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UNDERSTANDING THE HISTORICAL CONTEXT, INDICATORS, AND PREDICTIVE APPROACHES FOR BANKING CRISES

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Abstract
This paper examines the dynamics of banking crises, tracing their historical evolution, defining their key characteristics, and exploring the methodologies and indicators utilized in forecasting these crises. Beginning with an overview of significant , isruptions from the 18th to the 21st century, it highlights common patterns and causes. The research evaluates critical early warning indicators (EWIs) and methodologies, emphasizing their reliability, application, and limitations. With a focus on both global and country-specific contexts, the study underscores the role of EWIs in shaping macro prudential policies to mitigate future crises.
Keywords: [Banking Crises, Early warning Indicators, Macro- Prudential policies, Predictive Approaches]

Introduction

The breakdown of the banking industry during the subprime crisis caused severe losses, delaying economic recovery to pre-crisis levels. As banks are fundamental to the economy, a crisis in this sector can destabilize the entire financial system. Banking crises are contagious and often affect other economies, but history shows there is always scope to prevent such financial disasters.

The 2008 crisis in the USA prompted extensive research into predicting financial crises, leading to frameworks designed to forewarn approaching crises. While country-specific and universal frameworks have been proposed, accurately predicting crises remains a significant challenge.

A reliable framework that provides timely and accurate warnings is essential to minimize adverse effects, as false alarms can result in costly policy errors. Most research focuses on identifying leading indicators that signal vulnerabilities, though their predictive power varies across countries and economic contexts due to differences in financial systems and economic structures.

Credit-related variables consistently perform well in predicting financial crises. Metrics such as credit-to-GDP ratio, debt service ratio, property prices, credit growth, deposit ratio, and sovereign conditions often reveal stress in the financial system, making credit conditions a critical area of research.

Historical Overview of Banking Crises

Crisis History and Evolution: Caprio and Klingebiel presented for the first time a directory of crisis in their research in 1996 and then it was updated by Leaven and Valencia in 2012. They found that 147 banking crises and 218 currency crises had occurred from 1970 to 2011 while 16 cases of sovereign government default were identified. Research carried by them also investigated the situation of crises and the effect of policies made to sort out the problem. They found that it is difficult to predict crises but some indicators showed heat before the crisis. Some important crises are discussed below in the table.

Banking Crises in the 18th Century

Table 1.1 Details major crises:

Year	Crisis Name	Location
1763	Crisis of 1763	Amsterdam, Germany, Scandinavia
1772-73	Crisis of 1772-1773	London
1792	Panic of 1792	New York
1796-97	Panic of 1796-1797	Britain, United States

The instability of financial systems has been evident since the 18th century. These crises, often triggered by banking failures or speculative bubbles, laid the foundation for understanding systemic risks in interconnected economies.

Banking Crises in the 19th Century

Table 1.2 lists prominent crises in the 19th century:

Year	Crisis Name	Location
1819	Panic of 1819	USA
1825	Panic of 1825	Britain
1837	Panic of 1837	USA
1847	Panic of 1847	UK
1857	Panic of 1857	USA
1866	Panic of 1866	Europe
1873	Panic of 1873	USA
1884	Panic of 1884	USA, Europe
1890	Panic of 1890	UK, Australia
1893	Panic of 1893	USA
1893	Panic of 1893	Australia
1896	Panic of 1896	USA

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Table 1.2 shows the crisis that happened in the 19th century. A recession with bank failures, culmination of U.S.'s first boom-to-bust economic cycle was noticed in 1819. After that a panic was observed in Britain in which many banks failed, including the Bank of England. US recession followed by Britain panic in 1837 for five years of depression. The UK's crisis was observed in 1847. After that the USA felt a deep recession with many bank failures in 1857. Whole Europe faced a time of financial stress in 1866 which again was followed by many bank failures in the USA for four years of depression in 1873 which repeated in Europe and USA in 1884. The Panic of 1890 mainly affected the area of Argentina. The US again faced the shots of acute depression in 1893 and 1896. Australia also faced a crisis in 1893. It can be seen through the table that the US faced a crisis in almost the whole 19th century followed by Britain.

