Similarly, bailout cost is available only post-crisis after a time- lag. Non-Performing Assets (NPAs) also are a backward-looking indicator of asset quality.

[3] For instance no reasons are offered as to why the minimum bailout cost is fixed at 2% or why the threshold level for NPAs as percentage of total assets has to exceed 10% as in Demirguc-Kunt & Detragiache's (1998) definition of systemic banking crisis.

over the event-based approach. The index method requires no apriori knowledge of events to identify a banking crisis and there is thus a lower probability of recognizing a crisis too late. The most attractive feature of the index method is that it is based on monthly time series which implies more specific crisis timings. Recently some economists have developed their own index approach to date banking crisis (Hawkins & Klau, 2000; Kibritciouglu, 2002 and Hagen & Ho , 2003a & 2003b).

The 'signals' approach or the 'indicators' approach as it also known, was pioneered by Kaminsky, Lizondo & Reinhart (KLR, 1998), Kaminsky & Reinhart (1999), Kaminsky (1999) and Goldstein, Kaminsky & Reinhart (2000).[4] The 'signals' approach, has been recently applied to currency and banking crises to examine the impact of deteriorating fundamentals. The method works effectively when there are sharp changes between crises episodes and periods of tranquility. The advantage of this non-parametric approach is that it focuses on a particular variable's association with crisis and that it is based on high frequency data, thus facilitating a deeper understanding of the behavior of macroeconomic trends that pushes a country in to crisis. The other significant contributors of this approach include Edison (2000) and Bruggermann & Linne (1999 & 2002). A few country-specific studies have been made by El-Shazly (1999) for Egypt, Knedlik (2006) and Knedlik & Scheufele (2007) for South Africa and Yap (1998 & 1999) for Philippines to name a few.

Another line of approach in EWS literature, involves the use of discrete choice models for the analysis of banking and currency crises. Sachs, Tornell & Velasco (1996), Frankel & Rose (1996), Demirguc-Kunt et al (1998a). Demirguc-Kuntet al (1998b), Glick & Rose (1998), DCSD model (IMF, 1998), Hardy & Pazarbasiouglu (1999), Demirguc-Kunt et al (2000), Eichengreen & Arteta (2000), Glick & Hutchinson (1999), Hagen & Ho (2003a), Hagen & Ho (2003b), Komulainen & Lukkarila (2003), Feridun (2004a), Feridun (2004b) Feridun(2007a) and Feridun (2007b) are some of the significant contributors in this line of thought.

Both the signaling method and qualitative response models have their relative advantages and shortcomings. Taking this into consideration, some papers have recently combined both the approaches (Chang & Li, 2002; Krznar, 2004; Budsayaplakorn , Dubooglu & Mathur, 2006 and Feridun , 2007b)

[4] KLR (1998) propose a leading 'indicators approach' or signal extraction approach based on the methodology of Diebold and Rudebusch (1989), and Stock and Watson (1989) for leading indicators.

In the early 1990s, banking system in India was saddled with huge NPAs, largely due to the socially directed credit programs pursued by the government. Several measures were initiated and asset quality largely improved in due course of time. However, the continuously liberalizing Indian economy and its greater integration with the global economy have opened up fresh challenges for the Indian Banking sector. In recent years India's integration with the global economy is being witnessed distinctly by the growth of its merchandise export plus imports as a proportion of GDP growing from 21.2% in 1997-98 to 34.7% in 2007-08 and the ratio of gross current account and gross capital flows to GDP increasing from 46.8% to 117.0% during the same period (Reddy 2008a, p 3). The current account, as measured by the sum of current receipts and current payments, amounted to about 53 per cent of GDP in 2007-08, up from about 19 per cent of GDP in 1991. Similarly, on the capital account, the sum of gross capital inflows and outflows increased from 12 per cent of GDP in 1990-91 to around 64 per cent in 2007-08. With this degree of gradual openness, it is important that India needs to keep its antenna receptive enough to capture the developments in international markets and apprehend the implications for the domestic economic and financial systems. The emerging scenario largely demands developing an early warning model incorporating global and domestic macroeconomic indicators that may effectively signal future banking vulnerability in India and enable the authorities to take pre-emptive policy measures and avoid a banking disaster. This paper makes a modest and pioneering attempt in this direction.

3: Methodology and Data Sources

The index method of identification of banking crisis has been adopted in this essay.[5] A slightly modified version of Kibritcioglu's (2002) Banking Sector Fragility (BSF) index has been constructed to recognize the exact months during which the banking sector in India has experienced crisis.[6] The index in this essay has been termed as Banking Sector Soundness (BSS) index. The sample data is monthly and spans from April 1994 to March 2007.[7] The monthly BSS index has been constructed using the Scheduled Commercial Banks' (SCBs) month-wise

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[5]Event-based method has not been considered to identify the dates of banking crisis in India as one has to rely on media reports to procure information on those events. Some of the events such as recapitalization and true NPA levels are not often disclosed. Besides on account of several shortcomings of the qualitative approach as already mentioned, this paper bases the identification of banking crisis dates in India on the index method.

[6] In this paper, Hagen & Ho's (2003a & 2003b) IMMP quarterly index have not been considered for identifying banking crisis dates in India. As mentioned earlier, IMMP emphasizes on bank runs indirectly and cannot identify banking problems in economies with a strong presence of State Owned Banks as in India. Bank runs are rare in India due to government guarantees and frequent recapitalizations of weak banks. Banking problems do not arise from the liability side, but from a protracted deterioration in asset quality.

[7]In this paper, the financial year for each time series begins from 1st April in a particular year and ends on March 31st the next year.

data on aggregate deposits, credit and investments as proxies for liquidity risk, credit risk and interest rate risk, the three major risks faced by any commercial bank in India.[8] Data on deposits, credit, investments are obtained from www.rbi.org.in. Exchange rate risk has not been considered as a proxy for the BSS index for the reason the international assets and liabilities of Indian banks are very insignificant. Two variants of the BSS index have been constructed. BSS3 is defined as an average of standardized values of banks real credit, real deposits and real investments. Another index BSS2 is constructed excluding bank deposits. If the time path of BSS3 and BSS2 follow a more or less similar pattern it will be concluded that domestic bank runs have not played any prominent role in banking crises.

$$BSS3_t = \left[(Dep_t - \mu_{Dep})/\sigma_{Dep} + (Cred_t - \mu_{Cred})/\sigma_{Cred} + (Inv_t - \mu_{Inv})/\sigma_{Inv}\right]/3 \quad (1)$$

$$BSS2_t = \left[(Cred_t - \mu_{Cred})/\sigma_{Cred} + (Inv_t - \mu_{Inv})/\sigma_{Inv}\right]/2 \quad (2)$$

where $$Dep_t = (D_t - D_{t-12})/D_{t-12} \quad (3)$$

$$Cred_t = (Cr_t - Cr_{t-12})/Cr_{t-12} \quad (4)$$

$$Inv_t = (I_t - I_{t-12})/I_{t-12} \quad (5)$$

Time series on deposits, credit and investments, are deflated using the Consumer Price Index (CPI ,1993-94=100).[9] D_t Cr_t and I_t represent the banking system's real deposits, real credit and real investments in time t while Dep_t, $Cred_t$ and Inv_t represent the SCBs' annualized changes in real deposits, real credit and real investments in time t. Using 12-month percentage change in the data instead of month-to-month variations implies any seasonality that is incorporated in the data series is removed and the transformed series is stationary. This transformation also implies difficulties in the banking sector are not signaled merely by short-term fluctuations but by longer-term variations. μ and σ represent the mean and standard deviation of the proxies for the three risks. The weights of each component are calculated as the inverse of their standard deviation. By constructing the standardized values, the variance of the three components is equalized so that no individual component may dominate the index.

[8] Although the banking sector in India include both commercial and cooperative banking, SCBs alone account for 98% of banking systems' assets (Mehrotra, p 10, 2006).
[9] The base of CPI has been shifted from 1981-82=100 to 1993-94=100.

A fall in the BSS index is associated with decline in either deposits, credit and investment or a combination of them. During the 1990s there was no substitution between bank credits and bank investments in Government Securities (G-Secs) by banks. But with greater emphasis on reduction of NPAs over the years , banks have substituted very low risk government bonds for credit or the other way round when treasury losses have been impacted.. The exact month of substitution is determined endogenously by Zivot-Andrews (ZA, 1992) structural break test in the result section. Prior to that date BSS3 is considered as the sum of deposits, credit and investments but from that date BSS3 is the sum of deposits, credit and negative investments. When value of BSS is greater than 0, it is a no-crisis zone. However, when the value is below 0, it represents banking fragility situation. Based on the threshold of ψ, the standard deviation of BSS index , medium and high fragility episodes are distinguished.[10]

Medium fragility: $-\psi \le \text{BSS} < 0$ ……………………………………………...………..… (6)

High fragility: $BSS < -\psi$ ……………………………………………………………..…….….(7)

In this paper continuously alternating phases of medium and high fragility is considered as a systemic banking crisis. Isolated phases of MF not associated with HF do not constitute systemic banking crisis. Crisis stops when medium fragility phase is not followed by any high fragility phase. A banking system is considered to have fully recovered from crisis when value of BSS=0. Based on the continuum of values assumed by the BSS index, we get the binary crisis dummy series which takes a value of 1 when there is a banking crisis and a value of 0 when there is no crisis.

