Ordered Probit model of Early Warning System for Predicting Financial Crisis in India

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Abstract

The Indian economy is facing new challenges of maintaining financial stability with greater integration in terms of trade and finance with global economy. In the face of present global financial crisis which was triggered by liquidity shortfall in the overseas banking system, there is a need for developing an early warning system (EWS) incorporating global and domestic macroeconomic indicators for monitoring and maintaining financial stability in an economy.

The financial sector in India is still dominated by banking sector and they hold the key to the stability of the entire financial system in the country. With this background, an attempt has been made to predict the financial crisis (fragile situation) in India using ordered probit model. In this paper, using index method of recognizing exact month during which the banking sector has experience crisis, we constructed monthly banking sector fragility index (BSF) of India and developed the ordered probit model for predicting the banking crisis using macroeconomic indicators. The banking fragility index of India identifies nineteen phases of medium fragility and eight phases of high fragility during the studied sampled period, March 2000 to November 2009. The model could classify about 94 percent of different state of the crisis viz., no distress, medium and high fragility, in India.

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Keywords: **Banking Crisis, Early Warning System, Ordered Probit Model, Banking Fragility Index**

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1. Introduction

During last two decades, the world has seen a large number of financial crises in emerging market economies of Latin America and Asia with consequences of large cost at both national and international financial system. However, the recent financial tsunami which started in US during August 2007 was triggered by liquidity shortfall in the overseas banking system and has affected directly or indirectly to almost all the countries of the world after the collapse of Lehman Brother in September 2008. The consequence cost of this tsunami, according to the International Monetary Fund (IMF) in March 2009, projected the world growth to shrink by 0.5 to 1.0 per cent in 2009 in contrast to an expansion of 3.2 per cent in 2008; while, the World Bank estimated global GDP to contract by 1.7 per cent. The IMF also projects that the GDP growth of Emerging Market Economies (EMEs) will decelerate to a range of 1.5 to 2.5 per cent in 2009, down from 6.1 per cent in 2008. The economic activity in India too got slowed down during the period due to spillover effect of the global crisis. The growth decelerated sharply during the quarter October – December 2008 following the failure of Lehman Brothers in mid-September 2008. The growth rate during the first three quarters (April-December) of 2008-09 slowed down significantly to 6.9 per cent from 9.0 per cent in the corresponding period of the previous year (RBI, 2009a). Even though both the public sector and private sector of Indian banks were financially sound and were not directly exposed to the sub-prime mortgage assets; India experienced the knock-on effects of the global crisis, through monetary, financial and real channels. The financial markets viz., equity markets, money markets, forex markets and credit markets have all come under pressure mainly because of the so call 'the substitution effect'. As credit lines and credit channels in the overseas went dry, some of the credit demand earlier met by overseas financing is shifting to the domestic credit sector, putting pressure on domestic resources. The reversal of capital flows which took place as a part of the global de-leveraging process has put pressure on the forex markets. Together, the global credit crunch and de-leveraging were reflected at the domestic, in the sharp fluctuation of overnight money market rates in October 2008 and the depreciation of the rupee (Subbarao, 2009a). To avert and reduce such cost and effect of crisis, the prediction of distress/crisis situation has come to the fore for maintaining financial stability in a country as well as in international financial system.

There are theoretical models of financial crises to examined crisis (Currency, or Banking crises) and bank failure. The macro origin of financial crises model mainly relies on three generation models viz., first-generation models, second-generation models and third-generation models. According to the first-generation models weak economic fundamentals are more vulnerable to speculative attacks. While in second-generation model, it does not reject the role of weak fundamentals, but suggests that self-fulfilling expectations appear to be the main cause of crises. These two generation models are commonly known as currency crisis models. On the other hand, the third generation models combine weaknesses in the economic fundamentals of early generation models with weaknesses in the banking sectors, to the analysis of financial crises. For this reason, the third generation models are also known as twin crises, i.e. banking and currency crisis models. While according to the micro origin, financial crisis may be categorized by different groups of bank failure models, such as random withdrawal models, asymmetric information models, adverse shock/credit channel models and moral hazard models.

As an aftermath of the East Asian Crisis in 1990s, central banks across the globe pursue financial stability as its one of their goal. India too pursues it as one of its monetary policy objective. In India, the financial system is dominated by banking sector and commercial banks of the Indian banking system accounts for more than 90 percent of the banking system's assets (RBI, 2007). A significant aspect of banking trend in India is that so far it has never witnessed a banking crisis. However, the continuous liberalization and its greater integration with the global economy have opened up fresh challenges for the Indian banking sector. According to Arestis and Glickman (2002), the primary impact of openness in an emerging economy is to import the drive towards financial innovation, as foreign investors seek out investment opportunities and local households, firms and banks begin to look abroad for finance. Sooner or later, the economy falls into state of international financial fragility. It then become prone to crisis that is domestic in origin but impacts on its external situation or to crisis that is external in origin but impact on the domestic situation and combining the two, it identify the crisis (Anastasia, 2007).

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 per cent in 1997-98, the year of the Asian crisis, to 34.7 per cent in 2007-08. While the India's financial integration with the world measured in terms of ratio of total external transactions (gross current account flows plus gross capital flows) to GDP, has more than doubled from 46.8 per cent in 1997-98 to 117.4 per cent in 2007-08 (Subbarao, 2009b). With such degree of gradual openness and integration, it is important that India needs to keep a watch to capture the developments in international markets and apprehend the implications for the domestic economic and financial systems. This emerging scenario of India's integration with the global economy and in the light of current global financial crisis, a need is being felt for developing an early warning model incorporating global and domestic macroeconomic indicators which may effectively signal future banking vulnerability in India and enable the authorities to take pre-emptive policy measures and avoid a banking disaster.