Banking crises of 20th century

Table 1.3 showcases significant crises in the 20th century:

Year	Crisis Name	Location
1901	Panic of 1901	U.S.A.
1907	Panic of 1907	U.S.A.
1927	Showa financial crisis	Japan
1929	Great depression	Started from the USA & spread across the worls
1973-75	Secondary banking crisis	United Kingdom
1986-2003	Japanese asset price bubble	Japan
1986-1995	Saving and loan crisis	U.S.A.
1988-92	Norwegian banking crisis	Norway
1991-93	Finnish banking crisis	Finland
1990-94	Swedish banking crisis	Sweden
1990	Rhode Island banking crisis	Rhode Island
1992	Peruvian banking crisis	Peru
1994	Venezuelan banking crisis	Venezuela
1997	Enping financial crisis	Enping
1997	Asian financial crisis	Thailand
1998	Coll. of long-term cap. mgt.	Russia
1998	Russian financial crisis	Russia
1998-99	Ecuador banking crisis	Ecuador
1998-2002	Argentine economic crisis	Argentina

Table 1.3 highlights major financial crises of the 20th century. The first occurred in 1901 with the New York Stock Exchange crash, followed by the 1907 Banker's Panic. Japan's Showa Financial Crisis in 1927 and the global Great Depression starting in 1930 were significant events. Britain faced the Secondary Banking Crisis in 1973-75, while Japan experienced an economic bubble from 1986-1991. The U.S. Savings and Loan Crisis (1986-1995) and Norway's recession (1988-1992) stemmed from risky banking practices. Finland (1990-1993) and Sweden (1990) endured banking crises, with Sweden implementing reforms to recover. Other crises include Peru (1992), Venezuela (1994), the Asian Financial Crisis (1997), and economic troubles in Russia (1998), Argentina (1999-2002), and Ecuador (1998-1999). These events underscore the global financial vulnerabilities of the century.

Banking Crises in the 21st Century

The interconnected markets of the 21st century have heightened risks. Table 1.4 outlines recent crises:

Year	Crisis	Location
2002	Uruguay banking crisis	Uruguay
2003	Myanmar banking crisis	Myanmar
2007	Subprime mortgage crisis	United States
2008	UK bank rescue package	United Kingdom
2009	UK bank rescue package	United Kingdom
2008-09	Belgian financial crisis	Belgium
2008-09	Ukrainian financial crisis	Ukraine
2008-09	Russian financial crisis	Russia
2008-12	Iceland financial crisis	Iceland
2008-12	Spanish financial crisis	Spain
2008-11	Irish banking crisis	Irish
2009-10	Venezuelan banking crisis	Venezuela
2017-18	Ghana banking crisis	Ghana

Table 1.4 summarizes significant financial crises of the 21st century. In 2002, Uruguay faced a banking crisis due to overdependence on Argentina, causing investor panic and massive withdrawals. Myanmar experienced a similar issue in 2003, with bank runs triggered by a lack of confidence in private banks, starting with the failure of Asian Wealth Bank. The 2007 U.S. subprime mortgage crisis, caused by a housing boom, led to a global recession. The UK intervened in 2008 with a €500 billion bailout to stabilize its economy. Belgium's financial crisis in 2008-2009 followed the collapse of Dexia and Fortis banks, prompting government bailouts.

Between 2008 and 2012, global instability caused financial crises in Iceland, Spain, and Iran, while Russia and Ukraine faced economic distress in 2008-2009. Venezuela experienced a banking panic in 2009-2010 due to broader economic issues. Ghana's banking crisis in 2017-2018 stemmed from poor management and regulatory failures. Governments worldwide responded to these crises with interventions and bailouts to restore confidence and stability.

3. Causes of Banking Crises

From the above discussion it can be said that banking crises arise from various triggers and if these triggers can be identified crisis can be prevented. Here are some reasons summarised of banking crisis:

- **Bank Failures:** Sudden liquidity shortages can lead to systemic panic and bank runs.
- **Weak Regulatory Frameworks**: Loopholes in banking regulations exacerbate risks.
- **Speculative Investments:** Overexposure to risky assets or markets.
- **Global Interlinkages:** Contagion effects due to globalization.

