An ordered probit model of an early warning system for predicting financial crisis in India

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1. Introduction

During the last two decades, the world has seen a large number of financial crises in the emerging market economies of Latin America and Asia, with consequences of large costs for both the national and the international financial system. However, the recent financial tsunami that started in the US during August 2007 was triggered by a liquidity shortfall in the overseas banking system, and it affected directly or indirectly almost all the countries of the world after the collapse of Lehman Brothers in September 2008. The consequence cost of this tsunami, according to the International Monetary Fund (IMF) in March 2009, was that world growth would 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 that global GDP would 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. Economic activity in India also slowed down during the period owing to the spillover effects of the global crisis. 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 the private sector of Indian banks were financially sound and were not directly exposed to subprime 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-called "substitution effect". As credit lines and credit channels overseas went dry, some of the credit demand earlier met by overseas financing shifted to the domestic credit sector, putting pressure on domestic resources. The reversal of capital flows, which took place as a part of the global deleveraging process, has put pressure on the forex markets. Together, the global credit crunch and deleveraging were reflected at the domestic level 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 costs and effects of crisis, the prediction of distress/crisis situations has come to the fore for maintaining financial stability in a country as well as in the international financial system.

There are theoretical models of financial crises (currency or banking crises) to examine crisis and bank failure. The macro origin of the financial crisis model mainly relies on three-generation models, viz, first-generation, second-generation, and third-generation models. According to the first-generation models, weak economic fundamentals are more vulnerable to speculative attacks, while the second-generation model 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

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other hand, the third-generation models combine weaknesses in the economic fundamentals of early-generation models with weaknesses in the banking sectors in the analysis of financial crises. For this reason, the third-generation models are also known as twin crisis, 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 the 1990s, central banks across the globe pursue financial stability as one of their goals. India too pursues it as one of its monetary policy objectives. In India, the financial system is dominated by the banking sector, and commercial banks of the Indian banking system account for more than 90 per cent of the banking system's assets (RBI, 2007). A significant aspect of the 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 a state of international financial fragility. It then becomes prone to crisis that is domestic in origin, but that has an impact on its external situation, or to crisis that is external in origin, but that has an impact on the domestic situation, and combining the two identifies the crisis (Anastasia, 2007).

In recent years, India's integration with the global economy is being witnessed distinctly by the growth of its merchandise exports 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. Meanwhile, India's financial integration with the world, measured in terms of the 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 a degree of gradual openness and integration, India needs to keep watch to capture the developments in international markets and apprehend the implications for the domestic economic and financial systems. In this emerging scenario of India's integration with the global economy, and in the light of the 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 preemptive policy measures and avoid a banking disaster.

An early warning system (EWS) aims at anticipating whether and when an individual country may be affected by a financial crisis by developing a framework that allows a financial crisis to be predicted in a relatively open economy. There are basically three approaches to the development of predicting financial crisis, particularly a banking crisis, viz, the bottom-up approach, the aggregate approach and the macroeconomic approach.[2] In the bottom-up approach, the probability of insolvency is estimated for each individual bank and concern for systemic instability is warranted when the probability of insolvency becomes significant for a large proportion of the country's banking assets (i.e., for the sum of all banks in the country), while in the aggregate approach the model is applied to the aggregate bank data to determine the probability of systemic insolvency. In the third approach, instead of looking at bank balance sheet data for internal sources of unsoundness, it establishes 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

[2] See Lindgren, Garcia and Saal (1996).

model EWS based on the ordered probit approach for monitoring and predicting banking distress or crisis in India[3] using macroeconomic indicators.