An early warning system (EWS) aim at anticipating whether and when individual country may be affected by a financial crisis by developing a framework that allows predicting financial crisis in relatively open economy. There are basically three approaches to the development of predicting financial crisis, particularly the banking crisis, viz., Bottom-up approach, Aggregate approach and Macroeconomic approach[1]. In the bottom-up approach, the probability of insolvency is estimated for each individual bank and the concern for systemic instability is warranted when the probability of insolvency become significant for large proportion of country's banking assets (i.e for sum of all banks in the country); while the model is applied to the aggregate bank data to

[1] See Lindgren, Garcia and Saal (1996)

determine the probability of systemic insolvency in the aggregate approach. In the third approach, instead of looking at bank balance sheet data for internal sources of unsoundness, it established systemic relationships between economy wide variables and indicators of bank soundness. A number of macroeconomic variables are expected to affect the banking system or reflect its condition. With the above background, an attempt has been made in this paper to develop a model of EWS base on ordered probit approach for monitoring and predicting banking distress or crisis in India[2] using macroeconomic indicators

The rest of the paper is organized as follows. Section 2, gives a brief description about financial crisis and their associated features. Section 3, provides a review of the literature on methodological development of early warning system for predicting crisis. Section 4, describes the method of constructing monthly banking sector fragility index for India. Section 5, deal with identification of some potential macroeconomic indicators for predicting crisis. In section 6, we give a brief description on the methodology developed for predicting banking crisis in India. While, section 7, describes the data and its sources used in developing the EWS model. Section 8, present the empirical results of the model and concluded the paper with summary of observations in section 9.

2. Definition and Features of Financial crisis

The term financial crisis is applied broadly to a variety of situations in which some financial institutions or assets suddenly lose a large part of their value. In the 19th and early 20th centuries, many financial crises were associated with banking panics, and many recessions coincided with these panics. Other situations that are often called financial crises include stock market crashes and the bursting of financial bubbles, currency crises, and sovereign defaults[3]. Financial crises directly result in a loss of paper wealth[4]; they do not directly result in changes in the real economy, however may

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[2] Indian has a well diversified financial system which is still dominated by bank intermediation. Commercial banks together with cooperative banks account for nearly 70 percent of the total assets of Indian financial institutions (RBI, 2009b).

[3] See Laeven, Luc and Fabian Valencia (2008)

[4] Paper wealth means wealth as measured by monetary value, as reflected in the price of assets – how much money one's assets could be sold for. Paper wealth is contrasted with real wealth, which refers to one's actual physical assets.

indirectly do so, notably if a recession or depression follows. A financial crisis is a disturbance to financial markets that disrupts the market's capacity to allocate capital – financial intermediation and hence investments come to a halt (Richard Portes, 1998). Financial crisis may be accompanied by some of the features, which are highlighted below[5]:

i. A demand for reserve money so intense that the demand could not be satisfied for all parties simultaneously in the short run.
ii. A liquidation of credit that has been builds up in a boom.
iii. A condition in which borrowers who in other situations were able to borrow without difficulty become unable to borrow on any terms-a credit crunch or credit market collapse.
iv. A forced sale of assets because liability structures are out of line with market-determined asset values, causing further decline in asset values-the bursting of a price "bubble'.
v. A sharp reduction in the value of banks' assets resulting in the apparent or real insolvency of many banks and accompanied by some bank collapses and possibly some run.

All of the elements emphasized above could be present in a financial crisis and some may be more important than the other in a given situation of the crisis.

3. Literature Review on Early Warning System for Financial crisis

The first method used in the development of EWS is the signal approach to predict financial crisis, in particular currency crisis was the effort of the Kaminsky, Lizondo and Reinhart (1998) who monitor the evolution of several indicators. If any of the macro-financial variables of a specific country tends to exceed a given threshold during the period preceding a crisis, then this is interpreted as a warning signal indicating that a currency crisis in that specific country may take place within the following months. The threshold is then adjusted to balance type I errors (that the model fails to predict crises when they actually take place) and type II errors (that the model predicts crises which do not occur). Kaminsky (1999) and Goldstein et al. (2000) base their prediction of

[5] See Sundararajan and Balino, (1998)

a crisis occurring in a specific country by monitoring the evolution not only of a single macro-indicator, but also on a composite leading indicator, which aggregates different macro-variables, with weights given by inverse of the noise to signal ratio.

The alternative method in the EWS literature is to use limited dependent variable regression models to estimate the probability of a currency crisis. The currency crisis indicator is modeled as a zero-one variable, as in the signal approach, and the prediction of the model is interpreted as the probability of a crisis. More specifically, in line with the probit regression analysis put forward by Frenkel and Rose (1996), Berg et al. (1999) use this model specification with the explanatory variables measured in percentile terms. The study of Van Rijckeghem and Weder (2003) uses probit regression to examine the role of a common lender channel in triggering crisis events. They rely on disaggregate data on external debt produced by the Bank for International Settlements (BIS) to construct measures of competition for fund in order to explore the role played by a common lender channel.

Further, Fuertes and Kalotychou (2004) consider not only logit regression but also a non parametric method based upon K-means clustering to predict crisis events. They find that combinations of forecasts from the different methods generally outperform both the individual and naive forecasts. The empirical analysis reveals that the best combining scheme depends on the decision-makers preferences regarding the desired trade-off between missed defaults and false alarms[6].

There are also some studies which have constructed composite leading indicators of currency crisis events using diffusion indices rather than the weighting scheme suggested by Kaminsky (1999) and by Goldstein et al. (2000). The studies which rely upon the construction of diffusion indices using principal component analysis fitted to a large dataset. Mody and Taylor (2003) uses Kalman filter estimation of state space models in order to extract a measure of regional vulnerability in a number of emerging market countries, and, in order to produce in-sample prediction of the currency market turbulence. Another diffusion index is the one constructed by Chauvet and Dong (2004) who develops a factor model with Markov regime switching dynamics in order to

[6] See also the study of Bussiere and Fratzscher (2002), on the issue of designing the features of their EWS model according to the preferences and to the degree of risk-aversion of policymakers.

produce in-sample and out-of-sample prediction of nominal exchange rates in a number of the East Asian countries.