4. Review of Literature

The review of literature includes significant studies in the field of banking crises and early warning indicators:

1. **Kaminsky and Reinhart (1999):** This study laid the foundation for signal extraction methods in predicting crises. It identified the importance of current account deficits and external debt.
2. **Borio and Lowe (2002):** Their work emphasized the role of credit to GDP gap as an effective leading indicator for financial stress.
3. **Demirgüç-Kunt and Detragiache (2005):** Used a multivariate logit model to explore systemic crises across countries and established the role of macroeconomic vulnerabilities.
4. **Reinhart and Rogoff (2009):** Their extensive work provided historical perspectives on banking crises, highlighting recurring patterns like high debt levels.
5. **Laeven and Valencia (2012):** This research created a database of systemic banking crises and identified the effectiveness of policy interventions.
6. **Schularick and Taylor (2012):** investigated credit growth over long periods and its predictive power for banking crises.
7. **Taylor (2013)** emphasized credit booms over external imbalances as primary crisis indicators, supported by binary classification models.
8. **Antunes et al. (2014)** demonstrated the efficacy of dynamic probit models incorporating credit-to-GDP gaps and debt-service ratios.
9. Sarlin (2014) utilized neural networks, outperforming traditional logit models in identifying banking vulnerabilities.
10. **Bruno and Shin (2015)** explored international liquidity impacts, proposing a framework linking currency appreciation to banking stress.
11. **Banerjee and Murali (2017)** used macroeconomic stress testing in India, linking NPAs and asset quality to systemic vulnerabilities.
12. **Mishra and Sreeramulu (2017)** developed composite indices for systemic stability, integrating credit and deposit growth metrics.
13. **Aldasoro et al. (2018)** emphasized the predictive power of household debt and international financial indicators, cautioning against using Early Warning Indicators (EWIs) in isolation.
14. **Geršl and Jašová (2018)** found credit-to-GDP ratios to be effective EWIs for developing economies but cautioned against directly applying models from developed markets.
15. **Lang et al. (2018)** validated logistic models for real-time banking stress insights, benefiting macroprudential policymakers.
16. **Coudert and Idier (2018)** suggested variable-specific logit models for more robust policy formulation across Eurozone countries.
17. **Padhan and Prabheesh (2019)** highlighted the limitations of previous models in predicting the 2007-09 crises and proposed hybrid models with dynamic variables for timely identification of vulnerabilities.
18. **Ruza et al. (2019)** introduced a composite indicator system for banking resilience, tested on G7 countries, Spain, and Portugal, showing predictive efficacy for stress events.
19. **Chen and Katsiaryna (2022)** found that equity prices and the output gap served as the best indicators for advanced markets while equity prices, property prices and credit gaps proved better for emerging markets.
20. **Tran and Slike (2024)** found that political factors can remarkably enhance the predictive power of early warning systems if used along with financial variables.

This body of work reflects the evolution of methodologies and variables used in understanding and predicting banking crises.

5. Early Warning Indicators

These are the variables which indicate imbalances before the crisis happens. Although it is difficult to recognize the patterns of variables, if anyone sees the history of the crises carefully then it could be found that some variables were showing signs of heat in the system. All research in this area is based on the notion that if behavior of these factors could be read carefully there were chances to predict the crises.

Characteristics of Good Early Warning Indicators

There are many criteria discussed by different researchers for early warning indicators to be good. These are summarized as under:

Timing: Alarm given by EWI should be early enough so that the policy action can be taken on time. But these should not be so early that their real effects are difficult to measure and decide an action plan. Most of the researchers took a window of 6 to 18 months as it is not too early and not too late. Additionally, this is enough time to take action and to observe its response.

Stability: Early warning indicators' results should be stable enough. It should not happen that policymakers have made an action plan and situations have been changed enough to use that plan for the time being. Behavior of some indicators is quite disturbing near crisis time which makes it difficult to make decisions. Property prices are one of those indicators which start to decline near a crisis and then it is difficult to understand whether it is before crisis behavior or auto correction of the system.

Simplicity: Early warning indicators should be easily interpretable so that their signals cannot be ignored. For this reason, early warning indicators have to be simple as well as transparent to be used in identifying and forecasting the crisis.

Reliability: Predictions of early warning indicators should be reliable because policies made on the basis of their prediction would always be very costly to the country and mostly irreversible in nature. On the basis of these predictions the government diffuses a huge amount of money in some sectors which are in need according to the prediction. So, false alarms can prove very costly to the economy.

Types of Early Warning Indicators:

Early warning indicators were used by two ways in previous studies:

1 **Standalone:** Early warning indicators are assumed to be standalone when a single indicator is used to predict a crisis. Sometimes a single indicator is strong enough to give clues about forthcoming situations.

2 **Composite:** EWIs are assumed to be composite when two or more than two indicators are used simultaneously for prediction. In such situations a multivariate model is designed and EWIs are considered as variables and used according to the methodology of the design.

Previously Used indicators: Credit to GDP gap, Debt service ratio, Property prices, Household DSR, Household credit-to-GDP gap, foreign currency debt to GDP, Cross-border claims to GDP.