Unit root tests such as Augmented Dickey Fuller (ADF, 1979) and Phillips-Perron (PP, 1989) tests have been used to check for the stationarity of the variables used in the construction of the BSS index. An important feature of Indian Scheduled commercial banking activity is that there has been a shift over among the components of BSS index in response to the situations. The Zivot-Andrews (ZA, 1992) structural break test has been applied on the investment series to capture the most significant structural break. . Prior to the break date (henceforth TB), BSS3 is considered as the sum of deposits, credit and investments but from the TB it is the sum of

[10] Kibritciouglu (2002) identifies the medium fragility and high fragility based on a threshold value of -0.50. He recognizes a low fragility situation as non-systemic or borderline crisis and a high fragility situation as corresponding to a systemic banking crisis.

deposits, credit and negative investments. The null hypothesis in the ZA (1992) paper is as follows

$$H_0 : z_t = c + z_{t-1} + \varepsilon_t \quad \text{……………………………………………………………………….(8)}$$

against the following alternative hypothesis

$$H_\alpha : \Delta z_t = c + \alpha z_{t-1} + \beta t + \theta DT_t + \gamma DU_t + \sum_{j=1}^{k} d_j \Delta z_{t-j} + \varepsilon_t \quad \text{………………………………………………(9)}$$

$$DU_t = \begin{cases} 1........t > TB \\ 0.........otherwise \end{cases} \quad \text{…………………………………………………………………….(10)}$$

$$DT_t = \begin{cases} t - TB......t > TB \\ 0.........otherwise \end{cases} \quad \text{……………………………………………………………………(11)}$$

where z_t represents the real investment series, DU_t represents the indicator dummy variable for the mean shift occurring at each possible TB and DT_t is the corresponding trend shift variable. The null hypothesis is $\alpha = 0$, which implies z_t contains a unit root with a drift that excludes any structural break while the alternative hypothesis is $\alpha < 0$ which implies that the series is stationary with a one-time break occurring at an unknown point of time. The ZA test regards every point as a potential TB and runs a regression for every possible TB sequentially. The break date is selected where the t-statistic from the ADF test is at a minimum (most negative).

In the 'signals' approach, 'n' possible indicators of banking fragility are considered. Let X_t^j be the indicator variable j in time t. $\mathrm{X}_t^j *$ is the threshold value of this indicator.[11] Each indicator variable is converted into a signal variable. S_t^j is the signal variable in time t for indicator j. In the univariate event analysis each determinant of a crisis is examined individually. For indicators with positive expected signs with banking crisis , X_t^j signals a crises if it exceeds the given

[11] The cut- off threshold is the frontier that distinguishes between banking distress and banking crisis. (Gayatan & Johnson, 2002 , p 11). Problems like slowdown in economic growth, current account deficit do not necessarily stir problems in the economy. It is only when these problems are sufficiently severe that a country fails to avoid the banking crisis. The critical cut-off point or the threshold value is that point at which fluctuation of an indicator makes a crisis unavoidable

threshold level X_t^{j*}. Thus, $S_t^j = 1$, if $X_t^j > X_t^{j*}$ and $S_t^j = 0$, if $X_t^j \leq X_t^{j*}$ …….(12). For indicators with negative expected signs with banking crisis, X_t^j signals a crises if it falls below the given threshold level. Thus, $S_t^j = 1$, if $X_t^j < X_t^{j*}$ and $S_t^j = 0$, if $X_t^j \geq X_t^{j*}$ …….(13). So, S_t^j is a binary variable.

The Crisis Window (CW) or the signaling horizon is the period before a crisis during which the behavior of the indicators signal an impending crisis. Researchers use different window lengths like 24, 18, 12 and even 6 months as the signaling horizon. There is no general accepted criterion for the selection of "reasonable time period". The window horizon is chosen depending on the data sample and country specific factors (El-Shazly, p 7). Due to the short span of time series data, for this study a six-month crisis window has been selected for this paper. The window length is constant for all the potential variable indicators. The verification of the binary time series of a potential variable when compared with the actual crisis/non-crisis event yields the following 2x2 matrix (Table 1). For each variable there are four possible outcomes.

Table 1: 2X2 Matrix for Estimation of Potential Indicators assuming 6-month CW

	Crisis occurs within 6 months	**No crisis occurs within 6 months**
Signal issued	A	B
No signal issued	C	D

Source: Kaminsky et al (1998)

A is the number of months the signal is issued and a crisis follows within 6 months (good signal).
B is the number of months of false alarms as no crisis followed within 6 months (bad signal)
C is the number of months when no signal was issued but a crisis followed within 6 months (missed signal)
D represents the number of months no signal was sent and no crisis occurred within the 6 months (good and silent signal)

A perfect indicator issues signals in all 6 months prior to a crises and refrains from issuing signals in every month that are not followed by crises in the next 6 months. Thus a perfect indicator would produce outcomes A>0 (and C=0) or D>0 (and B=0). A and D are true signals while B and C are false signals. However in practice none of the indicators match the profile of a perfect indicator.

The Noise–to-Signal Ratio (NSR) provides information on the ability of an indicator to correctly signal banking crisis. It combines information about the indicators' ability to issue good signals and avoid bad ones in order to measure the noisiness of the indicator.

$$NSR = (B/B+D)/(A/A+C) \quad \text{...} (14)$$

$$= \frac{\text{Ratio of crises incorrectly predicted to all non -crises episodes (false alarms)}}{\text{Ratio of crises correctly predicted to all crises episodes(correct calls)}}$$

Thresholds are defined in relation to the percentile of the distribution of the observations of the indicators. For obtaining the optimal threshold a search is performed whereupon the NSR is calculated for a potential range of threshold values and the value, which minimizes the NSR becomes the optimal threshold for that variable. This translates into examining the tails of the distribution. The upper tail is considered if indicator is positively related to crisis probability while the lower tail is considered if there is a negative relation. Thresholds chosen for this study range between 5-35% for lower tail and 65-95% for upper tail.[12]

The criteria for ranking of indicators according to their predictive abilities is based on the following. a) The lower the value of NSR, greater the power of the indicator in predicting banking sector disturbances. For an indicator whose NSR > 1 produces more of false alarms than good signals. Such indicators are not useful in predicting crisis and should be removed from the list of potential indicators as they generate excessive noise. The persistence of a signal is the simple inverse of NSR expressing the existence of a signal in the pre-crisis period relative to a peaceful period. The more persistent the signals in the pre-crisis period (i.e. during the 6 month window) than at other tranquil times, the better the indicator. b) difference of probability of a crises conditional on a signal from the indicator and the unconditional probability of the crisis. If the indicator has useful information the conditional probability of crisis, A/(A+B) {i.e. probability of crisis occurring within 6 months conditional on a warning signal from a leading indicator} will be higher than the unconditional probability of a crises (A+B)/(A+B+C+D) (Ahec-Sonje , 1999-2002, p 70).

Thus if $\frac{A/(A+B)}{(A+B)/(A+B+C+D)} > 1$, then the indicator is useful.

Also, the two criteria for deciding on the predictive power of the indicators, namely the NSR and the difference between the conditional and unconditional probabilities of a crisis are equivalent (El-Shazly 2002 , p 10). When NSR > 1, the difference between conditional and unconditional probabilities is negative (Chang & Li , 2002, p 12) . c) Average number of months

[12] Usually the search is limited 25 percent percentile if the indicator falls prior to banking sector disturbances or 75% of the distribution if indicator rises prior to banking crisis. The threshold has been lowered to 33.3% or 66.67% in specific cases, when 25% or 75% thresholds were considered to be inadequate depending on country-specific circumstances (Ahec-Sonje & Babic, 2000-2002 p 65,).

prior to a crises which a signal is first issued. Lead time is calculated as the average number of months in advance of the crisis when the signal first occurs.[13]

In the case of univariate indicators the signals from different indicators are considered separately and the information on their joint signaling is ignored. Larger the number of signals from different sectors of the economy, greater is the probability of banking crisis. Compressing indicators into a Composite Indicator (CI) can provide more useful information about an impending crisis.[14] "Generally, a rise of the CI points to an increased potential of the crisis and conversely, a lower value indicates the relaxation of the macroeconomic situation" (Brugermann & Linne, 2002, p 8). Choice of leading indicators to form a potential CI for banking crisis will be based on the average NSR of the majority of indicators. [15]

In this paper, CIs from currency crisis literature have been used to construct similar indices for banking sector disturbances. Two such *CIs* which are elaborated below.

Let X be a vector of m 'leading' indicators which is a sub-set of n indicators (m<n). The un-weighted CI of banking crisis is the simple count of flashing signals. Thus,

$$CI_t^1 = \sum_{j=1}^{m} S_t^j \; / \; m \qquad \text{……………………………………………………………………….(15)}$$

, where S_t^j = 1 and S_t^j=0 have their usual interpretations. The simple composite index, CI^1 is calculated for each month by summing the number of indicators flashing at any point in time of crises. In any period there may be anywhere between 0 to m signals. [16] The second composite indicator, CI^2 is the weighted sum of the signaling indicators where each indicator is weighted by the inverse of its NSR. The index is weighed in favor of indicators with lower NSR as they receive higher weights. 'The weighted signal approach which takes into account both the number and the level of signals in selecting the indicators, is considered more appropriate than the conventional un-weighted approach' (Hsing, 2003 , p 133). Thus,

[13] Signaling by variables on an average should occur sufficiently early to allow authorities to take pre-emptive policy action.. If the number of signals only increases in the months prior to a crisis, the index of fragility will at the most be a coincident indicator . It is thus necessary to establish how many months prior to the crisis does the indicator produce the first warning signal.

[14] Composite indicators have been used by Kaminsky (1999), GKR (2000), Bruggemann & Linne (2001) and Edison (2000).

[15] KLR (1998) proposed the inclusion of those indicators with NSR< 1 into the CI. Krznar(2004) uses variables with NSR < 0.50 in the calculation of CI , due to the presence of a large number of indicator variables with NSR<1

[16] CI_t^1 does not account for the forecasting accuracy of each of the univariate indicators thus losing important information about country's banking fragility.

$$CI_t^2 = \frac{1}{m}\sum_{j=1}^{m} w_j S_t^j \text{ .... (..........16), where, } w_j = \frac{1/\theta_j}{\sum_{j=1}^{m}\left(\frac{1}{\theta_1} + ... + \frac{1}{\theta_m}\right)} \text{ ....(17)}$$

where S_t^j =1 if indicator X_t^j crosses the threshold and 0 otherwise.

