CHAPTER-2

2. LITERATURE REVIEW

2.1. Introduction

Financial crises have been a recurrent phenomenon, be it a currency crisis, banking crisis or a debt crisis. As discussed in Chapter-1, financial crises carry huge costs as they can cause severe economic damage to not only to the country from where it originates but also across the borders. Some long-lasting impacts of financial crisis include chronic poverty, output decline, and rising government debt.

Economists have been trying to develop systems that can predict a financial crisis and issue early warnings to prevent such happening. Almost every country should have a EWSs, especially the developing economies owing to their lack of competencies and institutional settings in order to facilitate the optimal utilization of resources. A well functioned EWS helps an emerging economy in integrating with the global economy avoiding and/or minimizing the costs of a financial crisis. Many central banks and international organizations have developed EWS models that aimed at anticipating the timing of a financial crisis and ensuring the stability of the financial system (Bussiere and Fratzscher, 2006). Some examples include the macro-prudential indicators (MPIs) and financial soundness indicators (FSIs) which have been adopted by IMF as early warning indicators. However, most of these indicators pertain to and designed primarily for more mature financial sectors of developed economies (Abdelsalam and Abdel-Latif, 2020). For example, FSIs which are contemporaneous indicators, lose their effectiveness if there is a delay in the data collection, which is a serious concern in developing economies. Therefore, there is a need to design and identify the most effective and efficient EWS better suited to the developing economies.

In the above backdrop, this chapter undertakes a comprehensive literature review on theories explaining different types of financial crises and the methodologies adopted in constructing EWSs. It attempts to touch upon critical aspects linked to nature of financial crises without narrowing down only to the construction of EWSs. The chapter provides a review of both currency and banking crises, also incorporating review on stock market crisis. The review attempts to discuss both development and advancement of different theoretical models as well as their importance in the present context, thus connecting the dots from past to present. It touches upon on all the critical areas, both theoretical and empirical, related to the underlying theoretical models, econometric methods employed and the role of behavioral variables that may contribute in effective identification of early warning signals to predict chances of occurrence of crisis.

The review framework consists of well-defined sections discussing literature on each of the area with a view to identify gaps for formulating research questions and objective.

2.2. What is a Financial Crisis?

Financial crises come in many forms and have many common elements. A financial crisis ensues from the extreme exchange between the financial sector and the real economy. During a crisis, there are huge mismatch problems in balance sheets, extensive changes in assets prices and credit volume, a disrupting external financing supply and a necessity for large scale government support (Claessens and Kose, 2013). The financial crises can be categorized as currency, banking, or a debt crisis.

2.2.1. Currency crisis

Over the past four decades, three generations of models have been developed to explain the incidences of currency crises that have taken place.

Krugman (1979) and Flood and Garber (1984) are the pioneers who developed the first generation models which focused on the conflicts among the domestic macroeconomic policies such as persistent government budget deficit and exchange rate commitments. According to Glick and Hutchison (2013), the deficit implied that government should either borrow forever or exhaust its assets, such as foreign reserves. However, government cannot borrow indefinitely or deplete its assets completely. Therefore, it must create money to finance its debt. But excess money creation results in inflation which is inconsistent with the fixed exchange rate regime and this eventually leads to the collapse of the regime.

However, the Exchange Rate Mechanism crisis in 1992-93 and the Mexican Peso crisis in 1994 rendered the first generation models insufficient in explaining the causes of these crises. Hence, new models called second generation models were created, in particular by Obstfeld (1994, 1997). These models emphasize the importance of multiple equilibria and show that currency crises and multiple equilibria can occur if there are worries about government's willingness to maintain its exchange rate peg (Obstfeld and Rogoff, 1986). In other words, a crisis can be triggered even in the presence of sound macroeconomic fundamentals. Obstfeld and Rogoff (1986) introduced the impact of rational expectations implying the possibility of multiple equilibria with favorable or adverse economic fundamentals depending on the investors' expectations. This meant that despite having consistent policy with the exchange rate regime, a speculative attack can occur and succeed. The creation of multiple equilibria is the result of interaction between government and the investors. Policymakers in first generation models had a fixed simplified and mechanical course of action against a speculative attack. However, in the second generation models, they had to adapt their policies in response to the anticipations of the investors, therefore either maintaining or abandoning the peg. Thus, these models rendered the exact timing of the crises unpredictable (Stanciu, 2012).

The third generation crisis models originated after the outbreak of the Asian Financial crisis in 1997. This crisis was the result of weaknesses prevailing in banking sector of a financially liberalized economy. Thus, the third generation models highlighted the role of banks and self-fulfilling nature of the crisis. In case of the Asian crisis, a number of macroeconomic fundamentals were already weak, yet manageable, however, the vulnerabilities stemming from banks and financial system led to a currency crisis in Southeast Asia.

2.2.2. Banking crisis

The first generation models of banking crises are similar to that of first generation models of currency crises as they are also based on weak macroeconomic conditions. These models used the experience of the Great Depression as a starting point as in Mishkin (1978). They focused on poor macroeconomic conditions which led to loss of consumer confidence resulting in defaults and business failures. As the bank customers speculated whether the banks will have or have not enough cash available upon their withdrawals owing to poor macroeconomic environment, they ran to banks to act first. Consequently, this led to a herd response from customers which resulted in failure of banks in meeting their withdrawal needs.

The second generation models of self-fulfilling attacks on bank deposits have been inspired by Diamond and Dybvig (1983) and Flood and Garber (1984). Attacks in these models can happen even if the macroeconomic conditions are good. These attacks got triggered when the speculators anticipated that the current policy would be traded off to secure another objective (Breuer, 2004).

The third generation models are in contrast to the first and second generation models. Gavin and Hausmann (1996), and Kiyotaki and Moore (1997) are the seminal studies in this context. These models focused on the asset side of a banks' balance sheet whereas first and second generation models were based on events on the liabilities (deposits) side (Breuer, 2004). They are referred to as the 'credit cycle' models characterizing the boom-bust nature of lending and borrowing. As the economy starts booming, the stock prices and real estate prices start climbing rapidly hence luring banks to fund larger loans owing to the increased value of collateral backing. Secondly, the rise in equities value of banks enables them to lend more. However, as the economy enters the 'bust' stage, the prices fall down rapidly leading to depreciation in the value of the collateral and equities, hampering the banks' ability to lend more and larger. This also causes an increase in defaults which ultimately leads to a crisis.