Credit to GDP gap: Borio and Lowe (2002) defined that it is the difference between credit to gdp ratio and its trend value. They claimed that it proved the best indicator about crisis information. But some researchers proposed that it is not a good indicator in setting buffer requirements due to its measurement issues and its low performance in case of emerging countries.

Debt service ratio: Debt service ratio shows the ability of repaying debts. Many previous researches show it a good anchor and it can alarm about the stress situation specifically in sovereign government default cases of countries. Borio and Lowe (2002) found it as the second best indicator in their study. Many other studies also claimed the same point of view.

Property prices: If the prices of property or real estate are exaggerated enormously then these may create bubbles in the economy which sow the seeds of depression and can create a difficult situation in near future. Many researchers claimed that property prices gave good results when credit conditions are interlinked with these.

Asset prices/Return on Assets: These are the prices on which stocks and bonds are valued. Just like property prices if the prices of assets are more than their intrinsic value it also can create a situation of bubbles in the financial system and ultimately could be a reason for a burst. Glick and Hutchinson (1999) found that there is a strong relationship between bank runs and asset prices in emerging and less developed countries. But Vila (2000) found the converse holds true in case of developed economies as her study claimed that there is a weak relationship between asset prices and banking crises.

External and Global imbalances: Most of the research carried out on this topic concludes that external and global imbalances cause financial stress in the system. There aren't any studies which only took these imbalances in relation to banking crises but many studies present which have taken external and global imbalances as a leading indicator in prediction of banking crisis.

Foreign currency debt to GDP: Ratio of debt taken in foreign currency to its total economic output is called foreign currency debt to GDP. Babecky, Jan et al. (2012) claimed in their research that this indicator performed very well in the prognosis of stressful events in the case of developed nations. Bordo M. et. al. (2009) claimed that foreign currency debt to GDP is the main reason for the East asian crisis in the late 1990s. They claimed the high value of this debt. can be a reason for the currency and banking crisis but it also depends on a country's reserve base and its policy's framework rather than on debt value alone.

Cross-border Claims to GDP: This is simply a ratio of foreign claims to GDP. Here it becomes necessary to explain foreign claims. It has cross-boundary claims in addition to overseas offices' local claims in all types of currencies. Local claims means the subsidiaries of indigenous banks' foreign affiliates. Dieckelmann (2019) claimed in his study that this indicator's performance was very good in case of small open economies and it was successful in predicting banking stress events.

Household Credit to GDP: Household debt is defined as the combined debt of all people in a household. It includes consumer debt and mortgage loans. Aldasoro et. al. (2018) studied that household credit to GDP contains useful information about the forthcoming banking crisis and if this variable is combined with crossborder debt and property prices then it can give good results. Tolo (2015) also proposed in his bulletin of the Bank of Finland that it proved a good indicator of banking stress in the European region.

Credit Growth: Year on year growth in bank credit is known as credit growth. Drehmann et. al. (2017) found that credit variables contain useful information about crises and could be proved very useful in predicting crisis events so BIS started regular monitoring of these variables. Their study also proposed that credit growth is the prime reason for enhanced DSR which ultimately causes credit booms and could be a reason for underlying vulnerabilities in the system. Research found that credit variables with DSR and property prices can give good results in crisis prediction of the banking industry.

Deposit growth: Year on year growth in bank deposits is called deposit growth. Han and Melecky (2013) noticed that during the financial crisis of 2007 the deposit growth declined sharply. It was proposed by the study that access to deposits can enhance the stability of the financial system. Research also added that at the time of crisis depositors try to withdraw their money and this can create anxiety and chaos. Paper suggested that this problem could be mitigated with the help of diversification of the customer base. Laina et. al. claimed that if deposit growth should be taken into account with loans then it can be proved as a very good indicator of a banking crisis.

CRAR: It stands for capital to risk weighted assets ratio. It is used to protect the interest of depositors and to enhance the stability of the system. It generally counts in tier 1 and tier 2 forms. Buehler et. al. (2009) investigated the situation of the financial crisis of 2007 to 2009 and found that capital ratios performed very well in predicting stress events when calculated as a function of risk weighted assets. Das and Amadou (2012) found that banks with high risk weighted assets performed badly during the crisis phase. Study confirmed that the result of Europe is also on the same line.