4. Monthly Banking Sector Fragility Index for India.

For predicting financial crisis, period of the crisis needs to be identified and dated. There are two commonly used approached for identifying the period of banking crisis viz., event-based method and the index method. The event-based method of crisis identification recognizes a systemic banking crisis only after the occurrence of certain events like bank runs, closures, mergers, recapitalization and huge Non-Performing Assets (Demirguc Kunt and Detragiache, 1998; Kaminsky and Reinhart, 1999; Caprio and Klingibiel, 2003 and IMF, 1998). This method however has several limitations. Identification of the crisis when it has becomes severe enough to trigger certain events can lead to delayed recognition of a crisis (Hagen and Ho, 2003a). Moreover, there is also certain amount of randomness inherent in the definitions. This method thus does not identify the different degrees of crisis severity. Further the event-based method does not clearly identify the beginning and end of a crisis. Finally, an event-based study which usually uses annual data, label an entire year as crisis even though the crisis may have occurred in just a few months of that year. However, the index method used for identification of banking crisis which is built on the lines of Exchange Market Pressure (EMP) index for dating currency crisis, has several advantages 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 and Klau, 2000; Kibritcioglu, 2002; Hagen and Ho, 2003a, 2003b).

Thus to identify and date the experiences of different state of distress or crisis by the Indian banking sector[7], we adopt the index method developed in Kibritcioglu (2002). According to Kibritcioglu (2002), a bank is potentially exposed to various types of economic risks such as liquidity risk, credit risk and exchange rate risk due to change

[7] In this paper, the banking sector means banking sector of a country excluding the Central Bank.

in the value of its asset and or liability in the financial markets. Therefore, a bank net worth[8] and hence a bank failure can be associated with excessive risk taking by the bank managers. A slightly modified version of Kibritciouglu (2002) has been considered in this study to recognize the dates during which the banking system in India has experienced a distress/crisis situation. The monthly banking sector fragility index of India was constructed by considering the risk taking behaviour of commercial banks in terms of its liquidity risk, credit risk and interest rate risk[9]. The variables considered in the construction of this index are aggregate time deposits, non-food credit, investment in other approved and non-Statutory Liquidity Ratio (non-SLR) securities, foreign currency assets and liabilities and the net reserves of Commercial Banks[10] in India. The banking fragility index is constructed by taking the weighted average of annual growth in real time deposits (Dep), real non-food credits (Cred), real investments in approved and non-SLR securities (Inv), real foreign currency assets (FCA) and liabilities (FCL) and the real net reserves (Resv) of commercial banks and weights are the inverse of their standard deviation. The constructed BSF index for India is defined as follows:

$$BSF\text{-}1 = \left[\frac{\left(Dep_t - \mu_{Dep}\right)}{\sigma_{Dep}} + \frac{\left(Cred_t - \mu_{Cred}\right)}{\sigma_{Cred}} + \frac{\left(Inv_t - \mu_{Inv}\right)}{\sigma_{Inv}} + \frac{\left(FCA_t - \mu_{FCA}\right)}{\sigma_{FCA}} + \frac{\left(FCL_t - \mu_{FCL}\right)}{\sigma_{FCL}} + \frac{\left(\mathrm{Re}sv_t - \mu_{\mathrm{Re}sv}\right)}{\sigma_{\mathrm{Re}sv}}\right] \Big/ 6$$

$$BSF-2 = \left[\frac{\left(Cred_t - \mu_{Cred}\right)}{\sigma_{Cred}} + \frac{\left(Inv_t - \mu_{Inv}\right)}{\sigma_{Inv}} + \frac{\left(FCA_t - \mu_{FCA}\right)}{\sigma_{FCA}} + \frac{\left(FCL_t - \mu_{FCL}\right)}{\sigma_{FCL}} + \frac{\left(\mathrm{Re}sv_t - \mu_{\mathrm{Re}sv}\right)}{\sigma_{\mathrm{Re}sv}}\right] \Big/ 5$$

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[8] The difference between the assets and liabilities of a bank equal its net worth, which in fact shows the bank's remaining values or equity capital after it has met all of its liabilities. The bank's net worth includes the capital contributed by the bank's shareholders and accumulated profits from doing business as intermediary in financial markets.

[9] Liquidity risk is the current and prospective risk to earnings or capital arising from a bank's inability to meet its obligations when they come due without incurring unacceptable losses. Credit risk is defined as the possibility losses associated with diminution in the credit quality of borrowers or counterparties due to inability of customers or counterparty to meet obligation. While, the interest rate risk is the risk in which the changes in the market interest rate might adversely affect the bank financial condition.

[10] According to Kibritciouglu (2002), bank failure is refer to a situation in which the excessively rising liquidity, credit, interest rate or exchange rate risk pushes the bank to suspend the internal convertibility of its liability.

where Dep_t, $Cred_t$, Inv_t, FCA_t, FCL_t and $\mathrm{Re}sv_t$ are the annual growth rate of real deposits, real credit, real investment, real foreign currency assets and liabilities and real reserves of Commercial Banks[11]. The BSF-2 index has also been constructed to implies and conclude that if the time path of both the indices moves in similar pattern, then the domestic bank run has not played any prominent role during the fragile period of the banking sector in India.

The dates of the crisis period are identified based on threshold level. When value of BSFs is greater than 0, it is a no-crisis zone. However, when the value is below 0, it represents fragile situation. Based on the threshold value φ, which is taken to be the standard deviation[12] of BSF index, medium and high fragility episodes are distinguished as follows.