2.2.3. Stock Market Crisis

2.2.3.1. Defining stock market crisis

Patel and Sarkar (1998) were the pioneer in quantifying the definition of the stock market crisis. According to them, "A 'crash' is defined as a relative decline in the regional price index of more than 20 percent for the developed markets and more than 35 percent for the emerging markets". A ratio called CMAX, was constructed which compared the values of regional index at time 't' to the maximum regional index over the previous 'T' periods, usually one to two years. A threshold was set at the mean of CMAX minus two standard deviations, such that the indicator would assume a value of unity whenever CMAX dropped below the threshold, zero otherwise.

A noticeable difference has been observed in the setting of the CMAX. For example, Guru (2016) quantified the extreme stress in stock markets using the similar methodology as Patel and Sarkar

(1998), however, used a period of T= 12 months for construction of CMAX so as not to lose too many data points. Whereas, Zouaoui et al. (2011) used a ratio with T= 24 months in the denominator.

2.2.3.2. What is Investor Sentiment?

The stock markets have been an area of interest for researchers since 1960s when Eugene F. Fama proposed Efficient Market Hypothesis (EMH) (Fama, 1965). The EMH states that securities prices will be equal to their fundamental value due to the presence of rational investors (Bathia and Bredin, 2013). A number of asset pricing models like Capital Asset Pricing Model (CAPM) have adopted EMH and attempted to explain the stock price movement and returns, assuming markets efficiency and investor rationality. These models leave no room for investor sentiment in asset pricing. However, the theoretical stand of traditional finance has failed time and again to explain price anomalies like Internet bubble of the late 1990s in the stock market. As an alternative, the behavioral approach to asset pricing seeks to answer such market anomalies embracing investor irrationality and market inefficiency. It involves the psychological biases and sentiments and their effect on movements on stock prices thus, coming up with a sensible explanation of market anomalies like bubbles and bursts. The seminal study by Baker and Wurgler (2006) defined investor sentiment, in context of behavioral asset pricing literature, as "the systematic error or biases in investors belief about future cash flows and investment risks that are inconsistent with the fundamental facts".

There is no consensus on how to measure investor sentiment (Zouaoui et al., 2011). Previous studies have identified different sentiment proxies and have attempted to determine its influence on aggregate stock market returns and its ability to predict future stock returns. The investor sentiment has been proxied either through direct or indirect measures. A direct measure is usually a market survey asking questions in order to gauge the investors' attitude towards markets while an indirect measure is a financial variable used as a public opinion indicator. According to Brown and Cliff (2004), both direct and indirect measures are related to each other. In many countries, surveys are regularly conducted to see how investors perceive the direction of both the stock market and the overall economy. For example, in the U.S., surveys like American Association of Individual Investors (AAII), University of Michigan's Consumer Confidence Index Survey, Investors Intelligence (II), UBS/Gallup Survey, and the Conference Board, are conducted on frequent basis. There are several studies which have used different surveys and confidence indices to proxy investor sentiment like Schmeling (2009) who used consumer confidence as a proxy of individual investor sentiment to investigate its effect on expected returns in 18 industrialized countries. The results revealed that sentiment negatively forecasted the aggregate stock market returns on average. Ho and Hung (2009) using three surveys namely CCI, II and MSCI suggested an important role of investor sentiment in conditional asset-pricing models for capturing the anomalies. Lemmon and Portniaguina (2006) found consumer confidence index to be useful in both forecasting the returns of small cap stocks and also the returns of stocks with low institutional ownership. Qiu and Welch (2006) found consumer confidence index to be useful predictor of excess returns on small deciles stocks. Brown and Cliff (2004) investigated the relationship between investor sentiment and near term stock market returns and found a relationship between the indirect and direct measures of investor sentiment.

The indirect measures of sentiment constitutes financial variables like the Closed-End Fund Discount (CEFD), dividend premium, number of IPOs, the first day returns on IPOs, retail investors trade, the market liquidity measured as trading volume, mutual fund flow, and insider trading to name a few (Wendenberg, 2015). These variables capture behavioral aspects which help in explaining the prevailing investor sentiment (Bathia and Bredin, 2013).

The study by Zweig (1973) found CEFD to be a measure of an individual investor's expectations. Another study by Lee et al. (1991)concluded CEFD as a measure of investor sentiment. Investors were found to be pessimistic about the future returns when CEFD was high, while optimistic when CEFD was low. Neal and Wheatley (1998) used three different sentiment proxies namely ratio of odd-lot sales to purchases, CEFD, and net mutual fund redemptions to examine their relationship with small firms expected returns. The study found only CEFD and mutual fund net redemptions to be positively related to the expected returns of small firms while, odd-lot ratio was not found to be a predictor of the small firm returns.

In recent past, there have been many studies that have used derivatives data such as Put- Call ratio (PCR), Volatility Index (VIX) to determine its importance in predicting future stock returns. PCR is a contrarian indicator as a low PCR indicates optimism in the market whereas high PCR indicates pessimism in the market. Pan and Poteshman (2006) examined the information contained in option volume in future stock price movement and found a strong evidence of informed trading in the option market. Bandopadhyaya and Jones (2008) compared the VIX and PCR in predicting future returns and found VIX to be better measure than PCR.

Many studies have also considered equity fund flow to be a proxy of investor sentiment. For example, Brown et al (2002) concluded that daily mutual fund flows could be used as an indicator for investor sentiment in order to predict stock market returns of Japan and the U.S. Frazzini and Lamont (2006) used mutual fund flows as sentiment proxy and found that high sentiment predicted low future returns. Another study by Indro (2004) attempted to examine the relationship between investors' survey and net aggregate equity fund flow and found that individual investor displayed bullish temperament when net aggregate equity fund flow was higher during any given week.

2.2.3.3. Stock market crisis and Investor Sentiment

The following section focuses on the studies related to stock market crisis prediction using investor sentiment.

Siegel (1992) attempted to study effect of investor sentiment on stock market crash of 1987. The study used Investors' Intelligence Sentiment Index as a proxy for investor sentiment. It did not find any evidence regarding its impact on the crash even though investor sentiment indexcorrelated with the stock market returns.

Baur et al., (1996) tested the proposition that investor sentiment played an important role in the stock market crash of 1987 and found no support in favor of the premise that changes in the U.S. stock market prices were related to the changes in investor sentiment. The study used weekly data and used the discount or premium of the prices on closed-end funds relative to their net asset values to measure investor sentiment. The insignificance of the investor sentiment in affecting the stock prices was attributed to the inappropriate measurement of the investor sentiment or simply to the ineffectiveness of the investor sentiment in the stock market crash of 1987.