By itself, CI^2 is just a value but it becomes useful when converted in to a conditional crisis probability corresponding to certain composite index crisis value intervals. Following Edison (2000, p 25-26) conditional probability of banking crisis for the weighted CI can be calculated using the formula given below.

$$\Pr\left(BCRISIS_{t,t+6} \middle| CI_l < CI_t < CI_u\right) = \frac{\sum \text{months where } CI_l < CI_t < CI_u \text{ subject to a crisis in next 6 months}}{\sum \text{months where } CI_l < CI_t < CI_u} \text{ .... (18)}$$

Where P denotes probability, $BCRISIS_{t,t+6}$ is the occurrence of banking crisis in the interval [t,t+6] , CI_l and CI_u are the lower and upper intervals for the CI . For each arbitrarily chosen interval between a lower and an upper limit the conditional probability can be calculated. Thus $P(BCRISIS_{t,t+6} | CI_l < CI_t < CI_u)$ denotes conditional probability that a banking crisis will occur within 6 months under the condition that the indicator ranges between the lower band CI_l and the upper band CI_u. For all the CIs the choice of the critical threshold (CI_t^*) is very crucial. A crisis is deemed to be imminent when $CI_t > CI_t^*$.

In the limited dependent variable models, the banking crisis dummy is modeled as a 0-1 variable. In this study, a probit model is chosen based on the assumption that there are more zeroes and few ones in the binary crisis dummy series. However, explanatory variables are not transformed in to dummy variables but are included in a linear fashion. The probability that crisis occurs is assumed to be a function of the vector of explanatory variables.

Probit equation takes the form : $y_t = \beta x_t + c$, ………………………………………………(19)

P($y_t = 1 | x_t, \beta_t) = F(x_t, \beta_t)$ ………………………………………………………………(20)

where, y_t is the crisis dummy series, x_t , a set of explanatory variables selected by the signaling method as the best predictors of vulnerability to an upcoming banking crisis are entered as exogenous variables in the probit model with multiple variables, β_t is a vector of free parameters to be estimated. F is the cumulative distribution function that ensures the predicted outcome of the model always lies between 0 and 1. Probit model assumes that the probability distribution (y_t conditional on x_t) corresponds to a normal distribution

The z-statistics reveal the significance of the estimated coefficients in the model separately. The z-statistics tests the following: $H_0 : \beta_i = 0$, that is β_i the estimated coefficient of the ith variable is zero. If H_0 is rejected as a result of the z-statistic, we conclude that the variable affects the crisis dummy significantly.

$$\frac{\partial E(y_i | x_i, \beta)}{\partial x_{ij}} = -f(-x_i' \beta)\beta_j , \quad \ldots\ldots (21)$$

where $f(x) = \frac{dF(x)}{dx}$ is the density function corresponding to F. The direction of the effect of the effect of a change in x_j depends on the sign of the β_j coefficient. The coefficients estimated by these models cannot be interpreted as the marginal effect of the independent variable on the dependent variable as β_j is weighted by the factor f that depends on all the regressors. A positive value of the coefficient may be interpreted as a rise in the crisis probability.

There are several diagnostic tests for probit models: One of the measures of goodness-of-fit for non-linear estimators is the McFadden R^2 -statistic.

$$\text{McFadden } R^2 = 1 - \frac{\log L}{\log L_0} , \quad \ldots\ldots (22),$$

where $\log L$ is the average of the Log-Likelihood(LL) function without any restriction and $\log L_0$ represents the maximized value of LL function under the restricted case that all the slope coefficients except the intercept are restricted to 0. Value of McFadden R^2 always lies between 0 and 1.[17]

The Likelihood Ratio (LR) statistic is used to test the joint null hypothesis of all the coefficients except the intercept is 0. Thus, $H_0 : \beta_1 = \beta_2 = \ldots\ldots = \beta_i = 0.$ ……………………………...…(23)

[17] In case of a perfect fit with no error McFadden R^2 takes value of 1 and vice versa.

LR = $-2(LogL_0 - LogL)$ ……………………………………………………………………(24).

This statistic used to test the overall significance of the model. Under null hypothesis , LR-statistic is asymptotically distributed as a χ^2 variable with degree of freedom equal to the number of restrictions under test. Probability of the LR –statistic is the p-value of the LR-statistic.

Hosmer-Lemeshow (HL, 1989) statistic is a measure of the lack of fit in discrete choice models. The idea underlying the HL test is to compare the fitted expected values to the actual values by group. If these differences are "large", we reject the model as providing an insufficient fit to the data.

$$G_{HL}^2 = \sum_{j=1}^{10} \frac{(O_j - E_j)^2}{E_j(1 - E_j / n_j)} \approx \chi_8^2 \qquad (25)$$

where n_j = Number of observations in the j^{th} group, $O_j = \sum_i y_{ij}$ = Observed number of cases in the j^{th} group, The HL statistic follows a chi-squared distribution with *G* -- 2 degrees of freedom. $E_j = \sum \hat{p}_{ij}$ = Expected number of cases in the j^{th} group. The null hypothesis tests the deviations between expectations and actual observations are zero. Rejection of null hypothesis means the model performs poorly.

The leading indicators can be assessed on the basis of a number of attributes such as accuracy and calibration . Accuracy of an indicator refers to closeness of average of predicted probabilities and observed realizations. One method used to evaluate the accuracy of the indicators is Quadratic Probability Score (QPS). Let $P_t = \Pr(C_{t,t+6})$ be the probability of occurrence of banking crisis within 6 months.

$$R_t = \begin{cases} 1 & \text{…….. if crisis occurs within 6 months} \\ 0 & \text{….. otherwise} \end{cases}$$

QPS $= \frac{1}{T}\sum_{t=1}^{T} 2(P_t - R_t)^2$ ……………………………………………………………………(26),

where $0 \le \text{QPS} \le 2$. T is the number of sample observations. P_t is the predicted probability of crisis/non-crisis event at time t. R_t is the realization of the event at time t. QPS measures the average difference between the event realization and the calculated event probability. The highest possible value of QPS is 2 while the perfect accuracy implies a value of 0 . When QPS = 0 , it corresponds to perfect accuracy and the prognostic quality of the indicator is best. QPS test determines the discrepancy between the realization of an event R_t and its estimated probability P_t (Diebold & Rudebusch, 1989). Calibration refers to closeness of forecast probability and observed realization frequency. Overall forecast calibration is measured by Global Squared Bias (GSB). GSB = $2(\bar{P} - \bar{R})^2$ … ……………………………………………………………..(27), where $\bar{P} = \frac{1}{T}\sum_{i=1}^{T} P_t$ and $\bar{R} = \frac{1}{T}\sum_{t=1}^{T} R_t$ and $0 \le \text{GSB} \le 2$. When GSB = 0 , it corresponds to perfect global calibration which occurs when average probability forecasts equals average realizations

Banking crises may be precede by a wide range of economic problems .To design an effective EWS possibility and identify future banking crisis a broad variety of indicators (33 variables representing different sectors of the economy) have been chosen. The broad set of indicator variables that have been chosen to reflect financial liberalization, current account, capital account, real sector; fiscal sector and the economy are explained in table below.[18]

Table 2: **Potential Indicators of Banking Crisis**

Financial liberalization
Money Supply (M0, M1 & M3) and money multiplier- High growth of money supply - excess liquidity – currency speculation- increase banking sector problems. Financial liberalization - decrease in statutory pre-emptions and increase in money multiplier - fuel inflationary expectations - resulting real appreciations - pressure on the exchange rate - increase disturbances in the banking sector.
Domestic private credit- episode of rapid credit growth -typically labeled “excessive” or as an unsustainable “credit boom” when the observed growth rates exceed a given threshold - banking crisis.
Domestic Real interest rate and Interest spread- High real interest rate - liquidity crunch - economic slowdown and banking fragility.

[18] The absence of monthly time series on bank reserves, bank assets and interest rates has resulted in the exclusion of such variables from the list of potential indicators of banking crisis in India.

Difference between RBI policy interest rate and 91-day T-bill- Increase in spread – increase in policy rate (Repo Rate or Reverse Repo Rate) by RBI to check inflation - repercussions on the banking sector.
Current account
Exports and imports- Overvalued exchange rate - slowdown in exports - loss of competitiveness and business failures of domestic enterprises -bank loan defaults import growth -worsening of its current account - pressure on the banking sector.
Real exchange rate overvaluation -. Currency overvaluation - deterioration in the current account - indication to devalue in future -affects corporate earnings and increases the interest burden of loans in foreign currency To arrest inflation arising out of excessive appreciation due to heavy capital inflows, interest rates are raised and this is likely to lead to increase in banking sector problems.
A surplus in the current account - diminish the probability to devalue and lower the probability of currency crisis; high current account deficit - disrupts generation of foreign exchange to finance balance of payments deficit - pressure on the exchange rate - banking sector problems .
Capital account
Reserves- low level of reserves below a critical threshold - speculative attack on the currency .- increases banking sector problems.
Broad money as a proportion of international reserves- assesses short term liquidity and convertibility of a country's currency. Currency crisis with insufficient foreign exchange reserves to defend the domestic currency - problems for the banking sector as well.
Increases in short term debt - increases the susceptibility to foreign exchange crisis. Short-term debt to reserves -a vulnerability indicator of exposure to crisis.
*Capital outflows-*Sudden stop/sharp decline in capital inflows can increase the probability of currency crisis).- deepens the banking sector problems. Higher amount of Foreign Direct Investment (FDI) implies attractive economic policies and a lower share of current account being financed by volatile capital inflows- lowers the probability of attack on currency and the banking sector.
Real sector
Banking crisis are often preceded by recession - more vulnerable economy to crisis
Inflation - adversely affects the banking system- increases of nominal interest rates -shrinking liquidity - general economic slowdown - banking sector problems.
Forward-looking asset prices - Declining asset prices - loss of investor confidence and - rise in loan defaults and possibility of future banking crisis.
Fiscal sector
Fiscal Balance/GDP- High fiscal deficits -increase the vulnerability to shocks - pressure on exchange rate.
Global economy
US T-bill rate- Higher US interest rates induce capital outflows - pressure on the currency and possibly increasing banking sector disturbances.
Indian financial and non-financial firms borrow at floating LIBOR(London Interbank Offered Rate)-linked rates. LIBOR hike- debt burden increases- increase in domestic demand for money - upward pressure on local interest rates -possible future loan defaults.
*World oil prices-*High oil prices - danger to the current account position - possibly lead to domestic recessions