Medium Fragility (MF): $-\varphi \leq BSF < 0$

High Fragility (HF): $BSF < -\varphi$

In this paper continuously alternating phases of medium and high fragility before the full recovery from the distress situation is considered as a systemic banking crisis. Isolated phases of MF not associated with HF do not constitute systemic banking crisis. A banking system is considered to have fully recovered from crisis when the value of BSF index is equal zero.

The constructed BSF indices for Indian are presented in Figure 1 with identified dates of high fragility shown by the shaded region. From the figure, it is observed that the movement patterns of both the indices (BSF-1 and BSF-2) are similar. Hence, we may say that the bank run does not contribute much to the experience of distress condition in the banking sector of India. This might have been due to coverage of deposit insurance[13].

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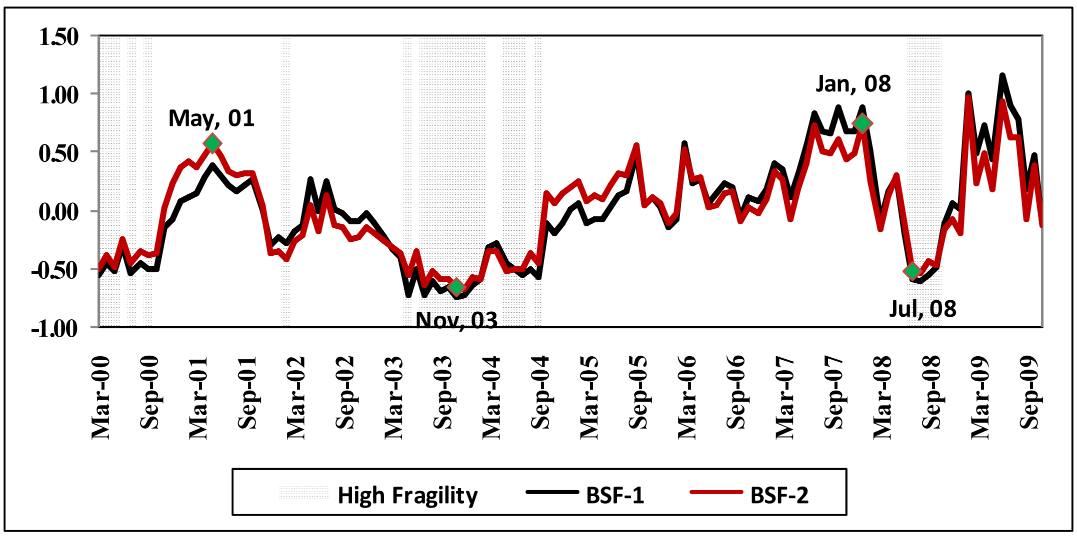
[11] The real time series of deposits, credit, investment, foreign currency assets and liabilities and reserves are obtained by deflating the corresponding time series with Wholesale Price Index (Base: 1993-94). The annual growth rate (same month-month a year ago) has been taken to remove any seasonality variation and also to indicate that the difficulties in the banking sector are signal by longer term variation in the indicators and not by short term fluctuations.

[12] In Kibritciouglu (2002), the threshold value is taken to be 0.5 for classifying medium and high fragility period.

[13] The deposit insurance provided by the Deposit Insurance and Credit Guarantee Corporation (DICGC) provides a safety net for the depositors. Deposit insurance in India is mandatory for all banks (commercial/co-operative/RRBs/LABs) and covers all deposits (upto a limit of Rupees one

The threshold values considered for BSF-1 and BSF-2 index in identifying the dates of distress/crisis in India are 0.43 and 0.39 respectively.

Figure 1: Banking Sector Fragility (BSF) index for India (Mar-00 to Nov-09.
(The high fragile period is indicated by the shaded region.)



Source: Author's computation

The constructed BSF index reveals that the banking sector in India experiences 19 phases of medium fragility and 8 phases of high fragility (including the recent global crisis period) during the study period. The dates of medium and high fragility situation experienced by the banking sector of India are presented in Table 1. Based on dates of fragile period, we may classify the period March 2000 – October 2000, December 2001-

lakh), except those of foreign governments, Central/State Governments, inter-bank deposits, deposits received abroad and those specifically exempted by DICGC with the prior approval of the Reserve Bank (RBI, 2010).

June 2002, August 2002 – September 2004 and June 2008 – November 2008 as systemic banking crisis.

Table 1: Medium and high Fragile period in Indian Banking Sector

BSF-1		BSF-2	
Medium	**High**	**Medium**	**High**
-------	Mar 00 - Oct 00	-------	Mar 00 - Jul 00
		Aug 00	Sep 00
		Oct 00	-------
Dec 01 - Apr 02	-------	Dec 01 - Jan 02	Feb 02
		Mar 02 - Apr 02	-------
Jun 02	-------	Jun 02	-------
Sep 02 - Apr 03	May 03 - Feb 04	Aug 02 - Apr 03	May 03
		Jun 03	Jul 03 - Feb 04
Mar 04 - Apr 04	May 04 - Sep 04	Mar 04 - Apr 04	May 04 - Jul 04
Oct 04 - Dec 04	-------	Aug 04	Sep 04
Mar 05 - May 05	-------	-------	-------
Jan 06 - Feb 06	-------	Jan 06 - Feb 06	-------
Oct 06	-------	Oct 06	-------
-------	-------	Dec 06	-------
-------	-------	Apr 07	-------
Mar 08	-------	Mar 08	-------
Jun 08	July 08 - Oct 08	Jun 08	Jul 08 - Oct 08
Nov 08	-------	Nov 08	-------
-------	-------	Jan 09	-------
-------	-------	Sep 09	-------
Nov 09	-------	Nov 09	-------

Source: Author's computation

5. Some Potential Macroeconomic Indicators for Predicting Banking Crisis in India

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 qualities were largely improved in due course of time. Based on the available literature and empirical evidence on financial crisis, some of the potential indicators for predicting financial crisis are described as follows.