Zouaoui et al. (2011) employed multivariate logit model to examine the influence of investor sentiment on the probability of stock market crisis for international stock markets during 1995-2009 using a panel of 15 European countries and the United States. Michigan Consumer Sentiment Index and the Economic European Commission calculated Consumer Confidence Index was used as the measure of investor sentiment. The results found the investor sentiment contributing positively to the likelihood of the occurrence of the stock market crisis within a one-year horizon.

Furthermore, investor sentiment provided an incremental predictive power of a crisis. The study also found that the impact of the investor sentiment was stronger for the countries which were more prone to overreaction and herd-like behavior, and countries which had low efficient regulatory institutions.

Zhang et al., (2019) studied the stock market crisis in China from the perspective of behavioral finance from January 2005 to June 2012. The empirical results concluded that the investor sentiment was positively related to the likelihood of the occurrence of stock market crisis in Chinese stock market after controlling for the economic variables. The study estimated a logit model and found that investor sentiment could predict the crisis for both in-sample and out of sample cases.

Wendenberg, (2015) used logit and Ordinary Least Square (OLS) models to investigate the relationship between stock market crisis and investor sentiment for nine different countries covering a period from 2000 to 2014. The study found a positive significant relationship between investor sentiment and the stock market crisis. According to the study, the investor sentiment helps in explaining the likelihood of a stock market crisis occurrence because it indicates the role of market psychology in explaining stock market prices. The study also concluded that stock prices might get overvalued due to excessive investor optimism.

2.3.Early Warning Systems, Need and Construction

Early Warning Systems (EWS) are the systems which are developed to provide warning signals to researchers, policy planners and investors about the onset of an approaching crisis. The EWSs are empirical in nature and constitute the indicators which signal an occurrence of a future crisis. The construction of EWSs comprises of three major steps. First step is identification of episodes of crises in selected time period and countries. Second step entails selection of potential variables which can act as warning indicators. Third step is estimating the models using selected econometric technique followed by the evaluation of the EWS in relation to its end use by the decision maker. According to Lestano et al. (2003), there are various EWSs which have been developed and differ in terms of the coverage of countries, definition adopted for identification of episodes of crises, time period covered, indicators selected, and econometric or statistical techniques employed.

Crises usually result in huge output losses and social costs in terms of currency devaluations, unemployment, rise in inflation etc. Hoggarth et al. (2002) estimate that "the average costs in terms of production loss is 20% of annual GDP" (Kauko, 2014). The study also suggests that emerging economies experience greater losses as compared to the developed economies in the event of twin crisis, while developed economies encounter longer duration of crises as compared to the emerging economies. The post crisis process of recovery also costs a lot (Hoggarth et al., 2002). Therefore, the need to develop models which can identify weaknesses and vulnerabilities in the economies well in advance so that necessary and appropriate preventive steps could be taken, is more pressing than ever. In addition to identification, these models are required to send correct and accurate signals cautioning sufficiently in advance to initiate proper course of action hence, making it highly relevant for policy planners. The EWS models can help in sustaining global growth and maintaining financial stability, especially in the light of increased intensity of the financial crises occurring in the current scenario.

2.3.1. Construction of EWS

As mentioned above, the construction of an EWS entails three major steps i.e. identification of the crisis episodes, selection of predictor variables and econometric technique, and finally evaluation of the performance of an EWS in predicting the occurrence of a crisis. This subsection is focused on the statistical and econometric methodologies employed for construction of EWSs.

Definition of the crisis event

The first pivotal step in designing and EWS is to define what is meant by a crisis event. The following sections throw some light on the definitions adopted for identifying the crisis episodes for currency and banking crises.

Currency Crisis

Most studies have adapted a common quantitative definition known as "Exchange Market Pressure" index (EMP). This index accounts for the build-up of pressure on the domestic currency and was developed by Eichengreen, Rose and Wyplosz in the 1990s (Edison, 2003). The index is constructed as a weighted average of the percentage change in each of the interest rate, the international reserves, and the exchange rate. The reason behind taking these three index constituents is to account for both successful (devaluation of currency) and unsuccessful (currency defended by increasing interest rates to invite foreign capital or by exhausting the foreign reserves) attacks on the local currency (Fratzscher, 2003). Following the construction of the index, a threshold value is chosen which helps in identification of a period as a crisis episode whenever the EMP crosses the specified threshold level (Dawood, 2016).

However, several differences have been noticed among various researchers who have adopted this quantitative index for defining currency crises. For example, on one hand some researchers have used nominal rates or the changes in the spread between the U.S. interest rate and the country's interest rate (Lin et al., 2008), while others have employed real interest rates and real exchange rate to account for disparities in inflation rates across countries and over time (Bussiere and

Fratzscher, 2006; Ari and Dagtekin, 2008). Furthermore, studies like Kaminsky and Reinhart (1999), and Arias and Erlandsson (2005) shelved the interest rate differentials from the EMP index due to data availability issues.

As mentioned above, the EMP index accounts for both successful and unsuccessful events of currency crisis, some authors like Frankel and Rose (1996) and Lestano et al. (2003) have argued to only include the successful attacks on domestic currency as currency crisis. Frankel and Rose, (1996) defined a currency crash " as a depreciation of the nominal exchange rate of at least 25% that is also at least a 10 per cent increase in the rate of nominal depreciation".

Zhang (2001) proposed the breakdown of the EMP index into its individual constituents as it was argued that when devaluation happens domestic interest rates rise in order to compensate domestic-currency bond holders while they fall back to foreign levels post devaluation. On the other hand, the reserves flow back to satisfy the increased money demand after the devaluation, which had rolled out of the domestic country before the crisis because of declined money demand. Thus, this can result in changes in interest rates and international reserves canceling out some of the changes in the exchange rate leading to no generation of signal while a currency crisis is anticipated actually.

Candelon et al., (2012) compared the performance of the index suggested by Zhang (2001) with that of the EMP index and found similar results i.e. crisis episodes. Furthermore, Lestano et al., (2003) identified the episodes of the currency crisis using four definitions from Eichengreen et al. (1996a); Kaminsky et al. (1998); Frankel. and Rose (1996); and Zhang (2001) and concluded that the definitions of Eichengreen et al. (1996a) and Kaminsky et al. (1998); are superior to those of the latter two.