Stock Prices: The prices of shares for which these are traded in the market are called stock prices. Kaminsky (1999) found that appreciation in stock prices could be a reason for banking crises. Study claims that this fact becomes more profound if financial institutions are more exposed to stock markets. The underlying situation makes the conditions more stressful for banks if the asset bubble bursts. There are factors like real estate prices, interest rates which combinedly act as catalysts for the situation. Studies have revealed that the noise ratio of this indicator is also less than 25 percent and it also proved a very good predictor of other similar situations like stock market collapses, currency crises etc.

CPI inflation: It is the measure of inflation and shows the change in prices over a period of time for a basket of goods and services. John and Kick (2012) found in their study that there are more chances of a banking crisis if the inflation rate is high. Babecky et. al. (2012) investigated that inflation was among better indicators for the banking crisis however global inflation proved better than domestic inflation. Babecky et. al. (2011) claimed in their study of 40 developed countries that inflation provided better clues about forthcoming banking crises.

Export and Import: Kameshwar (2015) in his study found that export performed very well in signalling crises events with low noise ratio at 5% significance level. Mitra and Nag (1999) claimed export and import as an important leading indicator for currency crises and investigated that export gave a number of signals before the crisis with low noise ratio. Lead time noted for export and import was 22 months. Individually, export proved a better indicator than import. Graciela (1998) added that negative shocks of exports and positive shocks of imports are signs of early warning indicators of banking and currency crises.

M1: It is the measure of money supply like coins, currency, checks, demand deposits and negotiable order of withdrawal. Percic et. al. (2013) found that M1 could be used as an early warning indicator of crisis. Bhattacharya and Nag (2002) also observed the same fact by choosing it as an early warning indicator in their study and suggested that excess money can cause loss in export competitiveness and crisis situations.

Growth rate of M2: It is the measure of M1 plus all near money instruments. Near money instruments are quite liquid in nature and can be converted into money easily like money market securities, mutual funds etc, however these are not as liquid as M1. Just like M1 Bhattacharya (2002) also took M2 (in the form of ratio) as an early warning indicator(in credit category) in the same study which was quoted in the previous paragraph and the results were same as they have claimed for M1 and stated that it can create shock to the economy and can cause a crisis like situation.

Credit to deposit ratio: It is a ratio of bank credit to bank deposits. It is mainly used for measuring liquidity position of banks. Chen and Svirydzenka(2021) found in their study that credit to deposit ratio offered a signal two years before the crisis happened. This indicator tells about the overborrowing position of banks in which reliance on wholesale funding can lead to asset price boom which finally results in bank failures.

Gross NPA ratio: Gross non-performing assets as a percentage to advance is described as gross NPA ratio. Basabi (2012) in her paper concluded that non-performing assets proved a backward looking indicator in prediction of the banking crisis. Demirguc-Kunt & Detragiache (1998) proposed in his paper that more than 10 percent NPA's of total assets is a sign of crisis in the banking industry. González-Hermosillo (1999) found in her study that the quality of assets deteriorates rapidly before bank failures.

Non-core liability ratio: AKDO?AN and YILDIRIM (2014) defined in their paper that sources of finance for banks which are less stable or not as reliable as household credit, time deposits etc. are called non-core liabilities like short-term foreign currency denominated debt, cross lending between domestic banks. The study also proposed that these non-core liabilities can create chaos in the financial system. Hahm et. al. (2012) also concluded in their study that dependence on non-core liabilities in the banking industry can enhance vulnerabilities in the financial system and likely to be a reason for banking or financial stress.

Indicators proved better for developed markets: Credit to GDP gap, DSR and property prices are the indicators that have proved very good in predicting crisis events in developed economies.

Indicators proved better for developing markets: Asset prices and global imbalances are the indicators that have given good results in estimation of stress events in emerging economies.

6. Predictive Methodologies for Banking Crises

6.1 Signal Extraction Approach

The approach was given by kaminsky et. al. (1998). It is the most used approach in prediction of stress events for financial systems. In this approach behavior of variables or indicators are observed and if any indicator behaves abnormally then that is taken as a warning signal for forthcoming stress or in-built vulnerabilities. Then a contingency matrix is made by chances of true and false alarm. An alarm is called to be true if any indicator indicates forthcoming crisis and crisis happening in reality. An alarm is called to be false if any indicator predicted a crisis and the situation did not happen in reality. Situation of false alarm can be proved very costly if any policy action has been taken on it. So, policymakers have to be very cautious in observing signals.