The rest of the paper is organized as follows. Section 2 gives a brief description about financial crises and their associated features. Section 3 provides a review of the literature on the methodological development of the early warning system for predicting crisis. Section 4 describes the method of constructing a monthly banking sector fragility index for India. Section 5 deals with the identification of some potential macroeconomic indicators for predicting crisis. In section 6, we give a brief description of the methodology developed for predicting banking crisis in India. Section 7 describes the data and their sources used in developing the EWS model. Section 8 presents the empirical results of the model, and the paper concludes with a 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.[4] Financial crises directly result in a loss of paper wealth;[5] they do not directly result in changes in the real economy. However, they may indirectly do so, notably if a recession or depression follows. A financial crisis is a disturbance in 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 highlighted below:[6]

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 built 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, accompanied by some bank collapses and possibly some runs.

3 India has a well-diversified financial system which is still dominated by bank intermediation. Commercial banks together with cooperative banks account for nearly 70 per cent of the total assets of Indian financial institutions (RBI, 2009b).

4 See Laeven, Luc and Fabian Valencia (2008).

5 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.

6 See Sundararajan and Balino (1998).

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

3. Literature Review on Early Warning Systems for Financial Crisis

The first method used in the development of EWS is the signal approach to predict financial crisis, in particular currency crisis; this was the effort of Kaminsky, Lizondo and Reinhart (1998), who monitored the evolution of several indicators. If any of the macrofinancial 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 (the model fails to predict crises when they actually take place) and type II errors (the model predicts crises which do not occur). Kaminsky (1999) and Goldstein et al (2000) base their prediction of a crisis occurring in a specific country by monitoring the evolution not only of a single macro-indicator, but also of a composite leading indicator which aggregates different macrovariables, with weights given by the inverse of the signal-to-noise 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 disaggregated data on external debt produced by the Bank for International Settlements (BIS) to construct measures of competition for funds 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 nonparametric 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.[7]

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 were fitted to a large dataset. Mody and Taylor (2003) use the Kalman filter estimation of state space models in order to extract a measure of regional vulnerability in a number of emerging market countries, and to produce in-sample prediction of the currency market turbulence. Another diffusion index is the one constructed by Chauvet and Dong (2004), who develop a factor model with Markov regime-switching dynamics in order to produce in-sample and out-of-sample prediction of nominal exchange rates in a number of East Asian countries.

[7] 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 the degree of risk aversion of policymakers.

4. Monthly Banking Sector Fragility Index for India

For predicting financial crisis, the period of the crisis needs to be identified and dated. There are two commonly used approaches for identifying the period of banking crisis, viz, the 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 such as bank runs, closures, mergers, recapitalization and huge nonperforming assets (NPAs) (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 become severe enough to trigger certain events can lead to delayed recognition of a crisis (Hagen and Ho, 2003a). Moreover, there is also a 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, labels an entire year as one of 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 crises, which is built on the lines of the Exchange Market Pressure (EMP) index for dating currency crises, has several advantages over the event-based approach. The index method requires no prior 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 crises (Hawkins and Klau, 2000; Kibritciouglu, 2002; Hagen and Ho, 2003a, 2003b).

Thus, in order to identify and date the experiences of different states of distress or crisis in the Indian banking sector,[8] we adopt the index method developed in Kibritciouglu (2002). According to Kibritciouglu (2002), a bank is potentially exposed to various types of economic risks, such as liquidity risk, credit risk and exchange rate risk, due to changes in the value of its assets and/or liabilities in the financial markets. Therefore, a bank's net worth,[9] 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 in order 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.[10] The variables considered in the construction of this index are aggregate time deposits, nonfood 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[11] in India. The banking fragility index is constructed by taking the weighted average of annual growth in real time deposits (Dep), real nonfood credits (Cred), real investments in approved and non-SLR securities (Inv), real foreign currency

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8 In this paper, "the banking sector" means the banking sector of a country, excluding the central bank.

9 The difference between the assets and liabilities of a bank equal its net worth, which in fact shows the bank's remaining value 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 an intermediary in financial markets.

10 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 of losses associated with diminution in the credit quality of borrowers or counterparties due to the inability of customers or counterparties to meet their obligations, while interest rate risk is the risk in which changes in the market interest rate might adversely affect the bank's financial condition.