The specification of the selected threshold values for the EMP index to identify crisis episodes constitutes another area of discrepancy. Usually, in binary models, when the EMP index crosses a the pre specified threshold value, those instances are marked as crisis incidences and are labelled as unity and zero otherwise. The threshold level is assumed to be crossed when the crisis index is above the country average by a certain multiple of standard deviations (s.d.) (Dawood, 2016). However, significant differences have been noted in several studies like Komulainen and Lukkarila (2003), Krznar (2004), Bussiere and Fratzscher (2006); Falcetti and Tudela (2006); Ari and Dagtekin (2008) used two standard deviations, Su et al. (2010); Lang (2013) used 1.5 standard deviations, 2.5 s.d. by Edison (2003); Kaminsky et al. (1998); Zhang, (2001); Lin et al., (2008) used three standard deviations; Kamin et al. (2001) used 1.75 and Andreou et al. (2009) used 0.75. It has been observed that the threshold values are mostly chosen arbitrarily, while in some studies, the authors have examined diverse thresholds and chose the one which was giving the best fit.

Banking crisis

The following section reviews the literature related to banking crises which is attracting more and more attention by researchers because of increased incidences and leading to wider implications over the years.

Caprio and Klingebiel (1996) defined systemic banking crisis as an event when " all or most of banking capital is exhausted"[2]. Demirguc-Kunt and Detragiache, (1998) used a more specific set of four criteria[3] where fulfilling any one of the four conditions stated would categorize the bank

[2] "They stipulate that non-performing loans as a proportion of entire loans of the banking system must be in the range of 5–10% or less."

[3] "The proportion of non-performing loans to total banking system assets exceeded 10%, or the public bailout cost exceeded 2% of GDP, or systemic crisis caused large scale bank nationalization, or extensive bank runs were visible and if not, emergency government intervention was visible."

failure as systemic. While Lindgren et al. (1996) and Kaminsky and Reinhart (1999) followed criteria similar to Demirguc-Kunt and Detragiache, (1998).

Davis and Karim (2008) mentioned that a banking crisis can be defined as "the occurrence of severely impaired ability of banks to perform their intermediary role". However, this definition is general as it included closure or mergers, bank runs or bank failures. Therefore, researchers like Casu et al. (2012) have adopted a number of proxies such as decrease in capitalization of the banking sectors by some basis points or fall in the net income of the banks as a percentage of their average balance sheet below some threshold, as indicators of solvency condition or general soundness.

Simpson (2010), on the other hand, used the variance of a country's banking sector stock price index to identify the banking sector's vulnerabilities to examine the 2008 subprime crisis.

Barrell et al. (2010) used IMF financial crisis episodes' database criticizing the definitions provided by Demirguc-Kunt and Detragiache (1998) arguing that it is unable to identify the true start and end dates of the crisis. It was reasoned that the criteria variables used in dating and identification of the crisis, "may take a while after the crisis breaks out or ends to start revealing its onset or termination, respectively".

Another study by Singh (2011) proposed to construct a "Bank Fragility Index" as the weighted average of six variables related to interest rate risk, liquidity risk, and credit risk for Indian banking system. The study criticized the event-based crisis dating mechanism as it delayed crisis identification and failed to take in account its severity.

Laeven and Valencia (2013) presented a comprehensive database of systemic banking crisis during 1970 to 2011 where they proposed policy indices as a methodology to date banking crises. According to the study, a banking crisis is defined as systemic, if two conditions were met[4].

Based on the above review, it can be observed that two methods have been commonly deployed for identification of financial crisis namely the index based method and the event-based method.

Event Based method: This method is also called 'qualitative method" for identification of crisis episodes. It identifies a systemic banking crisis after the occurrence of an event such as bank runs, closures, huge Non Performing Assets (NPAs). The approach however, suffers from several disadvantages. Firstly, event based studies utilize annual data. Due to the annual frequency of the data, an entire year is labelled as a crisis episode even though a crisis may have occurred for a few months. Secondly, as pointed out by Caprio and Klingebiel, (2003, p 1), that "All crises are not overt crises." involving bank runs. Thirdly, this way of identification is delayed in nature, as identification of an episode takes place when a certain event has been already triggered due to severe conditions (Von Hagen and Ho, 2003b). Other studies which have used this qualitative method for identifying banking crises are Demirguc-Kunt and Detragiache, (1998), Kaminsky and Reinhart, (1999), Beim, (2002), Laeven and Valencia, (2013).

Index method: The index method has been widely used for identifying currency crises in studies by Eichengreen et al. (1996), Lestano et al. (2003), Bussière (2013). This method has several advantages over event based method as firstly, it uses monthly data. Secondly, the method does

[4] "1) Significant signs of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system, and/or bank liquidations)"

"2) Significant banking policy intervention measures in response to significant losses in the banking system."

not require any prior knowledge of events. Thirdly, there is lesser probability of delay in recognition of a crisis[5]. There are studies utilizing the index method for banking crises/fragility which include Hawkins and Klau (2000), Kibritçioğlu (2002) and Von Hagen and Ho (2003).

2.3.2. Methodology adopted for developing EWS models

The second step in construction of an EWS constitutes adoption of a methodology for identifying potential early warning indicators. The empirical literature on construction of EWSs mainly deploys two main techniques namely signals approach, and the limited dependent variable (Logit/Probit) regression approach.

2.3.2.1. Signal Extraction approach

The signals approach was pioneered by Kaminsky et al., (1998) as an approach to design an EWS to study currency crises. The signals approach was used to study and contrast the behavior of individual indicators before and after a crisis, thus identifying the indicators useful in signaling an approaching crisis based on an indicator crossing its certain threshold level. The indicators which proved to be useful in foreseeing a crisis included domestic inflation, the real exchange rate, the behavior of international reserves, credit to the public sector, and domestic credit. Other indicators that found support included the performance of exports, fiscal deficit, trade balance, real GDP growth, and, money growth. Subsequently, they also studied and analyzed the "twin crisis", or the occurrence of both banking and currency crises, in a panel of 25 countries spanning the period 1970-1995. The findings suggested that banking crises were frequently related to large fluctuations in exchange rate which characterized currency crises. This study also established that banking

[5] Refer Basabi and Bhattacharya for studies based on event based method and index based method from 1993-2008.

crises are preceded by a decline in growth of exports, output, which reflect deteriorating terms of trade, credit growth and rising interest rates characterizing rapid financial liberalization, and appreciating real exchange rates (Duttagupta and Cashin, 2011).

Edison (2003) carried on the work of Kaminsky et al. (1998) by adding explanatory variables and using a broader set of countries. The study tested for regional differences as well as applied their model specifically for Mexico. The study reported mixed results attributed to a large number of false alarms due to few crisis episodes in the sample. However, the robustness of the performance of the indicators was established in anticipating a currency crisis across different countries.