Based on the EWS framework of Kaminsky (1999), the first procedure of selecting useful indicators applied in EWS is to identify economic symptoms which usually come to surface prior to financial crisis. Past experiences in some of the crisis-hit economies show that both banking and currency crises are linked to overborrowing cycles. In some cases, the substantial credit growth could be fueled by financial liberalisation and elimination of capital and financial account restrictions, which, however, are not quantifiable. The mirroring indicators include M3 multiplier.

Banking and currency crises can be preceded by bank runs. As depositors withdraws massively their deposits, the likelihood of bank default increases. The phenomenon has a destabilising effect, and the mirroring indicator is bank deposits, which correspondingly exhibit dramatic negative movements during bank panic. But as indicated earlier, bank run does not have much contribution to the banking distress/ crisis in India.

Current account problems are considered as one of the symptoms for financial crisis. Those problems could be reflected in the performances of external trade, terms of trade and real exchange rate. Real exchange rate overvaluation and a weak external sector are potential factors for currency crisis. A loss of competitiveness and weak external markets could lead to recession, business failure, and deterioration in loan quality.

Capital account problems become more severe in the context of enlarging foreign debt and increasing capital flight, which raise concern for debt unsustainability. Vulnerability of a country to external shocks is more likely to increase if foreign debt is dominantly concentrated in short maturities. The selected indicators of this area include foreign exchange reserves, ratio of M3 to foreign exchange reserves.

Reflecting the external positions of the banking sector, the ratio of foreign currency assets to foreign currency liabilities could be applied in a EWS to highlights the risk of currency mismatch in view of international exposure.

While considering the liquidity position of the banking sector, we may also consider the ratio of banks credit to the commercial sector to aggregate deposits of residents as it would depicts growth prospect of the corporate sector in the economy.

Severe slowdown in economic growth or recession as well as the burst of asset price bubbles could precede financial crises. Kaminsky (1999) argues that high real interest rates could be a sign of liquidity crunch, which leads to an economic slowdown and banking fragility. The mirroring indicators included output, real domestic interest rate, and stock prices.

Banking crises may be preceded by a wide range of economic problems. To design an effective EWS and identify future banking crisis, a broad variety of macroeconomic indicators representing different sectors of the economy may be chosen.

6. Description of Methodology

Based on the proxy series for crisis (BSF index) which identifies different phases of banking sector distress in India, we use ordered probit model which is a limited dependent variable model to predict these different phases of banking distress. In the limited dependent variable models, the dependent variable is categorized as 0, 1 and 2 corresponding to banking distress/crisis situation of 'no distress', 'medium fragility' and 'high fragility' respectively in Indian banking sector. The explanatory variables are not transformed into 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. The model is based on the latent regression utility function $y^* = x'\beta + \varepsilon$, where ε follows a normal distribution and utility function y^* is unobserved, but what is observed is their classified category y. The observed y is determined by using y^* which is provided as follows

$$y = \begin{cases} 0, & if \ \mathrm{y}^* \le \gamma_1 \\ 1, & if \ \gamma_1 < \mathrm{y}^* \le \gamma_2 \\ 2, & if \ \mathrm{y}^* > \gamma_2 \end{cases}$$

where, γ_1 and γ_2 are the classifying thresholds values.

The ordered probit equation takes the form $y = x'\beta + \varepsilon$, with probabilities of classifying different categories given as

$$\Pr(y = 0 \mid x, \beta) = F((\gamma_1 - x'\beta))$$
$$\Pr(y = 1 \mid x, \beta) = F((\gamma_2 - x'\beta)) - F(\gamma_1 - x'\beta)$$
$$\Pr(y = 2 \mid x, \beta) = 1 - F(\gamma_2 - x'\beta)$$

where, y is the crisis dummy series, x a set of explanatory variables, β is a vector of free parameters to be estimated and F is the normal cumulative distribution function which ensures that the predicted outcome of the model always lies between 0 and 1. The z-statistics reveal the significance of the estimated individual coefficients in the model by testing the null hypothesis $H_0 : \beta_i = 0$, 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.

The direction 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 i.e.normal density function, that depends on all the regressors. However, a fair amount of interpretation can be readily provided to assess the effect of explanatory variables on the probability of getting the specified state of crisis by considering the marginal effect which is defined as

$$\partial \Pr(y=0/x'\beta)/\partial x = -\beta f(\gamma_1 - x'\beta)$$
$$\partial \Pr(y=1/x'\beta)/\partial x = -\beta\left[f(\gamma_2 - x'\beta) - f(\gamma_1 - x'\beta)\right]$$
$$\partial \Pr(y=2/x'\beta)/\partial x = \beta f(\gamma_2 - x'\beta)$$

Thus the sign of β_j shows the direction of the change in the probability of falling in the lowest endpoint ranking i.e $\Pr(y=0)$, when x_j changes. $\Pr(y=0)$ changes in the opposite direction of the sign of β_j; while $\Pr(y=2)$ changes in the same direction as that of the sign of β_j. Hence a positive coefficient in the model may be interpreted that the corresponding variable has potential in raising the predictive probability of high fragility i.e. $\Pr(y=2)$.

There are several diagnostic tests for order probit models; one of the measures of goodness-of-fit for non-linear estimators is the Pseudo-R^2 statistic which is defined as,

$$\text{Pseudo-}R^2 = 1 - \frac{\log L}{\log L_0}$$

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 Pseudo R^2 always lies between 0 and 1.