11 According to Kibritciouglu (2002), "bank failure" refers 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.

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:

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

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

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.[12] The BSF-2 index has also been constructed to imply and conclude that if the time path of both the indices moves in a 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 a threshold level. When the value of the BSF indices is greater than 0, it is a no-crisis zone. However, when the value is below 0, it represents a fragile situation. Based on the threshold value φ, which is taken to be the standard deviation[13] of the 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 full recovery from the distress situation is considered as a systemic banking crisis. Isolated phases of MF not associated with HF do not constitute a systemic banking crisis. A banking system is considered to have fully recovered from crisis when the value of the BSF index is equal to zero.

The constructed BSF indices for India 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 conditions in the banking sector of India. This might have been due to coverage of deposit insurance.[14] The threshold values considered for the BSF-1 and BSF-2 indices in identifying the dates of distress/crisis in India are 0.43 and 0.39, respectively.

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[12] The real time series of deposits, credit, investment, foreign currency assets and liabilities and reserves are obtained by deflating the corresponding time series with the 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 signaled by longer-term variations in the indicators and not by short-term fluctuations.

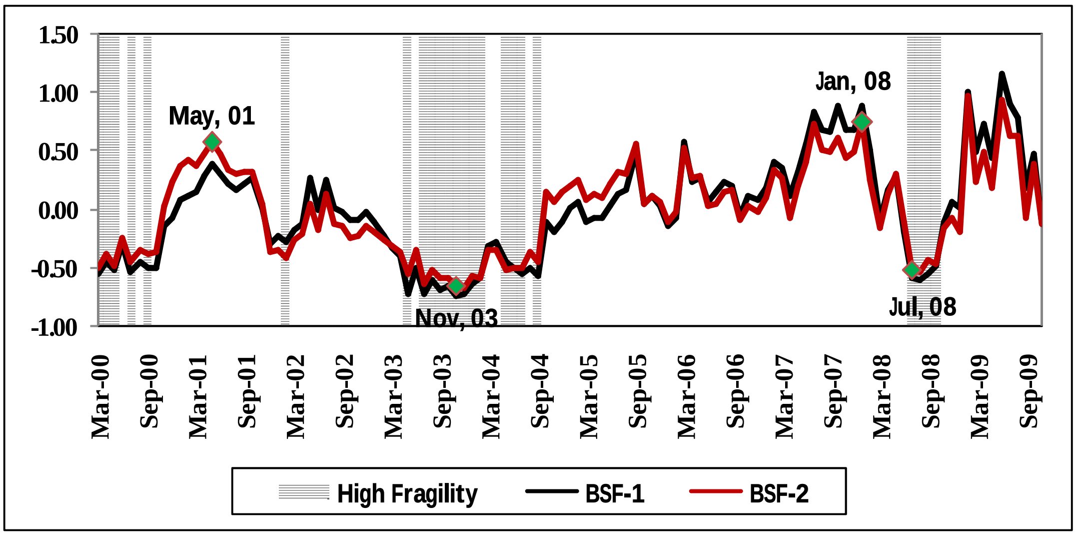
[13] In Kibritciouglu (2002), the threshold value is taken to be 0.5 for classifying medium- and high-fragility periods.

[14] 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/cooperative/RRBs/LABs) and covers all deposits (up to a limit of rupees one lakh), except those of foreign governments, central/state governments, interbank deposits, deposits received abroad and those specifically exempted by DICGC with the prior approval of the Reserve Bank (RBI, 2010).

Figure 1

Banking Sector Fragility (BSF) Index for India (Mar-00 to Nov-09)

(The high-fragility period is indicated by the shaded region.)



Source: Author's computation.

Table 1: Medium- and High-Fragility Periods in the 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.

The constructed BSF index reveals that the banking sector in India experienced 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 situations experienced by the banking sector of India are presented in Table 1. Based on the dates of the fragile period, we may classify the periods March-October 2000, December 2001-June 2002, August 2002-September 2004 and June-November 2008 as systemic banking crises.