All the indicator variables are in monthly frequency. Variables in annual or quarterly frequency are interpolated into their monthly form using the Gandolfo interpolation method. Save interest rates such as Prime Lending Rate(PLR), deposit rate, Bank Rate, call money rate, LIBOR, US-3 month T-Bill rate and REER deviation from trend all the variables are transformed into their yearly percentage (y_o_y) change ensuring variables are stationary. Data for LIBOR, US 3-

month T-Bill rate and global oil price have been obtained from IMF Financial Statistics CD ROM. The remaining data was procured from www.rbi.org.in

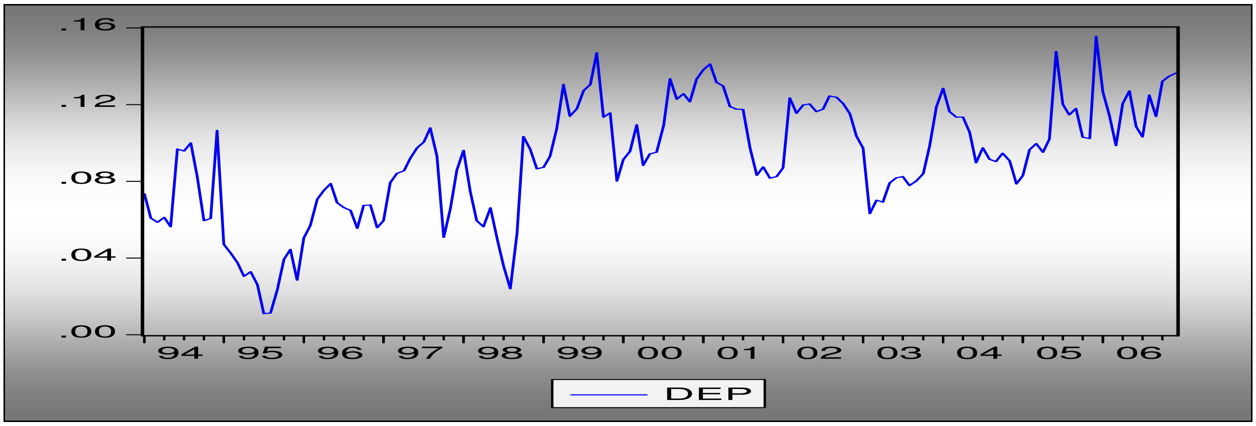
Table 3: Potential EWIs for Predicting Banking crisis in India:Symbols and data transformation

Variable indicator/ Symbol/ Frequency/ Variable transformation
Base money/ **M0_YOY**/monthly/ y-o-y change
M1 (Narrow Money)/ M1_YOY/monthly/y_o_y change
M1 Multiplier/**M1MULT_YOY/**/monthly/ y_o_y change
M3 multiplier/ **M3MULT_YOY/**/monthly/ y_o_y changE
Nominal credit growth/ **NCRED_YOY**/ monthly /y_o_y
Real deposit Rate **/RDRW** / monthly / none
Real lending rate / **RLRW** / monthly/none
Nominal interest rate / **NIR**/ monthly / y_o_y
Spread Ratio(PLR/deposit rate)/ **SPREAD_RATIO**/ monthly/none
Spread difference(PLR-deposit rate)/ **SPREAD_DIFF**/ monthly/none
Spread between Bank Rate and 91-day T-bill **/SPREAD_SIR/** Monthly/none
Weighted average (of high and low) Call Money Rate/ **WACMR/** /monthly/none
Return on BSE BANKEX / **BANKEX_RET**/ monthly / y_o_y
Exports / **EXPORT_YOY/**monthly/y_o_y
Imports / **IMPORT_YOY/**monthly/y_o_y
Real Effective Exchange Rate overvaluation(Hodrick Prescott Filter-REER)/ **REER_TREND**/monthly/none
Nominal Effective Exchange Rate/ **NEER_RT** / monthly/y_o_y
Ratio of Net Current Account Balance to GDP**/ CABGDP_YOY**/ monthly/y_o_y
Terms of trade **/TOTGDP_YOY**/ monthly/y_o_y
Foreign exchange reserves **/RESERVES_YOY**/monthly/y_o_y
Ratio of M3 and foreign exchange reserves/ **M3RESYOY**/y_o_y
Short -term debt**/ STD_YOY**/ monthly/ y-o_y
Short-term foreign debt as a proportion of reserves **/ STDRES_YOY**/ monthly / y_o_y
Foreign Direct Investment / **FDI_YOY**/ monthly/y_o_y
FDI as a proportion of GDP/ **FDIGDP_YOY/ monthly / y_o_y**
Real GDP growth/ **RGDP_YOY**/ quarterly/y_o_y
Index of industrial production (in real terms) / **RIIP_YOY**/monthly/y_o_y
Whole Sale Price Index/ **WPI_YOY**/monthly/y_o_y
S&P CNX return (CNX Nifty)/ **CNX_RET**/monthly/y_o_y
Ratio of Fiscal Deficit to GDP/**FDGDP_YOY**/monthly/y_o_y
London Interbank Offer rate for 1 month/ **LIBOR**/monthly/none
US 3 -month Treasury Bill Rate / **US3MTBR/** monthly/none
International oil price (Petroleum average crude price) / **OIL_PRICE/** /monthly/y_o_y

4: Estimation and Analysis of Results

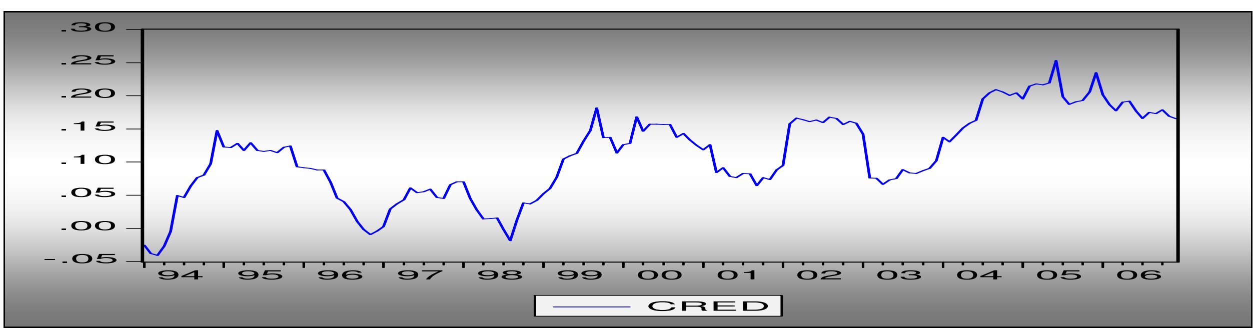
The broad results are shown and analyzed in the sub-sections below. To understand the time path of BSS index it is first necessary to observe the behavioral pattern of its constituents. Discernible patterns in real deposit growth rate can be explained by growth in time and demand deposits. While inflows under India Millennium Deposit (IMD) scheme, NRI remittances, buoyant economic growth, increase in demand for credit and the attitude of bank depositors in considering banks as safe havens for their investments resulted in positive growth rate of deposits of commercial banks , lower interest rates and high inflation regime particularly in 1996-97 adversely affected deposit growth rate.

Chart 1: Time Path of Annualized Growth Rate of Real Deposits of SCBs



A massive chunk of credit in India is devoted to the non-food sector. Credit growth of SCBs thus depends on cycles in industrial activity and export demand. Non-food credit off-take has remained relatively subdued in 2003-04 amidst buoyancy in industry reflecting increased recourse by corporates to internal sources of financing as well as external commercial borrowings.

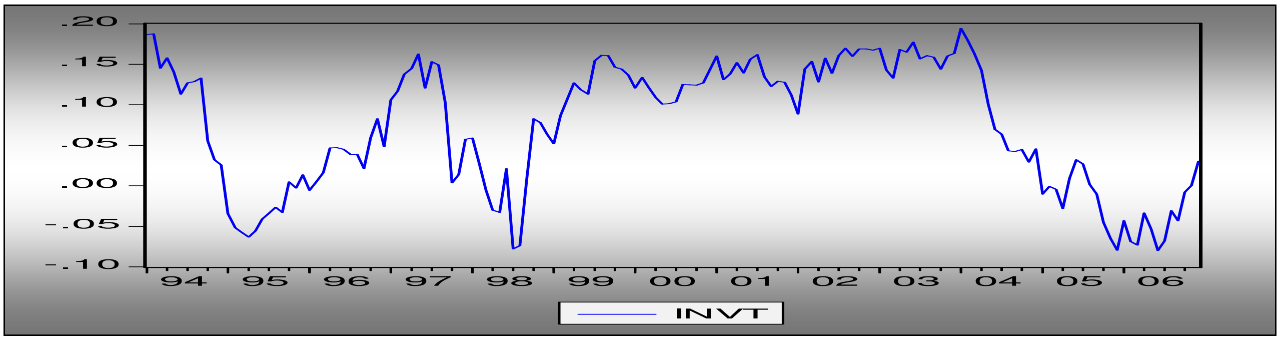
Chart 2: Time Path of Annualized Growth Rate of Real Credit of SCBs



Almost 89% of the investments of banks are in the Statutory Liquidity Ratio (SLR) securities. SCBs were holding investment around 35% to 41.3% of their Net Demand and Time Liabilities (NDTL) which was over the statutory prescription of 25 percent during 2001 to end-March 2004. The preference of banks towards G-Secs was primarily driven by lackluster credit demand. Commercial banks continued to invest heavily in Government paper, amidst surplus liquidity in financial markets as the sustained softening of interest rates continued to fuel a rally in gilt prices.