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

$$LR = -2(\log L_0 - \log L)$$

This statistic used is 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.

7. Description of Data and Sources

Since Indian financial system is dominated by banking sector and commercial banks accounts for more than 90 percent of the banking system's assets, we have constructed BSF index to date the experienced of distress/crisis in banking sector using the monthly data related to commercial banks in India. The variables considered for constructing the BSF index are time deposits of resident, Non-Food credit, Investment of banks in approved and non-SLR securities, Foreign currency assets and liability (which include non-resident foreign currency repatriable fixed deposits and overseas foreign currency borrowings) and net bank reserves (which includes balances with RBI, Cash in hand, loans and advances from the bank) of commercial banks. These variables are deflated by WPI index (base year 1993-94). While the indicators used for predicting the banking sector distress/crisis in India covered real sector, financial and banking sector and external sector of India. The variables considered are yield on 91 days treasury bills, weighted average call money rate, stock price index, aggregate deposits of resident, banks credit to commercial sector, M3-money supply, reserve money, foreign exchange reserves, export, import, real effective exchange rate, inflation and output (measured by IIP-Base year 1993-94). These indicators used in this study were based on the availability of their data during the period March 1999 to November 2009 at monthly frequency. All these data are taken from the 'Handbook of Statistics on Indian Economy' and various issues of Reserve Bank of India, Monthly Bulletin (i.e. September 2009, October 2009, November 2009, December 2009, January 2010 and February 2010 issues of Monthly Bulletin).

8. Empirical Results

The indicators are transformed so that they are stationary and free from seasonal effects. Except for interest rates, deviation of REER from trend[14]; all other variables on a given month was defined as the percentage change in the level of the variable with

[14] The deviation of REER from its trend was estimated using Hodrick-Prescott filter.

respect to its value a year earlier. The probabilities estimated by ordered probit model can give a fair idea about the possible onset of different phases of distress situation (including both the phases of high and medium fragility condition) in the banking system. An increasing trend in the estimated probabilities of each categories/state of the distress condition, signals the possibility of distress/crisis in the banking sector.

The time horizon within which the indicator is expected to give signal anticipating a banking sector distress or crisis situation is called the 'signaling horizon' and is taken apriori as 6 months in this study considering the policy prospect of 6 months ahead forecast.

Based on available data at monthly frequency, an ordered probit model is being developed to predict the different phases of banking sector distress/crisis in India within the time horizon of 6 months. The optimum model is obtained after an exploration through the model goodness of fit criteria viz., Akaike information Criterion (AIC)[15] and Pseudo-R^2 statistic, where the optimum model is chosen with minimum AIC and maximum Pseudo-R^2 statistic. The optimum model with significant coefficients at 5 per cent level of significance is obtained at AIC and Pseudo-R^2 value of 0.64 and 0.87 respectively. The estimated ordered probit model of the leading indicators with their lags is presented in Table 2. All the indicators except the REER deviation are found to be significant at 5 per cent level of significance. From the model, it is seen that increased in the ratio of foreign currency asset to foreign currency liability (FCA-FCL ratio), import, M3-multiplier, call money rate, real interest rate (91 days treasury bill), rise in stock price index and inflation increases the probability of high fragility in the banking sector; while decreased in ratio of money supply (M3) to forex reserve, output, export, forex and ratio between credit to commercial sector and domestic deposits, also increases the probability of high fragility in the banking sector.

[15] The AIC is given by $AIC = -2l/T + 2k/T$, where l is the log-likelihood function with k parameters estimated using T observations.

Table 2 : Estimated Ordered probit Model for Predicting Banking Crisis in India (6 month signal window)[16]

Variable	Coefficient	Std. Error	Z-Statistic	Prob.
FOREX RESERVES	-2.22	0.98	-2.26	0.0237
FOREX RESERVES(-5)	3.47	1.55	2.24	0.0249
FCA/FCL RATIO(-6)	57.31	25.78	2.22	0.0262
EXPORT(-2)	-0.47	0.22	-2.08	0.0373
EXPORT(-4)	-0.27	0.11	-2.39	0.0170
IMPORT(-4)	0.15	0.07	2.30	0.0213
M3/FOREX RESERVE RATIO	-32.00	14.34	-2.23	0.0256
M3-MULTIPLIER	62.83	29.09	2.16	0.0307
M3-MULTIPLIER(-1)	15.36	7.26	2.12	0.0344
CREDIT/DEPOSIT RATIO[17]	-1404.54	617.70	-2.27	0.0230
CREDIT/DEPOSIT RATIO(-2)	711.55	312.14	2.28	0.0226
OUTPUT(-2)	-4.10	1.71	-2.40	0.0164
CALL MONEY RATE	10.23	4.58	2.23	0.0255
CALL MONEY RATE(-1)	2.58	1.31	1.97	0.0484
REAL YIELD 91TB(-1)	14.73	6.71	2.20	0.0280
STOCK PRICE INDEX	0.38	0.17	2.16	0.0306
STOCK PRICE INDEX (-1)	0.20	0.09	2.22	0.0263
INFLATION	11.91	5.35	2.23	0.0260
INFLATION(-5)	-5.51	2.38	-2.31	0.0207
Limit Points				
LIMIT-1(γ_1)	-139.73			
LIMIT-2(γ_2)	-104.73			
Pseudo R-squared	0.87			
Akaike info. criterion	0.64			
LR statistic	190.25			
Prob (LR statistic)	0.0000			

Source: Author's Computation

It is observed that model predicted about 104 data point of different categories of banking crisis out of the total 111 data point series. The model could correctly predicts about 97 percent of no distress situation, 90 percent of medium fragility and about 89 percent of

[16] The deviation of REER from its trend is found to be insignificant at 5 per cent level of significance and hence it is not included in the estimated model.
[17] The credit and deposits are respectively the credit to commercial sector by banks and aggregate deposits of resident in India.

high fragility condition of the Indian banking sector. The overall predictive power of the model in classifying the different state of the crisis viz., no distress, medium and high fragility in India is about 94 percent. The predictive performance of the model in classifying different phases of the crisis is presented in Table 3.