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

In the early 1990s, the 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. Based on the available literature and empirical evidence on the 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 for selecting useful indicators applied in the EWS is to identify economic symptoms which usually come to the surface prior to financial crises. 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 liberalization and elimination of capital and financial account restrictions, which, however, are not quantifiable. The mirroring indicators include the M3 multiplier.

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

Current account problems are considered as one of the symptoms of financial crisis. Those problems could be reflected in the performances of external trade, the terms of trade and the 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 about debt unsustainability. The vulnerability of a country to external shocks is more likely to increase if foreign debt is predominantly concentrated in short maturities. The selected indicators in this area include foreign exchange reserves and the 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 an EWS to highlight 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 bank credit to the commercial sector to aggregate deposits of residents, as it would depict the growth prospects of the corporate sector in the economy.

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

Banking crises may be preceded by a wide range of economic problems. To design an effective EWS and identify future banking crises, 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 an ordered probit model, which is a limited dependent variable model, to predict these different phases of banking distress. In limited dependent variable models, the dependent variable is categorized as 0, 1 and 2, corresponding to banking distress/crisis situations of no distress, medium fragility and high fragility, respectively, in the Indian banking sector. The explanatory variables are not transformed into dummy variables but are included in a linear fashion. The probability that crisis will occur 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 threshold 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 is a set of explanatory variables, $\beta_.$ 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 $\beta_{.j}$ coefficient. The coefficients estimated by these models cannot be interpreted as the marginal effect of the independent variable on the dependent variable, as $\beta_{.j}$ is weighted by the factor f, i.e., the normal density function, which 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 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 the sign of β_j. Hence, a positive coefficient in the model may be interpreted as meaning that the corresponding variable has the potential to raise the predictive probability of high fragility, i.e., $\Pr(y=2)$.

There are several diagnostic tests for ordered probit models; one of the measures of goodness of fit for nonlinear 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 the LL function under the restricted case that all the slope coefficients except the intercept are restricted to 0. The value of pseudo-R^2 always lies between 0 and 1.

The likelihood ratio (LR) statistic is used to test the joint null hypothesis that all the coefficients except the intercept are 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 the null hypothesis, the LR statistic is asymptotically distributed as a χ^2 variable with a degree of freedom equal to the number of restrictions under test.

7. Description of Data and Sources

Since the Indian financial system is dominated by the banking sector and commercial banks account for more than 90 per cent of the banking system’s assets, we have constructed the BSF index to date the experience of distress/crisis in the banking sector using the monthly data related to commercial banks in India. The variables considered for constructing the BSF index are time deposits of residents, nonfood credit, investments of banks in approved and non-SLR securities, foreign currency assets and liabilities (which include nonresident foreign currency repatriable fixed deposits and overseas foreign currency borrowings), and net bank reserves (which include balances with the RBI, cash in hand, and loans and advances from the bank) of commercial banks. These variables are deflated by the WPI index (base year 1993-94). The indicators used for predicting the banking sector distress/crisis in India covered the real sector, the financial and banking sector, and the external sector of India. The variables considered are the yield on 91-day treasury bills, the weighted average call money rate, the stock price index, aggregate deposits of residents, bank credit to the commercial sector, the M3 money supply, reserve money, foreign exchange reserves, exports, imports, the real effective exchange rate, inflation and output (measured by the Index of Industrial Production, base year 1993-94). The indicators used in this study were based on the availability of their data during the period from March 1999 to November 2009 at a monthly frequency. All these data are taken from the "Handbook of Statistics on the Indian Economy" and various issues of Reserve Bank of India, Monthly Bulletin (i.e., the September 2009, October 2009, November 2009, December 2009, January 2010 and February 2010 issues).