Megersa and Cassimon (2013) used the signals approach to assess the currency crisis in Ethiopia, a low income developing economy, from January 1970 to December 2008. The study found the M2 multiplier, exports, bank deposits, lending–deposit ratio, terms of trade, and deviation of real exchange rate from trend to be significant.

Heun and Schlink (2004) implemented a prototype of a currency crisis model and employed signals approach to develop an EWS for Uganda. The study also constructed composite index and calculated conditional probabilities of currency crisis for Uganda.

Reinhart et al. (2000) is the most comprehensive study on signal extraction approach and its application as EWS for predicting a banking crisis. This study identified the banking crisis as the events when "bank runs that lead to the closure, merging or take over by the public sector of one or more financial institutions; and if there are no bank runs, the closure, merging, takeover, or large-scale government assistance of an important financial institution". It used signal extraction approach to study the macroeconomic variables as leading indicators helpful in warning for an approaching banking crisis.

Borio and Lowe (2002) suggested constructing simple composite indicators of banking crisis in assessment of future financial distress and found that the composite indicators were able to foresee a banking crisis with a reasonable degree of confidence. The study used an annual data from 1960-99 of 34 countries constituting 21 industrial and 13 emerging market economies and examined the behavior of the indicators, when all the countries were pooled together and separately for emerging and industrial market economies. However, the thresholds identified could not be said to be statistically precise, even though performance of indicators was good in the period examined. Secondly, out of sample performance of the indicators was not tested to justify the prediction of future events.

The other significant contributors of Signal approach include Edison (2003) and Brüggemann and Linne (2002). The country-specific studies using Signal Approach have been made by El-Shazly (2002) for Egypt, Knedlik (2006)and Knedlik and Scheufele (2007) for South Africa and Yap (1999) for Philippines.

2.3.2.2. The Limited Dependent Variable models

The second approach in EWS literature involves the use of the limited dependent variable (LDV) models like Logit or Probit regressions. These models fit a specific stable relationship between the latent dependent variable translating to the probability of a crisis and changes in a group of selected indicator variables at different points in time. The following section covers multitude of studies utilizing this approach in analysis of single type of crisis followed by studies examining the twin crises. This is followed by the review of studies comparing the limited dependent variable models with other techniques.

The LDV approach is a parametric technique as it involves distributional assumptions on the relevant parameters as well as estimation and tests of significance to determine critical variables elucidating and predicting a financial crisis, be it a currency or banking crisis. The advantage of using this methodology is that each of the indicator variables can be assessed in terms of their contribution and performance based on statistical tests (Gaytán and Johnson, 2002). One of the earliest application of binary choice models for the prediction of currency crisis using a probit model is Frankel and Rose (1996). The study used a panel of 100 developing countries from 1971 to 1992 to characterize currency crashes using a probit model. It was concluded that the economies become vulnerable to currency crashes and sharp recessions when reserves are low, FDI inflows dry up, domestic credit growth is high, real exchange rate is overvalued, and Northern interest rates rise.

Demirguc-Kunt and Detragiache (1998) and Eichengreen and Rose (1998) were pioneers in adopting the LDV approach to study banking crisis. Eichengreen and Rose (1998) used multivariate probit model to analyze banking crises in emerging economies. The study followed Caprio and Klingebiel (1996) in identifying the 39 episodes of banking crisis. The results highlighted that the changes in foreign conditions were important factor in the occurrence of banking crises in emerging economies. The domestic business cycle, high foreign debt levels and the exchange rate overvaluation were found significant in setting stage for financial problems. The study did not find much contribution of the variables related to the exchange rate regime, and the fiscal policy in increasing the probability of the banking crisis.

Demirguc-Kunt and Detragiache (1998) employed a multivariate binomial logit model to explore the determinants of the banking crises in 65 developed and developing countries. The results found the macroeconomic environment to be an important element contributing to banking fragility. The probability of crisis increased with growth in slowdowns, high inflation and rising interest rates. Poor institutional development and explicit deposit insurance mechanism also contributed increasing the likelihood of a banking crisis. The follow up study in 1998 emphasized the role of liberalization in increasing financial fragility. However, the impact was less for the countries with strong institutional environment (as proxied by the level of corruption and the rule of law).

Hardy and Pazarbaşıoğlu, (1998) examined the role of macroeconomic, banking and real sector indicators in the lead up to the episodes of banking distress in 38 countries during 1980-97. A multivariate multinomial logit model was used, and the findings suggested that rising real interest rates, boom bust cycles in inflation, large falls in real GDP growth, credit expansions and capital inflows, a declining incremental capital output ratio, a sharp decline in the real exchange rate, and an adverse trade shock were associated with banking distress.

Glick and Rose (1999) studied the importance of trade linkages as a channel for currency crisis contagion over macroeconomic and financial influences. The study used multivariate probit modeling over cross sectional data from five different episodes of important and widespread currency instability. The study found strong evidence that trade linkages were the reason for currency crisis spread.

Hutchison and Mcdill (1999) examined periods of banking distress for 97 countries out of which, 53 countries faced episodes of severe banking distress while 44 countries did not face severe banking problems, for the period of 1975 to 1997. The study used probit models to link the likelihood of banking problems to institutional and macroeconomic environment. Common characteristics of banking problems consisted of a sharp decline in asset prices and deep recession. The study also focused particularly on the crisis of Japan in 1990s, where the institutional variables like explicit deposit insurance and financial liberalization were found to be contributing to the likelihood of the crisis by creating conditions related to moral hazard. In addition, two macroeconomic variables namely stock prices and real interest rates also found to be statistically significant leading indicators of banking distress for all the countries.

Eichengreen and Arteta (2000) attempted to determine the causes of a banking crisis using sample of 75 emerging markets from 1975 to 1997 using probit models. The study found deposit-rate decontrol, large bank liabilities to reserves, and rapid domestic credit growth to be robust causes of banking crises in emerging markets.

Feridun (2004a, 2004b) attempted to identify the indicators of the Brazilian real crisis and Russian financial crisis through a probit model including 20 political, financial, and macroeconomic indicators from 1980-1999 for Brazilian and 1980-1998 for Russian crisis. Feridun (2007) attempted to identify the reasons behind the Mexican Peso crisis of 1994-95. The study used a probit model including 20 financial, political, and macroeconomic variables for the period 1970-1995.