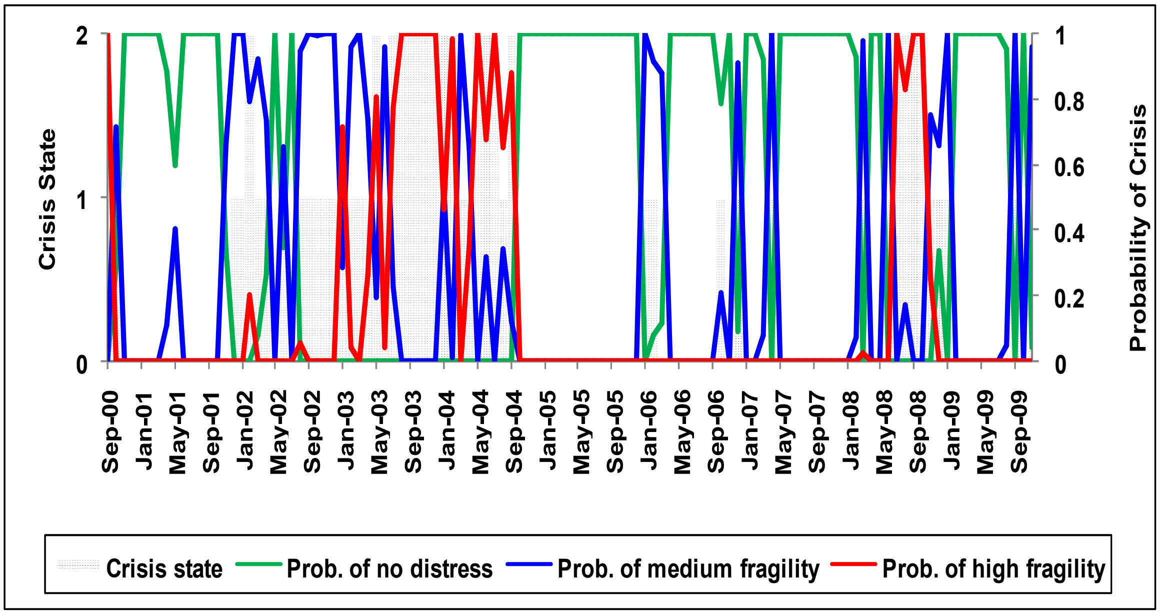
Table 3: Prediction Performance of Ordered Probit Model

Dep. Value	Obs.	Correct	Incorrect	% Correct	% Incorrect
0	61	59	2	96.72	3.28
1	31	28	3	90.32	9.68
2	19	17	2	89.47	10.53
Total	**111**	**104**	**7**	**93.69**	**6.31**

Source: Author's computation

One of the significant aspects of the proposed model is that it could also predict the recent global financial crisis prior to 6 months quite accurately. The probabilities of 6 months ahead in-sample prediction of different phases of banking sector crisis by the model is presented in Figure 2. From the figures, it can be observed that the model has been able to forecast the probability of various phases of banking crisis quite accurately. It is also seen that during the period of medium and high fragility condition in the banking sector, the probability of no distress during the period forecasted by the model is very low. Similarly, during non fragile period, the forecasted probabilities of fragile state are found to be reasonably quite low.

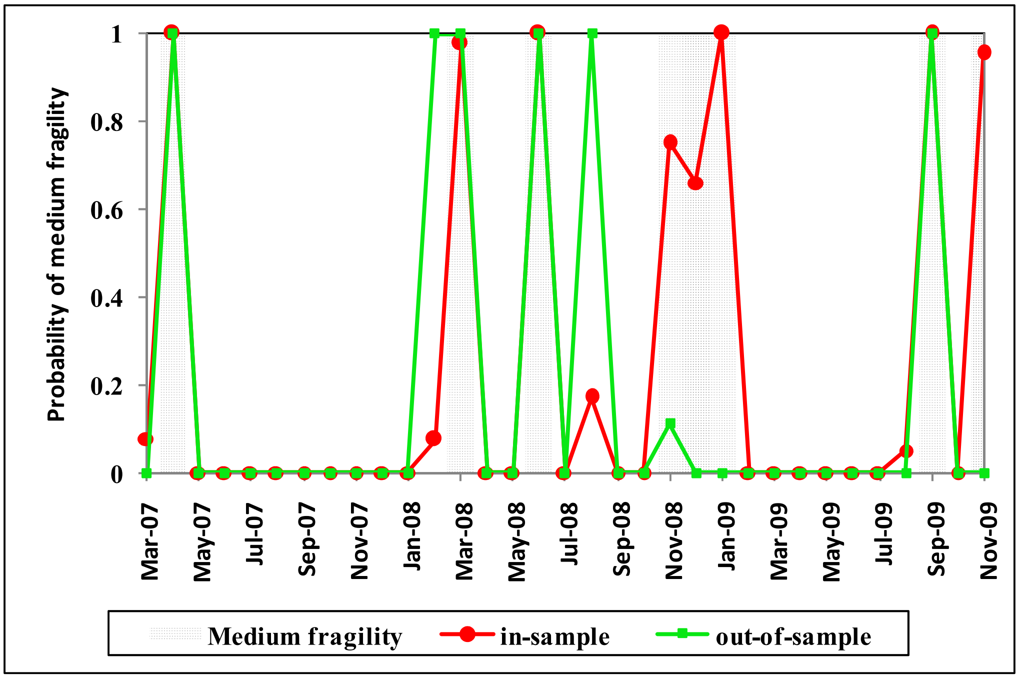
Figure 2: The in-sample forecast of different state of banking crisis in India