8. Empirical Results

The indicators are transformed so that they are stationary and free from seasonal effects. Except for interest rates and the deviation of the real effective exchange rate (REER) from the trend,[15] all other variables in a given month were defined as the percentage change in the level of the variable with respect to its value a year earlier. The probabilities estimated by the ordered probit model can give a fair idea about the possible onset of different phases of a distress situation (including the phases of both high- and medium-fragility conditions) in the banking system. An increasing trend in the estimated probabilities of each category/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 a signal anticipating a banking sector distress or crisis situation is called the "signaling horizon" and is taken a priori as 6 months in this study, considering the policy prospect of the 6 months ahead forecast.

Based on the available data at a monthly frequency, an ordered probit model is being developed to predict the different phases of banking sector distress/crisis in India within a time horizon of 6 months. The optimum model is obtained after an exploration through the model goodness-of-fit criteria, viz, the Akaike information Criterion (AIC)[16] and the pseudo-R^2 statistic, where the optimum model is chosen with the minimum AIC and maximum pseudo-R^2 statistic. The optimum model with significant coefficients at a 5 per cent level of significance is obtained at AIC and pseudo-R^2 values 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 a 5 per cent level of significance. From the model, it is seen that an increase in the ratio of foreign currency assets to foreign currency liabilities (FCA-FCL ratio), imports, the M3 multiplier, the call money rate, the real interest rate (91-day treasury bills), the stock price index and inflation increase the probability of high fragility in the banking sector, while a decrease in the ratio of the money supply (M3) to forex reserves, output, exports, forex and the ratio between credit to the commercial sector and domestic deposits also increase the probability of high fragility in the banking sector.

It is observed that the model predicted about 104 data points of different categories of banking crisis out of the total 111 data point series. The model could correctly predict about 97 per cent of no-distress situations, 90 per cent of medium-fragility situations, and about 89 per cent of the high-fragility conditions of the Indian banking sector. The overall predictive power of the model in classifying the different states of the crisis, viz, no distress, medium fragility and high fragility in India, is about 94 per cent. The predictive performance of the model in classifying different phases of the crisis is presented in Table 3.

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15 The deviation of the REER from its trend was estimated using the Hodrick-Prescott filter.

16 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)[17]

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[18]	-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.

Table 3: Prediction Performance of the 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.

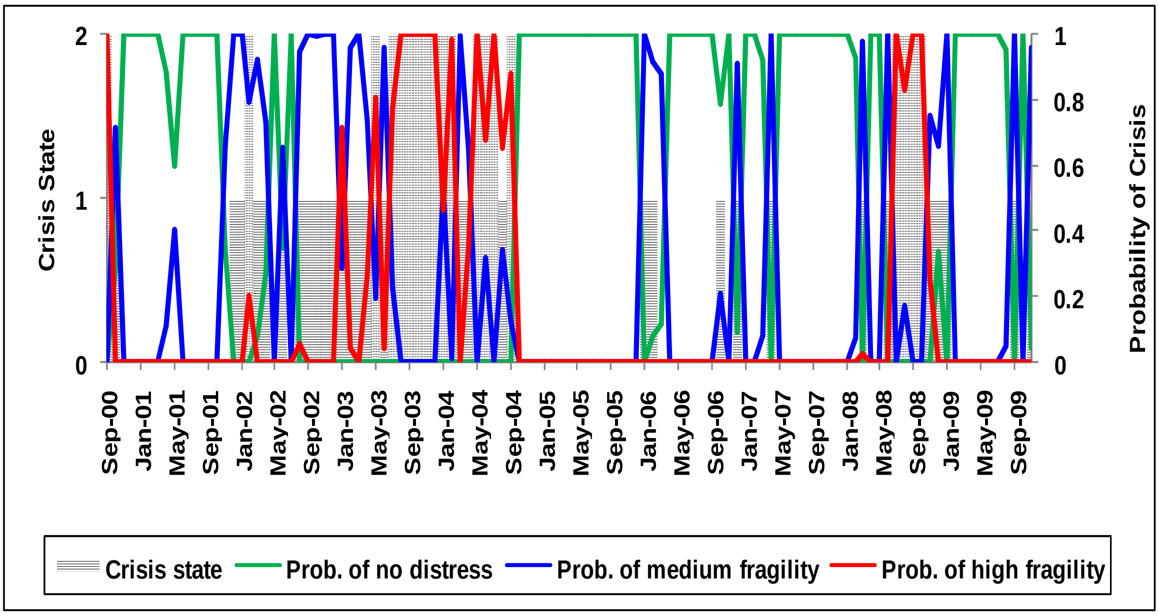
[17] The deviation of the REER from its trend is found to be insignificant at a 5 per cent level of significance and hence it is not included in the estimated model.