Bussière and Fratzscher (2006) criticized the results of both the binomial logit/probit models. The study came up with a new concept called "post- crisis bias". It claimed that binomial regression models are actually clubbing the tranquil period observations with the post crisis periods into one group instead of contrasting the indicators' behavior during the tranquil periods with their behavior on the brink of a crisis. This could introduce a bias in the estimation results and therefore, a multinomial logit model was adopted. Thus, using a sample data of 32 emerging market economies from 1993 to 2001, the study revealed that the predictive performance of multinomial model improved for both in-sample as well as out of sample analysis for predicting the currency crises.

Lambregts and Ottens (2006) investigated the leading indicators of a banking crisis in 22 emerging countries spanning the period from 1980 to 2003 using a multivariate logit model. The results indicated that rising inflation, rapid lending growth, and high real interest rates are the most significant predictors of a banking crisis. In addition, the findings also suggested that absence of explicit deposit insurance, flatter US yield curve, and lower FDI inflows also drive the banking sector in emerging economies.

Dagtekin (2007) employed dynamic logit models and OLS models to examine the 2000-01 Turkish crisis. The sample data composed 215 observations spanning the period from January 1987 to December 2004. The findings revealed that the Turkish crisis was influenced by the indicators of current and monetary imbalances, and by banking sector fragility indicators.

Wong et al. (2011) developed a panel probit model to identify the leading indicators of banking distress for the 11 member countries of Executives' Meeting of East Asia Pacific Central Banks (EMEAP) from 1990 to 2007. The model found contagion effect to be playing a significant role in determining the probability of banking distress. Other significant indicators included rising inflation rate, slowing GDP growth, increase in money supply relative to foreign reserves, deteriorating creditworthiness of banks and non-financial companies, and significant gaps in asset prices of equity markets and property prices, especially fueled by strong credit growth.

Comelli (2014) compared logit and probit based EWSs for 29 emerging economies from January 1995 to December 2012. The study found similar out of sample performance for both the models and concluded that the performance is based on the estimation sample size and the definition of the crisis adopted. The variables like higher net foreign assets and stronger real GDP growth rates were found to be significantly reducing the likelihood of a currency crisis while high levels of credit to the private sector was found to be increasing its probability of occurrence. The study also emphasized the usage of the crisis definition identifying more crisis episodes so as not to miss any alarms, at the cost of getting false alarms as missing of a crisis leads to a greater damage.

Duca and Peltonen (2013) developed a framework to predict systemic crises using Logit model for the period from 1990 Q1 to 2009 Q4 for 28 developed and emerging countries. The study combined both global and domestic indicators of macro-financial vulnerabilities to predict systemic financial crises. The findings revealed that combining domestic and global indicators helped in improving the model's ability to forecast systemic events.

Candelon et al. (2014) used logit models to predict currency crises in 16 emerging countries from 1985 to 2011. The study took into account the persistence of the crisis by using dynamic logit models through incorporating lagged index and lagged binary dependent variable as the independent variables in both country by country basis and panel framework. The dynamic logit models were found to be consistently outperforming the static models in both in-sample and out of sample analysis.

Hmili and Bouraoui (2015) attempted to determine the leading indicators of a banking crisis in 6 Asian emerging economies during 1973 to 2012 using a multivariate panel logit model. The results revealed that inflation played the most important role in predicting a banking crisis. Credit to private sector to GDP, economic growth, short term debt to external debt, the ratio of M2 to foreign exchange reserves, and real exchange rate were also found to be important indicators of a banking crisis.

Studies related to Twin crisis

Glick and Hutchinson (2001) attempted to find the dynamics of twin crisis and estimated the probability of either currency or banking sector crisis using a multivariate probit model on an unbalanced panel data set for both developed and developing economies over 1975-97 and found that financially liberalized emerging markets mostly experiences the twin crisis phenomenon.

Von Hagen and Ho (2003a) examined the empirics of twin crisis using 49 countries spanning the period 1980-2001 by estimating multivariate probit models and concluded that banking crises are good leading indicators of currency crises but only for emerging markets. Von Hagen and Ho (2003b) developed an index of money market pressure to identify the banking crisis and examined the determinants of banking crisis using data from 47 countries over a period from 1980 – 2001. The study used conditional logit model and found that lower real interest rates, slowdown of real GDP, large fiscal deficits, over-valued exchange rates and extremely high inflation tend to lead banking crises.

Komulainen and Lukkarila (2003) used a probit model to examine the causes of financial crisis in 31 emerging countries from 1980 to 2001. The study revealed that currency and baking crises are linked with each other. And, thirdly, the importance of indebtedness indicators increased post-liberalization period in predicting a crisis while the significance of real variables declined.

Combined/ Comparative studies

Lestano et al. (2003) developed an EWS for six Asian countries using logit models for currency, banking and debt crises spanning the data from January 1970 to December 2001. The study used factor analysis to reduce the information and combine the explanatory variables into groups namely external, financial, domestic, and global indicators. The results suggested that the bank deposits, rates of growth of money (M1 and M2), GDP per capita and national savings correlated with all three crises, "whereas the ratio of M2 to foreign reserves, the growth of foreign reserves, the domestic real interest rate and inflation played an important role in banking crisis and some varieties of currency crisis." Furthermore, the study also compared four different dating definitions of currency crisis. A within-sample signal extraction experiment revealed that some currency crisis dating schemes outperformed others.

Davis and Karim (2008) using a similar approach as Demirgüç-Kunt et al. (2006), improved the prediction of systemic banking crises by using data of 105 countries spanning from 1979 to 2003. The study assessed signal extraction and multivariate logit EWS and showed that terms of trade and real GDP growth are leading indicators of banking crisis. It also suggested the use of multinomial logit model to develop a global EWS while the signal extraction approach for country-specific EWS. This was attributed to the finding that given the same dataset, the estimation technique chosen affected the robustness and performance of the indicators. Furthermore, the study also highlighted the importance of considering policy maker's objectives while setting threshold values and designing the predictive models.

Budsayaplakorn et al. (2010) employed both signal approach and probit models to examine the likelihood of a currency crisis for Southeast Asian countries from January 1975 to April 1997. The study used 16 indicators to assess whether there were any early warning signs for Asian Crisis of 1997. The top three indicators included GDP, international reserves, and stock market indices. The results indicated that the excess money balances and the ratio of domestic credit to GDP were positively related with the crisis occurrence while the stock indices and the growth rate of exports had a significant negative correlation with likelihood of a crisis. Another interesting result reported by the study was the superior performance of signals approach in predicting the likelihood of the crisis which was 10-20% higher than the performance of the probit model. Overall, government policies, investor panic/ self-fulfilling expectations and macroeconomic environment were found to be playing role in the building of the crisis.