The increasing preference of banks for G-Secs reflected their efforts toward improving CAR(Capital Adequacy Ratio). But with a turnaround in the interest rate scenario, for the first time since the nationalization of banks in 1969, as bond prices fell investment of SCBs in SLR securities in absolute terms declined by Rs.21,699 crore during 2005-06 thus reversing the earlier trend and resulting in huge treasury losses for banks.

Chart 3: Time Path of Annualized Growth Rate of Real Investments of SCBs



It may also be noted from Charts 2 and .3 that there is a clear reversal in the time paths of lending and investment behaviour of SCBs.

Table 4 presents the ADF and PP unit root test results of the SCBs' aggregate real deposits, credit and investment series in their level form and growth rates. The tests reveal that the real deposits, credit and investments are non-stationary in levels, when considered with a trend. But they become stationary in growth rates. This confirms that all the variables under investigation depict I(1) behavior.

Table 4: Unit Root Test Results without Structural Break

	Dep	*Dep_gr*	*Cred*	*Cred_gr*	*Inv*	*Inv_gr*
ADF test (1 lag) Constant & trend	4.260	-15.031	7.535	-14.506	-1.516	-14.957
Phillips-Peron test	5.914	-23.832	14.856	-14.525	-1.511	-14.942

Note: Mackinnon critical values at 1%, 5% and 10% are -4.00, -3.43 and -3.13 respectively for ADF and PP tests.

To test for structural break of the investment series model 'C' of the Zivot-Andrews (ZA, 1992) method (Table 5) is applied. Since the Investment series exhibit upward trend we estimate the model 'C' including the βt term.

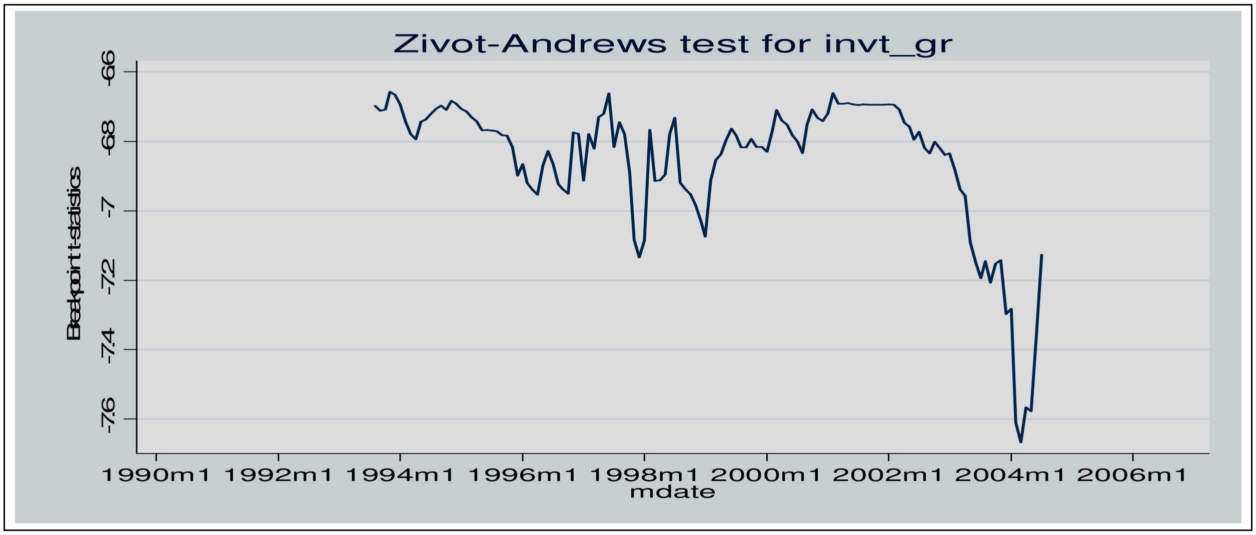
Table 5: ZA Test for Endogenous Structural Break in the Real Investment series (in both intercept & trend)

	Minimum t-statistic	**Month of structural break**
Inv_gr	-7.588*	2004m5 (August 2004)

Note: Critical values of Zivot-Andrews test are -5.575 and -5.08 at 1% and 5% levels of significance respectively. * denotes significance at 5% level.

The ZA test rejected the null hypothesis of unit root for the investment series in their growth rates and accepted the alternative hypothesis of the break-stationary alternative. The ZA test identifies endogenously the point of the single most significant structural break in August 2004 where the break-point t-statistics is minimum (Chart 4). This finding conforms to the pattern of SCB investment in G-Secs which shows a remarkably significant decline since 2004 as seen in chart 3

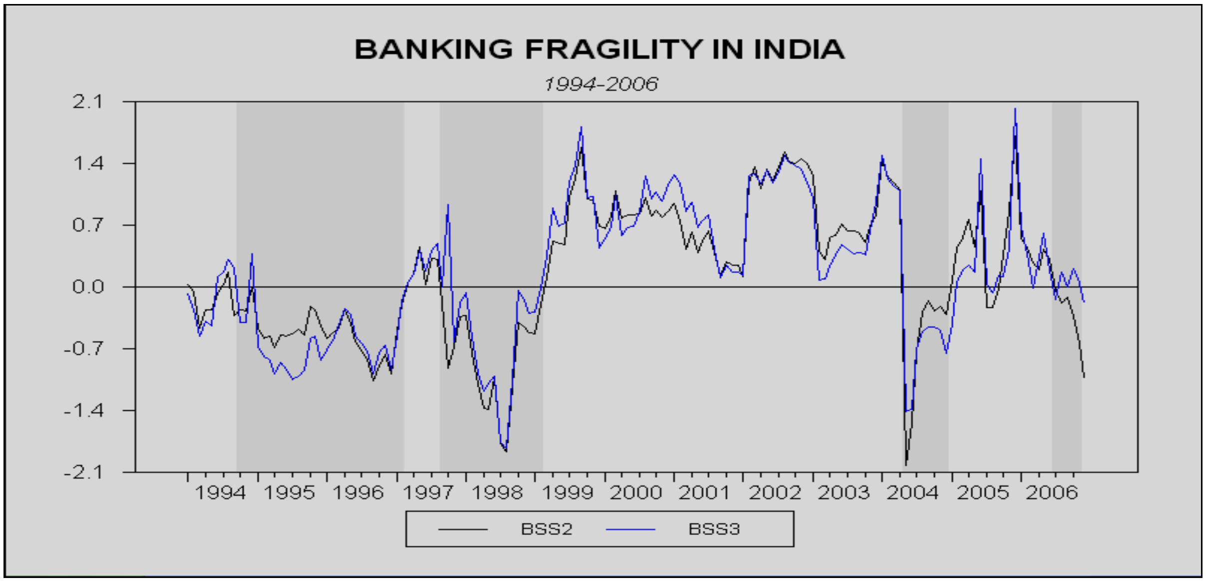
Chart 4: ZA Endogenous Structural Break in the Annualized Growth Rate of Real Investments



Thus from the charts presented in this section a clear substitution is discernible since mid -2004 between credit and investments. While investments declined credit showed a clearly increasing trend. To reduce pressure on CAR, banks had earlier resorted to large scale investments in G-Secs .But as interest rates rose and bond prices fell banks faced huge treasury losses. To compensate for the treasury losses banks embarked on a lending spree again. The significant decline in investments is also confirmed by the ZA structural break test.

The shaded regions in the Chart 5 highlight the periods of turbulence in the banking sector. Chart 5 shows that the time path of BSS2 and BSS3 have identical patterns suggesting that bank runs (deposit withdrawals) have played no major role in causing banking distress in India during 1994-2006. Therefore the crisis period is determined based on the BSS2 index.

Chart 5: Banking fragility in India: 1994:1-2006:12



Based on the structural break in the investment series on August 2004, we have derived the BSS2 for two phases: a) April 1994 to July 2004 and b) August 2004 to the end of the period of study. [19] Prior to August 2004, when the economic growth was robust banks usually assumed more risks. Consequently, both credit and investments increase. The BSS2 index registers time path significantly above 0 and this gives a signal for future problems in the banking sector due to current accumulation of bank risks.[20] In economic downturns, banks realize the growing risks they gradually begin to avoid them by lending less credit and also investing less in government securities. BSS2 index thus starts falling. In the risk-avoidance phase, banking sector fragility increases significantly and the BSS2 index falls below zero. The standard deviation of the BSS2 index is 0.66. [21] A 'medium fragility' situation persists when $-0.66 \leq BSS2 < 0$. As the risk-aversion continues BSS2 falls further below 0 and the banking system enters into a 'high fragility phase' when $BSS2 < -0.66$. There are alternating phases of medium and high fragility when the index value is below zero. Once the crisis is over the banking system recovers and the BSS2 index gradually starts increasing and is very close or equal to 0. The crisis stops when the BSS index reaches a value of zero. As economic conditions start improving banks assume risks all over again. Banks start assuming risks all over again. Since August 2004 a distinct trade-off

[19] Prior to August 2004, BSS2 is considered as the sum of credit and investments but from that date $BSS2$ is the sum of credit and negative investments
[20] Banks lend aggressively and are likely to pile up more NPAs. Oversubscribing in G-Secs exposes banks to market risk also.
[21] The threshold value of -0.66 corresponds to the 20th percentile.

in SCBs behavioral patterns in lending and investment was noticeable. To make up for treasury losses banks increased credit and reduced statutory investments. The steep fall in the BSS2 index in 2004 reflects this scenario.