The main concern in this approach is about setting the threshold limit. It is difficult to decide which number should be the threshold limit. There is no hard and fast rule to decide it. So, it is at researcher's discretion to choose a threshold limit according to research objectives. Some researchers have also been carried out in this context and most of them are of the view that the threshold limit should be universally acceptable and the same for all countries for a particular variable. Results of signal extraction approach can be compiled in a contingency matrix and can be summarized as given below:

	Signal issued	No signal issued
Financial stress event	A	B
No financial stress event	C	D

It can be seen from the matrix that situation A and D are favourable while situation B and C are unfavourable and can be problematic. Situation C can be proved costly if any policy measure has been taken on the basis of it. And situation B is a question mark on the early warning system itself.

6.2 Statistical Models

Probit Model: The probit model is a form of regression in which the dependent variable has only two possible values. The model's goal is to forecast the likelihood that an observation with given features would fall into one of the categories; also, classifying observations based on their predicted probabilities is a sort of binary classification model. A frequent specification for a binary response model is the probit model. As a result, it uses similar strategies to solve the same set of issues as logistic regression. The probit model uses a probit link function when viewed through the lens of a generalised linear model. The maximum likelihood approach is commonly used to estimate it.

Logit Model: Logistic regression is a classification model that uses a logistic function to represent a binary explanatory variable in its most basic form, though there are several more advanced variants. Logistic regression (or logit model) is a method of estimating the parameters of a logistic model in regression analysis (a form of binary regression). A binary logistic model mathematically has a dependent variable with two possible values, such as pass/fail, which is represented by an indicator variable, with the two values labelled "0" and "1."

Multivariate Regression Model: This model is used when more than one variable is used for prediction. If any researcher wants to test the statistical power of a standalone variable then a simple regression model can be used but if someone wants to test the results of more than one variable in prediction then a multivariate regression model is used. Multivariate regression model is an extension of multiple regression model. In this model there is one dependent model and many independent variables.

Steps of Multivariate Regression Analysis:

1. Variable selection
2. Normalizing feature
3. Select loss function and framing hypothesis
4. Set hypothesis parameters
5. Minimize the loss function
6. Test hypothesis

6.3 Advanced Techniques

- **Machine Learning:** Machine learning models are iterative and data-driven, using past data to train algorithms to identify crisis patterns. These models are increasingly used for early warning systems due to their adaptability.
- **Neural Networks:** Neural networks mimic the human brain's functionality to analyze complex relationships among financial variables. They are especially valuable in scenarios requiring detailed time-series analysis.

7. **Macro prudential Regulation and Early Warning Indicators:**

Macro prudential Regulation is the framework that helps in reducing risk and enhancing stability to the financial environment so that growth in the economy can be sustained. These policies are generally made by government and central banks of the countries so that overall growth of the country can be maximised. The following image illustrates the grandness of these policies.

It contains:

- Monetary policy
- Fiscal and structural policies
- Competition policy
- Micro prudential policies
- Crisis management and resolution policies

It is clearly visible from the figure that crisis management and formulation of resolution policies for crises is just a part of the macro prudential framework. When these policies are made, synchronization between all of these policies is ensured by the economists so that stability of the financial system can be certained. Early warning indicators mostly are the fragments of these policies or somehow related with variables which identify heat in the system in time and then by timely alteration in these policies a crisis can be prevented.

Role of early warning indicators in policy decisions

Helps the policy makers in making macro prudential policies: Early warning indicators give a sign of heat in the financial system which help policymakers to decide what type of policies should be necessary to remove heat from the system. Policies need some basis and early warning indicators provide that basis to policy makers.

Helps in deciding levels of buffers: Financial assistance which is necessary to boost the economy is decided by policymakers. An early warning system acts as a basis to decide the quantitative assistance of packages and the necessary capital for banks like limits of basel 1,2 and 3.

Helps in understanding the framework of the financial system: Early warning indicators help policymakers in deep understanding of the financial system as these are the variables which define the interdependence of the financial system and those variables. The exploration of such a relationship is helpful in the deep sightedness of the underlying system.

Helps in preventing crisis at an early stage: If the leading indicator gives results on a good lead time then crisis can be prevented at an early stage which can save huge costs involved in managing the aftermath.

Conclusion

Banking crises are deeply rooted in systemic vulnerabilities and external shocks. Identifying reliable EWIs and leveraging advanced methodologies are critical in mitigating future crises. Policymakers must integrate robust frameworks to enhance resilience in financial systems, ensuring stability and sustainable growth.

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