2.3.2.3. Other alternative studies

Several other less popular techniques have been proposed to construct an EWS for predicting financial crisis. Following are some studies which have utilized different methods in their studies.

Nag and Mitra (1999) used Artificial Neural Networks (ANN) to construct an EWS for predicting currency crisis. The study compared its performance to the indicators approach for Malaysia, Thailand, and Indonesia from 1980 to 1998. The results found that ANNs performed better than the signal approach.

Burkart and Coudert (2002) used Fisher's Linear Discriminant analysis to build an EWS for predicting currency crisis in 15 emerging countries for a period starting from 1980 to 1998. The model produced relatively unbiased ratio of correct predictions.

Abiad (2003) proposed an alternative EWS using Markov Switching models with time varying transition probabilities of a currency crisis for five Asian countries during January 1972 to December 1999 taking a country by country approach. The proposed model was found to be outperforming the traditional EWSs in terms of signaling crisis and reducing false alarms. The study also highlighted that the performance of indicators varied greatly across countries. Although some indicators were common like real exchange rate, the relevance of different set of indicators changed for different countries. It was also suggested that the poor performance of the earlier EWSs was due to pooling of countries with different dynamics.

Fioramanti (2008) analyzed data for 46 emerging countries from 1980 to 2004 to develop EWS for predicting the sovereign debt crisis. The study used ANNs and compared their performance with probit models and CART models and found ANNs outperforming both in predicting the crisis. However, one of the drawback of ANNs constituted problem with interpretations. The ANNs are suggested to be only forecasting models and not policy models and hence, should be used with traditional methods.

Sarlin and Marghescu (2010) used Self-Organizing Map (SOM) – a non-parametric neural network based visualization tool for prediction of currency crisis for 23 emerging markets from 1970 to 1997. The SOM model was then compared with the multivariate probit model and the results found a similar performance for the two.

Duttagupta and Cashin (2011) used Binary Classification Tree (BCT) to examine banking crises in 50 developing and emerging countries from 1990 to 2005. The study identified three conditions at which the likelihood of a banking crisis increased: i) highly dollarized bank deposits with nominal depreciation or low bank liquidity, ii) low bank profitability highlighting foreign currency risk macroeconomic instability, and poor financial soundness, and iii) very high inflation.

Minoiu et al. (2013) examined the ability of global financial linkages to predict systemic banking crises in a cross-country setting during 1978 to 2010 for 14 advanced countries using a data mining technique called classification algorithm and probit model. The findings suggested that financial connectedness can predict crisis.

Sevim et al. (2014) developed an EWS to predict currency crisis in Turkish economy using Artificial Neural Networks (ANNs), decision trees and logistic regression. The study covered the period from January 1992 to December 2011 and 32 macroeconomic indicators as the independent variables. The results indicated accurate predictions of a crisis within upcoming 12- months period. The study also revealed the effective utilization of machine learning models to predict financial crisis.

Babecký et al. (2014) constructed and explored a new quarterly database of currency, banking, and debt crisis episodes in 40 developed countries from 1970 to 2010. Using panel Vector Auto-regression model, the study found that banking and debt crisis often precede the currency crisis, but not the vice versa. Bayesian Model Averaging was used to identify the leading indicators out of total 30 potential warning indicators. The findings revealed rising domestic credit preceding the banking crisis in addition to money market rates and global corporate spreads. Rising domestic private credit and money market rates were also found to be indicators for currency crisis in addition to domestic currency overvaluation. The role of other indicators was found to be changing with the type of crisis and the warning horizon selected. Signal extraction was also employed to derive the threshold value of the best indicator and a composite early warning index was also provided to increase the usefulness of the model.

Holton and Rodriguez (2015) attempted to identify a set of indicators that could characterize the conditions preceding the onset of a currency and banking crisis. The data spanned 36 advanced countries from 1970 to 2010 and Classification and Regression Tree (CART) approach and its Random Forest extension was employed. An interesting finding of this study was that it found that crises were more varied than they were similar. High domestic short-term rates and the overvalued exchange rates were found to be most powerful short term indicator for currency crisis while low net interest rate spreads in the banking sector and a shallow or inverted yield curve proved to be best short term indicators for banking crisis. In long term, high house price inflation came out to be significant player for banking crisis. The study also reported domestic credit gap as an important unconditional predictor.

Dabrowski et al.(2016) used dynamic Bayesian networks as systemic banking crisis EWS for the European countries between 1980 and 2013 on dataset employed by Lainà et al. (2015). In particular, the study used the hidden Markov model, the switching linear dynamic system and the naïve Bayes switching linear dynamic system models and found that these models provided more accurate and precise early warnings when compared with the signal extraction and logit model approach.

Holopainen and Sarlin (2016) conducted a horse race of conventional statistical methods and recent machine learning methods to compare the predictive performance of the models in predicting systemic banking crisis. The quarterly data covered 15 European Union countries from 1976 Q1 to 2014 Q3. The results showed that the advanced machine learning methods generally outperformed the conventional statistical models.

Alessi and Detken (2018) updated and slightly amended the dataset assembled by Babecký et al. (2014) covering 28 EU members from 1970 Q1 to 2012 Q4 aimed at identifying the vulnerability of the financial system owing to asset price developments and aggregate credit. The methodology adopted was a Classification Tree Ensemble technique called the "Random Forest" to predict the banking crisis. This model was then compared with logit models for their both in sample and out of sample performances. The results revealed that Classification tree fared well than the Logit models in both the analyses.

2.3.3. Shortcomings of Signal Extraction and Limited Dependent Variable models

Although, both the signals approach and logit/probit models have gained significant popularity in the field of EWSs, they suffer with their own limitations. The signal methodology, except initial selection of indicators, has no economically meaningful assumptions or statistical tests base. It does not take into account the potential correlation among the variables as individual indicator is analyzed at a time. In addition, this approach issues binary signals and hence, there is no measure of the strength of the signal that is potentially related to the extent to which it exceeds its threshold. Logit/ probit models overcome these disadvantages. However, the traditional probit and logit models are static models: they do not take into account dynamic interactions between variables.

The model isolates the marginal effect of each explanatory variable on the probability of a crisis, holding other explanatory variables at a constant, average level (Ghosh and Ghosh, 2002). Secondly, the logit approach is weak in discovering nonlinear variable combination that can help anticipate the outcome of the dependent variable, as it does not take care of all possible permutations and combinations but relies on the researcher to specify a particular interaction (Manasse et. al., 2003). Thirdly, an econometric model usually pre-specifies the mathematical relationship between the probability of a crisis and the macroeconomic and financial input variables, which is otherwise unknown. It does not consider ‘ model uncertainty’ and this limitation reflects in the poor prediction accuracies of LDV models (Roy, 2009).