Table 6 and Table A (in the appendix) shows months of medium fragility and high fragility based on the $BSS2$ index. In the two episodes between 1994:10 (January 1995) to 1997:2 (May 1997) and 1997:9 (i.e December 1997) till 1999:2 (i.e May 1999) there were alternating phases for medium and high fragility. The Indian banking sector experienced systemic banking crisis in each of these periods.[22] The crises were almost overlapping except for a short span of relief during 1997:3 to 1997:8 as the value of BSS2 index became positive during that time.[23] The deepest banking fragility in these two episodes occurred in 1998:8 (i.e November 1998) and in 1996:9 (i.e December 1996)**.** Each crisis in the 1990s had a sufficiently long duration of nearly one and a half to two and a half years. Two short isolated periods of banking fragility in 2004 & 2006 have also been revealed in the study. The BSS2 index shows crises from 2004:5 (i.e August 2004) to 2004:12 (i.e March 2005). Another bout of banking fragility was observed in 2006:7 (i.e October 2006). However, since our data set ranges from 1994:1 to 2006:12 for this last phase of banking fragility in our study we are unable to give the month when the fragility ended.

The crisis episodes in this study have tallied to some extent with the findings of many cross-country studies on banking crises. Using annual data and event-based method these studies show banking crisis in India has been persistent in the 1990s. [Caprio & Klingebiel (1999), 1991-ongoing; Glick & Hutchison (2001)1993-97; Glick, Moreno & Speigel (2001), 1993-97; Caprio & Klingebiel (2003) 1993-ongoing, Thorsten, Demirguc-Kunt & Levine (2003) 1993-97, Boyd, Gomis, Kwak & Smith (2004) 1993- , Laeven & Valencia (2008) 1993-]. The findings in this study however, make a marked departure from the event-based studies based on annual and quarterly data in the sense by identifying the exact months under the spell of banking crises. This is possibly why a large number of studies labeled the entire period (1993 onwards) under the spell of banking crisis while a 6-month short relief from crisis was found by the index method

[22] Any isolated phase of medium fragility not followed by a high-fragility phase as during 2005:07-2005:09 is not termed as a crisis

[23] Due to overlapping crisis researchers focus on using exclusion windows , though determining the width of these windows is a problem. 'Setting the exclusion window too broad could screen out the true indicators of a coming crisis, and reversely a too narrow exclusion window could result in false alarms.' (Bao Anh Thai, 2003, p 9). This study has however, not considered any exclusion window. This has been done to increase the number of crises events so that the KLR or signal extraction method (which works effectively when there are multiple crisis in an economy) may be used

used here.[24] Besides the beginning, end and the deepest banking fragility months have also been identified for the sample period covered in this essay using the index method.[25]

Table 6: **Months of Medium and High Banking Fragility in India (1994:1-2006:12)**

Period of Medium fragility	Period of High fragility	Date of highest fragility	Crisis duration
1994:02-1994:06@	Nil	Nil	nil
1994:10-1996:07 1997:01-1997:02	1996:08-1996:12	1996:09	1994:10-1997:02 (29 months)
1997:09,1997:11-1998:02, 1998:10-1999.02	1997:10, 1998:03-1998:09	1998:08	1997:09-1999:02 (16 months)
2004:08-2004:12	2004:05-2004:07	2004:05	2004:05-2004:12 (8 months)
2005:07-2005:09@	nil	Nil	Nil
2006:07-2006:10	2006:11-2006:12	2006:12	2006:07- # (end-date unknown)

@This was an isolated period of medium banking fragility not followed by any high fragility months. So this period cannot be termed as a crisis. # 2006:12 is not the end-point of the fragility phase rather it is the end-point of the data set.

The optimal threshold (corresponding to which NSR) is minimum for each of the indicators is determined. In Table 7, the NSR is calculated for all the indicators. 30 variables have NSR< 1, while only three variables have NSR >1. This suggests a large number of macroeconomic indicators gives less of false alarms and effectively signaled the impending banking crisis. The best indictor with the largest number of good signals is SPREAD_SIR while the indicator with the lowest share of good signals is OIL_PRICE . The spread of the policy interest rate (the Bank Rate) and the 91-day T-bill is a market signal and functions without any lags. The increasing spread signals rising interest rate scenario in the periods to come and possibly more loan defaults and asset-liability mismatches. The Indian economy imports about 70% of its oil requirements from international markets. This makes the economy vulnerable to any increases in oil prices in the international markets. However, oil-price shocks not being fully effective in India due to the government's administered pricing policies that diffuse the hikes by raising subsidy etc. The second last column of Table 7 shows the difference between conditional and unconditional crisis probability of the indicators. For the three indicators with NSR less than unity, the difference between conditional and unconditional crisis probability is negative. The last column of the table presents the average number of months in advance of the crisis when the first signal occurs (lead

[24] Due to lack of monthly data for many potential indicators prior to 1994 , this study could not capture banking fragility in the pre-1994 period.

[25] However, the two short phases of crisis in 2004 and 2006 identified in this study are not reflected in the latest cross-country studies.

time). Due to large number of variables with a NSR not exceeding one, the NSR value of 0.50 seems to be an appropriate choice for selecting indicators to be used in the construction of the composite indicator.[26] Due to issues related to data availability and multicollinearity, we have restricted our choice of the best indicators from 5 broad sectors to the following set of indicators: SPREAD_SIR, M0_YOY , STDRES_YOY, RGDP_YOY, REER_TREND and LIBOR.[27] These indicators have an average lead time of 8 months approximately. When IIP replaces GDP, average lead time increases to 9.5 months. Thus, it can be concluded that the identified leading indicators are indeed 'leading' as they, signal, on average, sufficiently early to allow for preemptive policy actions. Among all the sectors represented in this study the real sector has the lowest average NSR of 0.16 . Thus it seems from this result that real sector disturbances broadly and most effectively signals banking crisis in India compared to all other sectors mentioned here.

Table 7: Optimal Threshold, NSR and Lead time of Univariate Potential EWIs

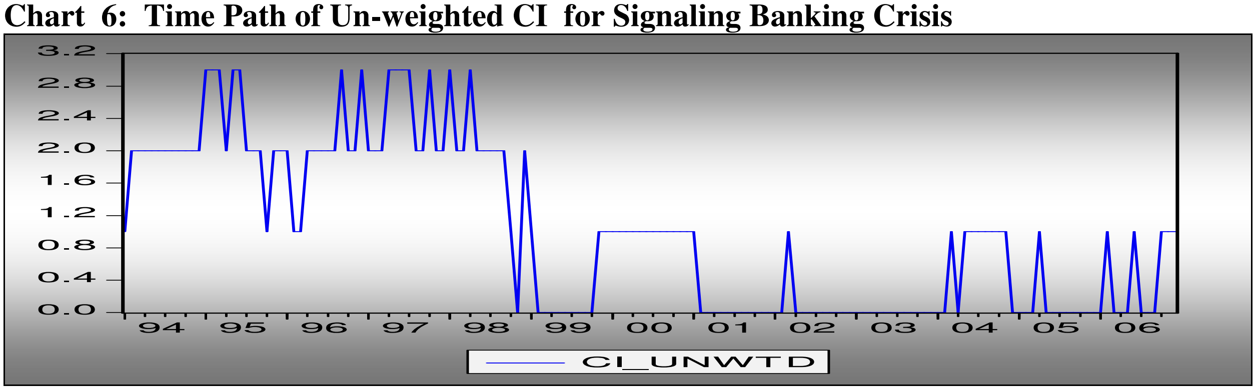
Potential Variable Indicator	Optimal threshold	Threshold value	Relation of variable with banking crisis	NSR	$\frac{A}{A+B} - \frac{A+C}{A+B+C+D}$ (%)	Lead time
Financial liberalization						
M0_YOY	85	18.78	Positive	0.121	37.74	3
M1_YOY	75	18.01	Positive	0.331	57	7
M1MULT_YOY	65	2.88	Positive	0.830	24	19.25
M3MULT_YOY	95	10.00	Positive	0.136	36.63	5
NCREDYOY_TREND	90	5.88	Positive	0.568	13.46	17.25
RDRW	85	9.22	Positive	0.162	41.89	31
RLRW	85	12.22	Positive	0.081	52.09	14
NIR	65	11.55	Positive	0.690	8.66	31
SPREAD_RATIO	65	1.75	Positive	0.935	0.0153	17.5
SPREAD_DIFF	70	4.75	Positive	0.634	10.87	9.5
SPREAD_SIR	85	1.79	Positive	0.048	48.52	5.6
WACMR	80	9.70	Positive	0.230	33.55	16
BANKEX_RET	15	18.79	Negative	0.500	16.67	18
Current account sector						
EXPORT_YOY	35	13.38	Negative	1.082	-0.0197	20

[27] Instead of headline inflation we chose money supply as the proxy for inflation.