[18] "Credit" and "deposits" are, respectively, credit to the commercial sector by banks and aggregate deposits of residents in India.

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 the 6 months ahead in-sample prediction of different phases of the 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 the banking crisis quite accurately. It is also seen that during the period of medium and high fragility in the banking sector, the probability of no distress during the period forecasted by the model is very low. Similarly, during the nonfragile period, the forecasted probabilities of a fragile state are found to be reasonably quite low.

Figure 2

The in-sample forecast of different states of banking crisis in India

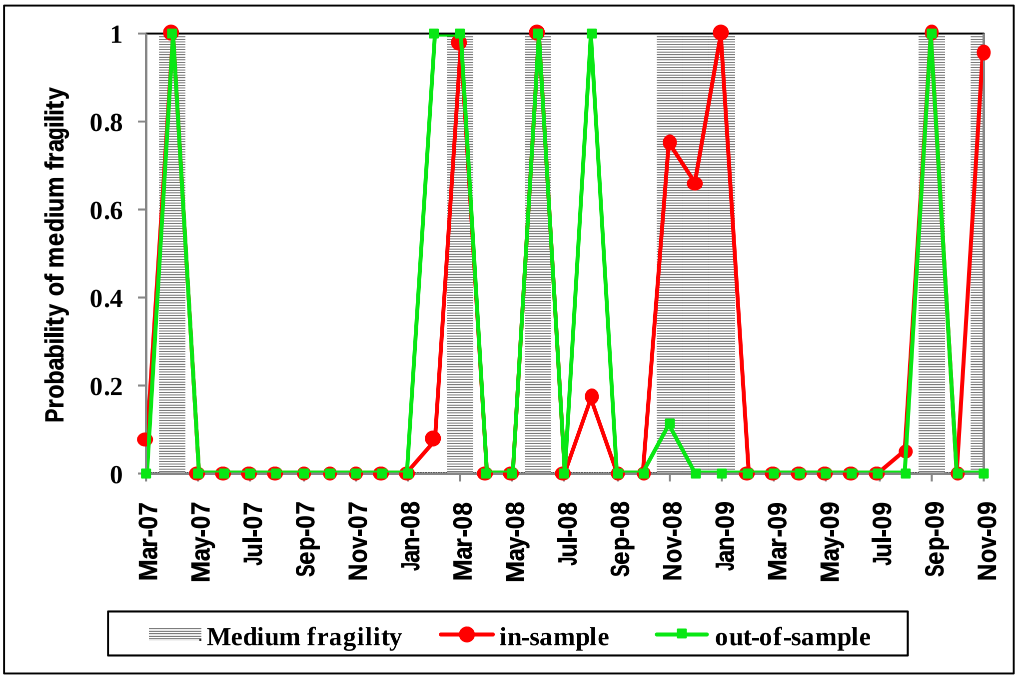


Source: Author's computation.