2.3.4. Artificial Neural Networks as an alternative

One of the main problems faced by the economists is the determination of the functional relationship among the input and output variables or uncertainty about the model. Thus, assuming the non-linear nature of the functional relationship among the variables, neural networks have been proposed as universal function approximators (Hornik et al., 1989) that can map any non-linear function. The uniqueness of ANNs lies in the way it can mimic the human brain in processing of information and constant learning from the environment and adjusting. Against this backdrop, Roy (2009) proposed an alternative EWS for currency crises based on ANNs. Unlike LDV and signal models, a neural network model does not involve any assumption on the coefficients or of the functional form describing the data. In this sense, from a statistical perspective, ANN models are semi-parametric in nature. The superiority of ANNs lies in the fact that it devises the relationship among the variables based on experience instead of hypothesizing a linear relation among the variables, like LDV models, which may not be the case in reality. The unique properties of neural networks have inspired many applications in finance other than financial crisis prediction (see Deboyeck, 1994; Kaastra and Boyd, 1996; Wong and Selvi, 1998; McNelis, 2005; Guoqiang Zhang and Eddy Patuwo, 1998; Fethi and Pasiouras, 2010; and Nan *et al.*, 2012).

2.4. Summary of Literature Review

The summary of detailed literature review covering broad areas, number of papers reviewed, studies by prominent authors and their key findings are presented in Table 2-1. The studies have been broadly classified under methodologies used, types of crises examined and indicators used in predicting the occurrence of a financial crisis. The selected studies were segregated into five year periods from 1995 to 2020 which showed that studies related to prediction of financial crises are growing over years. There were only 15 studies during the period 1995-1999 while, the number grew to 20 during 2005-2009. Post GFC, there were 62 studies found during 2010-2020 which have attempted to address the issue of crisis prediction.

Table 2-1: Literature Review Summary

Topic	Papers Reviewed	Papers Referred	Key Findings
Type of Crises	111	Eichengreen and Arteta, (2000), Eichengreen and Rose, (1998); Hardy and Pazarbasioglu, (1998); Knedlik, (2006); Knedlik and Scheufele, (2007); Reinhart et al., (2000); Rose and Spiegel, (2009), Wong et al. (2011), Hmili and Bouraoui (2015), Alessi and Detken (2018), (Bluwstein et al., (2019, 2020), Petropoulos et. al. (2020)	• Financial crises can take various forms and can occur as a currency, banking, debt at a time or simultaneously. • The majority of the episodes during the period 1970s-2012 have been related to currency and banking crises. • The episodes of banking crises have started growing as is the number of studies focusing on understanding the dynamics behind them.

			• The debt crises have low incidences.
EWS construction: Methodologies employed	111	Kaminsky et al., (1998), Demirguc-Kunt and Detragiache (1998), Edison (2003), Knedlik (2006), Wong et al. (2011), Hmili and Bouraoui (2015), Alessi and Detken (2018), Virtanen et. al. (2019), Coffinet and Kien (2019), Beutel et. al. (2019), Petropoulos et. al. (2020), Bluwstein et. al. (2020)	• The two most famous methodologies have been signal extraction approach and logit/probit models. • Other methodologies employed consist of Markov switching models, classification regression techniques etc. • Machine learning techniques have been used for construction of EWSs but they are few in number.
Behavioral Finance: Investor sentiments and their aggregate effect on stock price movements	30	Jagadeesh (1990), Shiller (2000,2003), Baker and Wurgler (2006,2007), Dash and Mahakud (2013,2014)	• Presence of investor sentiment in emerging markets such as India and China is evidenced through studies. • The predicting power of aggregate sentiments is shown through various sentiment indices constructed for various countries such as U.S., Japan etc.
Stock market crash/crises	20	Klein (2001), Mishkin and White (2000), Sornette et. al. (2015), Kumiega et. al.(2011)	• Studies have focused on the underlying dynamics of occurrence of stock market crashes of October 1987, 1929 and 2008-09. • The role of investor sentiments has been emphasized during the market crashes.
Stock market crash and investor sentiment	5	Siegel (1992), Baur et al., (1996), Zouaoui et al. (2011), Wendenberg, (2015), Zhang et al., (2019)	• The investor sentiment does help in prediction of a stock market crisis. • The predictive power of local investor sentiment has been shown through direct and indirect measures of investor

			sentiment for a panel of countries.
Single country vs Multi country	111	Kaminsky et al., (1998), Demirguc-Kunt and Detragiache (1998), Edison (2003), Knedlik (2006), Wong et al. (2011), Hmili and Bouraoui (2015)	• The studies based on a panel of countries were found to be more (84 studies) in comparison to the country-specific studies (27 studies).

2.5. Research Gaps

The detailed literature review as presented in previous sections reveals the following gaps:

- Very few studies explore the relationship between sentiment indicators and stock market crisis. There are many studies which use investor sentiment to predict asset price fluctuations and stock returns, however, there are limited studies which use sentiment indicators in predicting the probability of occurrence of a stock market crisis.
- The studies on developing EWSs are primarily focused on predicting a currency, or a banking, or a twin crisis, or a stock market crisis only for a pool of countries. There have been very few studies which have examined the indicators for predicting a crisis from all aspects combined. Further, studies focusing solely on a single country context like India are scant.
- Majority of studies have employed signal approach and logit/probit models for predicting a crisis. However, only few studies have explored the usage of Machine learning tools and techniques like ANNs in predicting a crisis.

2.6. Research Questions

The following are the research questions posed for undertaking this this study to frame the objectives:

- What are the leading indicators which can predict a brewing financial crisis in Indian context?
- Does investor sentiment act as a predictor of stock market crisis? And if yes, how can it be used to predict the crisis?
- Do Artificial Neural Networks improve upon the predictive ability of Early Warning Systems?

2.7. Objectives of the Study

The following research objectives are defined for undertaking this study to address above mentioned gaps in the literature review in Indian context. The main objective is to study the dynamics of stock market and banking crisis in Indian context which has been carried out in three steps as following:

- To investigate the leading macroeconomic and financial variables and develop an Early Warning System for predicting the probability of a financial crisis.
- To study the role of investor sentiment as an indicator in predicting the probability of a financial crisis.
- To explore the domain of ML techniques in developing the EWSs for financial crisis prediction and compare the predictive performance with that of the conventional techniques.