IMPORT_YOY	65	26.34	Positive	0.590	15.82	20
REER_TREND	5	-3.79	Negative	0.180	33.79	5
NEER_RT	20	-0.04	Negative	0.209	31.86	6.5
CABGDP_YOY	15	-2.33	Negative	0.679	9.48	18
TOTGDP_YOY	10	-20.70	Negative	0.986	.00354	5.3
Capital Account						
RESERVES_YOY	5	-1.86	Negative	0.430	19.51	4.75
M3RES_YOY	85	.05	Positive	0.185	33.08	2
STD_YOY	75	38.95	Positive	0.470	18.01	9.3
STDRES_YOY	85	25.14	Positive	0.050	45.71	8.6
FDI_YOY	35	.009	Negative	0.480	17.40	21
FDIGDP_YOY	10	-27.86	Negative	0.627	11.46	20.5
Real Sector						
RGDP_YOY	30	-1.48	Negative	0.129	39.08	7.5
RIIP_YOY	20	-1.58	Negative	0.260	29.31	15.5
WPI_YOY	90	8.94	Positive	0.073	41.49	13.75
CNX_RET	5	-24.86	Negative	0.289	28.55	13
Fiscal Sector						
FD_GDP	70	12.69	Uncertain	1.910	-15.82	20
Global Sector						
LIBOR	65	5.52	Positive	0.467	18.06	19.25
US3MTBR	70	5.16	Positive	0.609	12.02	19.25
OIL_PRICE	65	3.20	Positive	2.360	-19.65	25

The 'leading' univariate indicators by themselves are not useful as all of them may not flash signals simultaneously. So the 6 'leading' indicators are compressed into the composite indicator CI^1. The threshold value of CI^1 is set at 75% percentile of the distribution. Warning signals are issued by CI^1 if the critical value is exceeded. Before the systemic crisis began in 1994:10, the value of the unweighted CI issued appropriate signals as seen from Chart 6.

Chart 6: Time Path of Un-weighted CI for Signaling Banking Crisis



In case of weighted composite indicator CI^2, corresponding to the weighting scheme introduced (equation 17) highest weight is given to indicator with the best performance or the lowest NSR (Table 8 here).

Table 8: **Weightage of 'Leading' Univariate Indicators**

Early warning indicator	w_i (%)
1) SPREAD_SIR	32.24
2) STDRES_YOY	30.95
3) MO_YOY	12.79
4)RGDP_YOY	12.10
5)REER_TREND	8.59
6)LIBOR	3.31
TOTAL	100

Table 9 compares the performance of the weighted and un-weighted signals approach in terms of their forecasting capabilities. The weighted composite indicator has lower NSR than the un-weighted indicator. This gain in efficiency in terms of lower NSR and higher lead time of CI^2 compared to CI^1, results primarily from the focus on the combination of variables and their respective NSR. The values of QPS and GSB also show significant improvement for CI^2, indicating the weighted CI's superiority to the un-weighted CI.

Table 9: Comparison of Performance of Weighted and Un-weighted CIs of Banking Crisis

	B/B+D (%Share of bad signals in total signals	**A/A+C (%Share of good signals in total signals)**	**NSR= B/B+D / A/A+C**	**A / A+B (%)**	**A / A+B - A+C / A+B+C+D**	**Lead time (average no. of months)**	**QPS**	**GSB**
CI_UNWTD	29.33	83.95	**0.349**	75.55	23.63	11	0.52	0.07
CI_WTD	8.00	77.78	**0.103**	91.30	47.07	19.5	0.35	0.01

The time-path of weighted CI (Chart 7) shows prior to the 1997 the value of CI increased sharply signaling deep-rooted banking problems. The goodness-of-fit measures indicates the fine performance of the weighted CI in signaling banking crisis in India (Table 10).

Chart 7: Time Path of Weighted CI for Signaling Banking Crisis

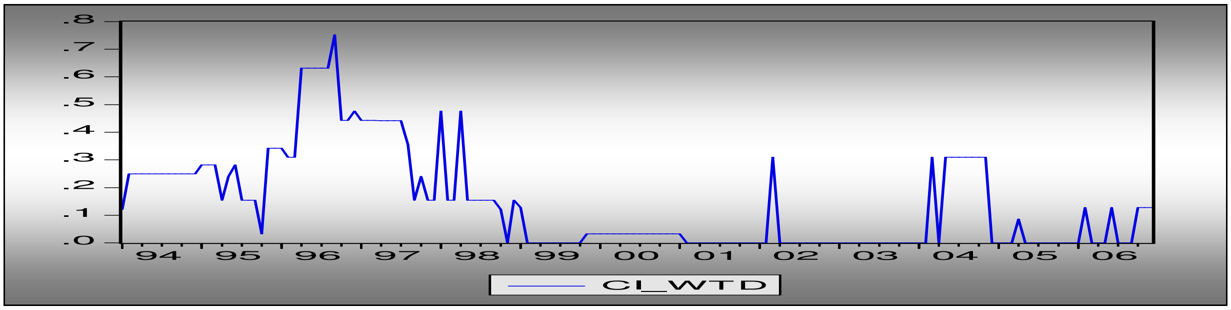


Table 10: **Goodness-of-fit of Weighted CI in Predicting Banking Crisis**

Predicted by CI_t^2	
% of months with accurate crisis prediction [a]	80.28
% of months with accurate prediction of tranquil periods [b]	85.54
% of months with inaccurate crisis prediction [c]	8.54

Crisis is accurately predicted if the estimated probability exceeds the probability threshold and a crisis starts in the course of the next 6 months. [b] A tranquil period is accurately predicted if the estimated probability does not exceed probability threshold and a crisis does not start in the next 6 months. [c] An inaccurate signal is an observation in the situation when the estimated probability exceeds the probability threshold and a crisis does not start in next 6 months

Table 11 reports the conditional probabilities of a banking crisis associated with different values of the weighted composite index. Once the value of the CI exceeds 0.205, the probability of future banking crisis increases alarmingly. The probability threshold of 0.219 (conditional probability of banking crisis of the CI in the interval of 0.01 to 0.20) has been chosen as the cut-off probability. This particular probability threshold is the best compromise between the prediction of a crisis when it does not happen and the prediction of a crisis when it happens.

Table 11 : Distribution of Conditional Probabilities of Banking Crisis based on Weighted CI

Composite indicator values	**Conditional probability**
0.01-0.20	**0.219**
0.21-0.40	0.903
0.41-0.60	1
0.61-0.80	1

Chart 7 shows the composite indicator value of 0.205 is breached prior to crisis in 1994, 1997 and 2004. However there is also a false signal in 2002. But there is no signal for the crisis in 2006.The 'leading' indicators identified under the signal extraction method are entered as exogenous explanatory variables in the multivariate probit regression. The descriptive statistics are given in Table 12.

Table 12: Descriptive Statistics of 'Leading' EWIs of Banking Crisis

	Observations	Mean	Median	Max	Min	Std dev	Skew -ness	Kurtosis	Jarque-Bera
RGDP_YOY	117	-.0002	.005	.087	-0.15	.04	-0.91	4.85	32.97*
RIIP_YOY	144	.98	1.78	9.04	-15.73	4.25	-1.13	4.77	48.26*
SPREAD_SIR	132	0.56	0.41	7.81	-3.73	1.76	0.96	4.98	42.16 *
M0_YOY	156	13.17	12.72	30.27	0.77	5.20	0.39	2.93	4.05*
REER_TREND	156	6.41E-09	-0.11	8.74	-6.12	2.48	0.29	3.62	4.61*
STDRES_YOY	141	-8.27	-18.56	66.55	-52.92	28.51	0.58	2.27	10.91*
LIBOR	144	4.26	5.27	6.69	1.09	1.85	-0.60	1.77	17.45*

Note: * and *** indicate significance at 1% and 10% levels.

The leading indicators in the signal extraction approach have been chosen from different sectors. This has avoided multicollinearity to some extent. The correlation matrix shows no evidence of strong correlation between any series. The correlation between any two variables is not even close to 0.50 (save for GDP and IIP but they are not used together) as shown in Table 13

Table 13: Correlation Matrix of 'Leading' EWIs of Banking Crisis

	RGDP_YOY	RIIP_YOY	SPREAD_SIR	M0_YOY	REER_TREND	STDRES_YOY	LIBOR
RGDP_YOY	1	0.51	0.05	0.08	-0.25	-0.15	-0.38
RIIP_YOY	0.51	1	-0.11	0.10	-0.26	0.12	-0.42
SPREAD_SIR	0.05	-0.11	1	-0.26	-0.17	0.13	-0.18
M0_YOY	0.08	0.11	-0.26	1	0.15	-0.25	-0.34
REER_TREND	-0.25	-0.26	-0.17	0.15	1	0.38	-0.20
STDRES_YOY	-0.15	0.12	0.13	-0.25	0.38	1	-0.17
LIBOR	-0.38	-0.42	-0.18	-0.34	-0.20	-0.18	1

The six selected indicators SPREAD_SIR, STDRES_YOY, MO_YOY, RGDP_YOY, REER_TREND and LIBOR are included incorporated as exogenous variables in the binomial multivariate probit regression model (Model 1). All the variables have the expected sign. Lower GDP, REER overvaluation (lagged by 16 months) , increase in LIBOR , base money supply, short-term debt over reserves and a higher spread of the Bank Rate over 91 day T-bill increase the probability of banking crisis. The statistical characteristics of the model are favorable. All the variables are significant at the usual conventional significance levels. The LR measure confirms the general statistical significance of the model. In addition, McFadden R^2 of nearly 70% indicates a fairly good model fit. Real GDP has been replaced by Real IIP (Model 2). The results of both the models are quite similar. Model 2 has a lower but modest goodness-of-fit of 60%. Both the models are estimated up to 2004:12 (Table 14 here).