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 was performed. The model was estimated utilizing the data from the beginning of the sample (March 2000) to March 2007, and then this model was used to forecast the post-model-building period. All the coefficients of the variables estimated in the model for the period from March 2000 to March 2007 were also found to be significant at a 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 periods of medium and high fragility in the banking sector are presented in Figures 3 and 4, respectively. From the figure, it could be seen that most of the fragile period (both medium and high) was predicted with high probability by the model, except for the period from November 2008 to January 2009 and November 2009, in the case of medium fragility, and August 2008 for high fragility. However, it is seen in Figure 4 that November 2008, which the model fails to classify as a medium-fragility 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

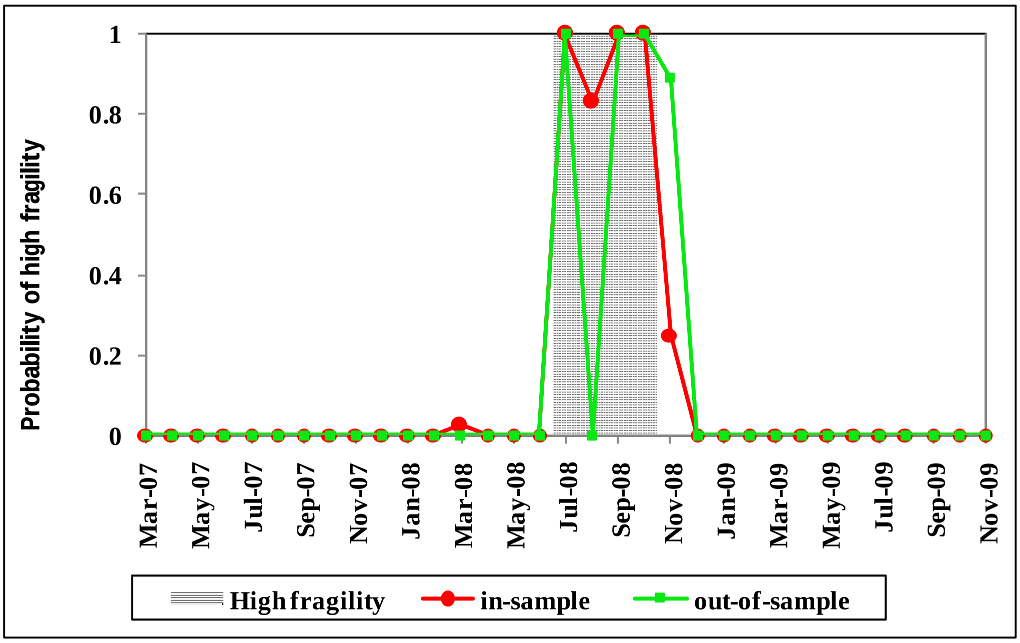
In-sample and out-of-sample probabilities of medium fragility



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 such an event using the early warning system have become essential, as it causes huge losses at both the national and international levels. The early warning system (EWS) aims at anticipating whether and when an individual country may be affected by a financial crisis by developing a framework that allows a financial crisis to be predicted in a relatively open economy.

In order to identify and date the different states of distress situations in the banking sector of India, a banking sector fragility (BSF) index has been developed. Based on the 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 states as no distress, medium fragility and high fragility. The ordered probit model is being developed and 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 policymaker to take corrective action to avert the onset of a potential distress/crisis situation by generating signals about an impending distress/crisis situation. The model indicates that increases in the ratio of foreign currency assets to foreign currency liabilities (FCA-FCL ratio), imports, the M3 multiplier, the call money rate and the real interest rate (91-day treasury bills), a rise in the stock price index and high inflation raise the probability of high fragility in the banking sector, while decreases in the M3 forex reserve ratio, output, exports, forex and the ratio between credit to the commercial sector and domestic deposits also increase the probability of high fragility occurring in the banking sector.

The model could predict about 104 data points of different categories of banking crisis out of the total 111 data point series. The model could correctly predict about 97 per cent of no-distress situations, 90 per cent of medium-fragility and about 89 per cent of high-fragility conditions 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 felt effect of the recent global financial crisis in India. The proposed model could be used to monitor developments in the banking sector of India, as indicators used in 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 out-of-sample probabilities for different phases of fragile conditions in India.

In this paper, banking crisis prediction is based on the BSF index. However, newer crises 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 of banking distress/crisis in India is just a preliminary step in the direction of exploring alternative methods of predicting banking crises.

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