Source: Author's computation

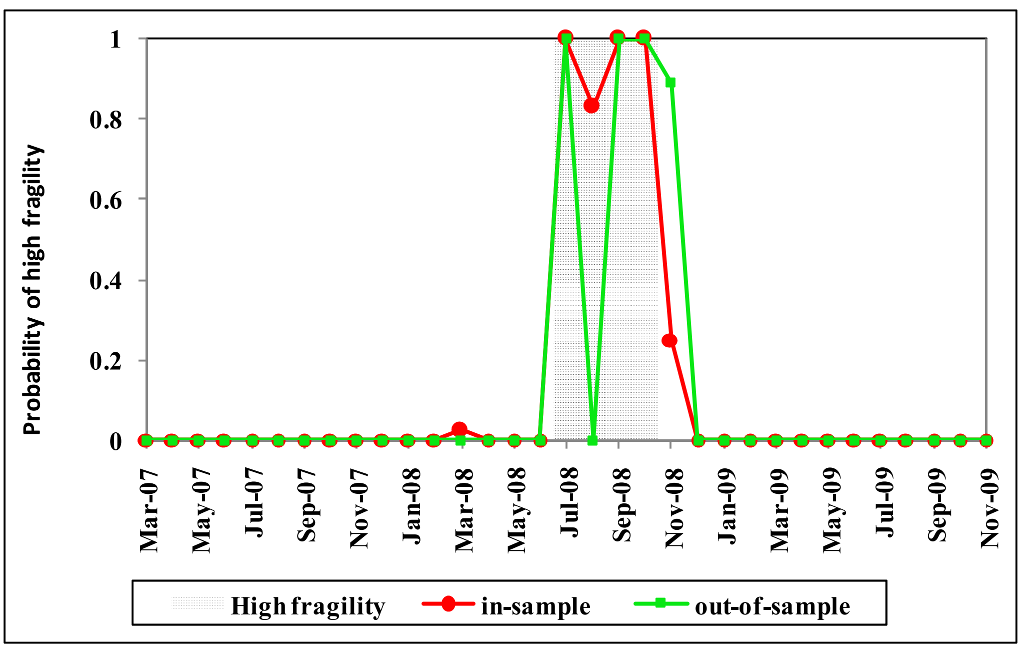
However, a good forecasting performance of a model within the sample does not guarantee that the model will do well in forecasting out-of-sample too. So, to evaluate the forecasting performance of the model, an out-of-sample forecast test of the model has been performed. The model is estimated utilizing the data from the beginning of the sample (March 2000) to March 2007 and then this model is used to forecast the post model building period. All the coefficients of the variables estimated in the model for the period March 2000 to March 2007 were also found to be significant at 5 per cent level of significance. Thus, the out-of-sample performance of the constructed model is judged through the predicted probabilities of different phases of crisis generated in the post model building period. The in-sample and out-of-sample forecast probabilities for medium and high fragile period of the banking sector are presented in Figure 3 and Figure 4 respectively. From the figure, it could be seen that most of the fragile period (both medium and high) has been predicted with high probability by the model except for the period Nov-08 to Jan-09 and Nov-09 in the case of medium fragile and Aug-08 for high fragility. However, it is seen in Figure 4 that Nov-08 which the model fail to classify it as medium fragile period has been classified by the model as a period of high fragility. Thus the model could provide useful information about the possible onset of distress in the banking sector.

Figure 3: In-sample and out-of-sample probabilities of medium fragility



Source: Author's computation

Figure 4: In-sample and out-of-sample probabilities of high fragility



Source: Author's computation

9. Conclusions

In the face of the recent global financial crisis, monitoring and predicting of such event using the early warning system has become essential as it causes huge loss both at national and international level. The early warning system (EWS) aim at anticipating whether and when individual country may be affected by a financial crisis by developing a framework that allows predicting financial crisis in relatively open economy.

In order to identify and date the different state of distress situation in the banking sector of India, a banking sector fragility index (BSF) has been developed. Based on BSF index, we have identified and dated 19 medium and 8 high fragility situations in the Indian banking sector. These phases of distress in the banking sector are identified based on some chosen threshold level and are categorized into three state as no distress, medium and high fragility. The ordered probit model is being developed and is used to predict these different phases of banking crisis in India. The signaling window for predicting the crisis is taken to be 6 months in this study. This model would help the policy maker to take corrective action to avert the onset of a potential distress/crisis by generating signals about an impending distress/crisis situation. The model indicate that increased in the ratio of foreign currency asset-foreign currency liability (FCA-FCL ratio), import, M3-multiplier, call money rate, real interest rate (91 days treasury bill), rise in stock price index , high inflation raises the probability of high fragility in the banking sector; while decreased in M3-forex reserve ratio, output, export, forex and the ratio between credit to commercial sector and domestic deposits also increases the probability of occurring high fragility in the banking sector.

The model could predict about 104 data point of different categories of banking crisis out of the total 111 data point series. The model could correctly predicts about 97 percent of no distress situation, 90 percent of medium fragility and about 89 percent of high fragility condition in the Indian banking sector. Thus the model could classify about 94 per cent of different phases of the fragile periods. The model developed in this study also captured the effect recent global financial crisis felt in India. The proposed model could be used to monitor the development in the banking sector of India as indicators used is this model are available with lags of about two months. While calibrating the model, it is also observed that the ordered probit model could generate reliable probabilities of out-of-sample for different phases of fragile condition in India.

In this paper banking crisis prediction is based on BSF index. 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 are dynamic and keep changing. The EWS devised in this paper to forecast different phases banking distress/crises in India is just a preliminary step in the direction of exploring alternative methods on predicting banking crisis.

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