Table 14: Estimates of Multiple Variable Binomial Probit Model of Banking Crisis

	Model 1	**Model 2**
Constant	-5.59* (1.42)	-6.14* (1.65)
RGDP_YOY	-0.62* (0.16)	
RIIP_YOY		-0.29* (0.08)
SPREAD_SIR	0.35** (0.15)	0.40* (0.13)
M0_YOY	0.196** (0.08)	0.22* (0.08)
REER_TREND(-16)	-0.32* (0.110)	-0.23* (0.09)
STDRES_YOY	0.016* (0.003)	0.013* (0.003)
LIBOR	0.58* (0.19)	0.67* (0.20)
Log Likelihood	-22.96	-27.81
Restricted Log Likelihood	-75.14	-71.18
LR stat (degrees of freedom) **Probability of LR stat**	104.35(6) (0.00)	86.75(6) (1.11E-16)
McFadden R^2	0.694	.609
Hosmer-Lemeshow statistic **Probability**	9.17 (0.327)	5.53 (.699)
No. of observations **No. of observations = 0** **No. of observations = 1**	1996:1-2004:12 (108) 60 48	(1996 :1 – 2004:12) (108) 60 48

Note: The REER_TREND lag of 16 months was found to be optimal showing the minimum value of Schwarz criterion
The figures in parentheses indicate standard errors. * and ** indicate significance at 1% and 5% respectively.

The real sector slowdown (falling GDP or IIP) is a sign of future banking problems. Increase in inflation (as proxied by growth of base money supply) also marginally increases the future probability of banking crisis. Rising interest scenario as reflected by the increasing SPREAD_SIR may lead to future loan defaults. REER_TREND appreciation is a common feature in countries receiving large capital flows and India is no exception. This eventually hurts exports and increases the current account deficits. Also the overvaluation of the REER above its trend leads to tightening of interest rates and protracted deterioration of bank asset quality.

Liberalization of capital flows has exposed the Indian economy to speculative short-term capital movements and rendered them vulnerable to stock market collapses. India has accumulated large buffer of foreign exchange reserves but they are largely built from capital account surpluses and are thus encumbered by liabilities making the economy vulnerable to financial contagion. (Subbarao, 2008b, p 7). Due to the presence of a large number of foreign investors the ups and downs of the stock market are related to the short-term capital flows and their high degree of volatility and liquidity. They are able to move quickly in and out of a country or currency in response to speculative expectations, domestic conditions in the recipient country or to macroeconomic conditions in the industrial countries and their movements are not related to economic fundamentals. Under tight regulatory control STDRES_YOY may not pose much vulnerability of the banking sector. Further, excessive reliance on External Commercial Borrowings (ECB) may also pose a problem for domestic borrowers with repercussions on the banking sector in the event of a global economic turmoil and hike in LIBOR. These results confirm the significance of global economic conditions, and suggest that financial liberalization has rendered the Indian banking sector vulnerable to crises.

In order to be able to use the estimated model as a EWS of banking crisis it is necessary to estimate the power of the model in predicting a crisis in the sample. The standard method in literature compares the estimated probability of a crisis with actual occurrences. To this end various probability thresholds are chosen to serve as criteria for the decision whether the chosen model signals the crisis or not (Table 15).

Table 15: Goodness–of-fit of Multivariate Probit Regression Model of Banking Crisis

	Model 1	**Model 2**
Goodness-of-fit (Cut-off probability of 50%)		
% of observations correctly called	**92.31**	**93.80**
% of crises periods correctly called (Dep=1)	**92.50**	**90.38**
% of tranquil periods correctly called (Dep=0)	**92.21**	**96.10**
Goodness-of-fit (Cut-off probability of 22%)		
% of observations correctly called	**88.31**	**89.92**
% of crises periods correctly called (Dep=1)	**97.50**	**96.15**
% of tranquil periods correctly called (Dep=0)	**91.45**	**85.71**
Goodness-of-fit (Cut-off probability of 10%)		
% of observations correctly called	**79.22**	**72.73**
% of crises periods correctly called (Dep=1)	**97.50**	**96.15**
% of tranquil periods correctly called (Dep=0)	**85.47**	**82.17**

The probability threshold as the value separating the pre-crisis period from the tranquil period is set in the same manner as the signaling method and for similar reason at 0.219. However model performance at other probability thresholds is also checked and are found to be satisfactory .

The in-sample and out-of-sample predictive abilities of the models are estimated in Table 16. Model 1 lends itself to in-sample forecasting only due to shortage of quarterly data on GDP.[28] At the time of writing this paper quarterly data on GDP was available till 2006 which when converted to monthly data was up to 2005:09 rendering in insufficient number of observations for out-of-sample prediction of the banking sector disturbance in 2006. However IIP data was till 2006. Thus Model 2, where RIIP_YOY replaces RGDP_YOYand lends itself to both in-sample and out-of-sample forecasting tests. Though the forecasting capabilities of both the models are similar, in-sample, model 1 slightly outperforms model 2. The out-sample predictions of model 2 for the period 2005:1 to 2006:12 which includes the banking fragility phase in 2006 is quite satisfactory.

Table 16: In-sample and Out-of-sample Forecasting Results of Probit models for Banking crisis

	In-sample(1994:1-2004:12)		Out-of sample(2005:1-2006:12)
	Model 1	Model 2	Model 2
Root Mean Squared Error	0.237	0.280	0.363
Mean Absolute Error	0.119	0.162	0.270
Mean Absolute Percentage Error	5.84	8.07	5.30
Theil Inequality Coefficient	0.213	0.245	0.461
Bias Proportion	0.0001	0.000	0.204
Variance Proportion	0.089	0.117	0.045
CovarianceVariance Proportion	0.910	0.882	0.749

5: Concluding Observations and Policy Implications

This paper is a pioneering study in the Indian context and has attempted to devise an EWS for future banking crisis based on both the 'signals' approach and the probit regression method, the two popular methodologies used in crisis literature. Using the index method and monthly observations the paper has identified four episodes of systemic banking crisis during April 1994

[28] At the time of writing this thesis quarterly data on GDP was available till 2006 which when converted to monthly data was up to 2005:09 rendering in insufficient number of observations for out-of-sample prediction of the banking sector disturbance in 2006. However IIP data was updated till 2006.

to March 2007. The results of the 'signals' approach indicate growing interlinkages of domestic and external financial liberalization with the Indian banking sector. Macroeconomic fundamentals such as increasing spread of RBI Policy interest rate over 91-day T-bills, increase in money supply growth due to capital inflows, slowdown in GDP growth, increase in short-term debt over international reserves, REER overvaluation lagged by 16 months and increase in LIBOR are some of the 'leading' indicators that may flash signals of an upcoming banking crisis. Some other indicators that could emit signals before a banking turmoil in India and should not be overlooked are real lending and deposit rates and stock prices.[29] However, it is important to note that the 'leading' univariate indicators of this study may not flash signals simultaneously and thus it is necessary to aggregate them into some form of composite indicator. The weighted composite indicator has a lower NSR and sufficiently higher average lead time than the un-weighted composite indicator thus allowing a modest time period for the government to initiate appropriate policy action to thwart future banking crisis. Based on the 'leading' indicators one interesting result of this study shows that if the value of the weighted composite indicator breaches the value of 0.205, the probability of banking crisis increases alarmingly. However, these observations are based on the findings of this study. As we incorporate additional indicators into the EWS model, or change the sample period, the optimal cut-off probability of banking crisis will also change. The significance of the 'leading' indicators as found in the 'signals' method has also been confirmed by the probit regression results indicating robustness of our proposed EWS model. The probit model also performs well corresponding to the various probability thresholds chosen to serve as criteria for the decision whether the model signals the crisis or not. The out-of sample prediction for 2006 banking crisis is also quite commendable.

[29] Larger number of market-based indicators should be incorporated into the EWS to avoid the problem of reporting lags that usually exist in non-market based-data.

The early warning model proposed in this paper cannot give the exact timing of the next banking crisis, but at least can provide an indication of the susceptibility of the Indian banking sector to future crisis based on the behavior of the crucial indicators. The importance of this study rests in the fact that the significant early warning indicators can be stress tested to rightly apprehend future banking crisis in India

A few of the leading indicators as found in this study, started behaving in an expected manner long before the current global financial turmoil hit the Indian banking sector. Sharp REER appreciation for a considerable period of time in mid 2007s prior to the current backlash was a prominent signal of future banking sector problems. Besides the hike in LIBOR, inflationary persistence, deceleration in GDP growth and depletion of foreign exchange reserve in relation to short-term foreign debt, all pinpointed in the direction of banking turmoil in the months to come. NPAs of several banks increased significantly in the first half of 2008-09.[30] In fact the bad assets have started increasing across industries following huge losses in companies of India Inc since September 2008. The CAR of banks has also been impacted but continuous government recapitalization is helping them to overcome the situation.

The knock-on effects of the global economic meltdown on the Indian economy and the banking sector, is reflected in the spillover of the external crisis initially affecting the real sector of the Indian economy. Perhaps for this reason the Indian banking system, posed to be comparatively resilient, is currently being affected by the backlash of the global economic and financial imbalances. It is proposed in this context, that monetary easing and simple fiscal stimulus package in the form of reduction in policy interest rates, recapitalization of banks and injection of liquid money are pure stop-gap measures and the like may not be adequate to pull the economy from the disturbed state without addressing the specific factors or variables

[30] 'Rising Tide of NPAs Hit Banks', *Economic Times* 9.12.2008

contributing towards the crisis. Rather this paper suggests that timely policy action based on the unusual behavior of indicators can possibly stave of the potential banking crisis or limit its effects.

6: Limitations and Scope for Future Research

In this paper, future banking crisis prediction is based on crisis history itself. However, newer crisis may emerge from newer characteristics. Thus the proposed early warning model has to be updated continuously as the global and domestic macroeconomic conditions keep changing. Further, due to data limitations, all SCBs irrespective of their size and ownership are assumed to be equally exposed to common macroeconomic and global shocks. Data considerations have also led to the exclusion of bank-specific variables and non-quantifiable factors affecting health of the banking system from the study. The EWS devised in this paper to forecast banking crises in India is just a preliminary step in the direction of exploring alternative methods on banking crises prediction. Several other approaches like Markov Switching Model and Classification and Regression Trees (DuttaGupta & Cashin , 2008) can be alternatively used to examine the robustness of the early warning model for banking crisis prediction in India.

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