

Louvain School of Management

**What is the extent of the applicability of
Financial Stability Indicators (FSIs) in
evaluating the
financial stability of banks during periods
of crisis?**

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Introduction

Financial stability analysis is crucial to understand and predict the economic behavior of financial institutions. The ability to assess the resilience of banks is essential for economic decision-making.

This study focuses on assessing the limits of financial stability indicators (FSIs) using a statistical model (Generalized Additive Model (GAM)) to distinguish between crisis and non-crisis periods. Our aim is to understand the extent to which financial variables have an impact on financial stability, by analyzing in particular how these effects vary according to the presence or absence of a crisis. Our objectives are to quantify the limitations of FSIs in explaining financial stability.

Our research question is : **What is the extent of the applicability of Financial Stability Indicators (FSIs) in evaluating the financial stability of banks during periods of crisis?**

We use a GAM model to estimate the non-linear relationship between FSIs and financial stability (represented by the Z-Score). The model includes smooth terms for all FSIs, GDP and inflation, as well as interaction terms to capture the effect of crisis periods. The underlying assumptions of our model are that the relationships between these variables and the Z-Score may be non-linear, and that the effects of economic crises may modify these relationships.

Understanding the effects of crises on these indicators - and on stability - could help formulate appropriate risk management strategies and highlight the importance of taking specific economic conditions into account when assessing an institution's financial performance.

Our thesis is structured as follows: after this introduction, we explain the concept of financial stability and the different ways of measuring it through our literature review, and then, in the empirical part, we describe the methodology and data used for the GAM model and the forecasts. We then present the results of our analyses and, finally, draw a conclusion on our results and forecasts.

Literature review

In order to understand the concepts that will help us in our research on the applicability of Financial Stability Indicators (FSIs) in evaluating the financial stability of banks during periods of crisis, we will begin with a literature review.

The aim of the literature review is to provide the theoretical underpinnings needed to carry out empirical analyses. We will divide this review into two parts: the first chapter will deal with the definition of financial stability, followed by an explanation of the various tools that can maintain and control this state of stability. We will conclude with an explanation of Financial Stability Indicators (FSIs), which are at the heart of our analysis, as our aim is to determine their limits.

The second chapter of this theoretical framework will enable us to explain different types of economic crises.

1 Chapter 1 : Financial Stability

1.1 Definition of financial stability

The first subject we are going to tackle is financial stability. In recent years, financial stability has become an important economic policy objective. This growing trend is linked to several factors : firstly, the important role played by finance in our economy.

Finance plays several key roles in the development of our economy. Firstly, finance enables the efficient allocation of available resources between different sectors but also all over time. Secondly, finance enables maturities transformation to please all users. (Houben, Kakes and Schinasi, 2004)

Thanks to finance, we are able to allocate efficiently the available resources between different sectors, and over time. Economic agents have different needs which can be satisfied thanks to finance. Indeed, finance enable maturities transformation and allow users to manage their own risk/return couple.(Ibid.)

A.Houben, J.Kakes and G.Schinasi (2004) define finance as: " *a temporary exchange of the*

means of payment of fiat money for the promise of a superior store of value."

To maximise the efficiency of finance, it is essential that the three constituent elements of a financial system -i.e the financial infrastructure, the institutions and the financial markets – are functioning properly. Indeed a well-functioning financial system benefits all economic actors. (Ibid.)

But the difference between financial transactions and instantaneous exchanges lay in the inherent uncertainty of the financial ones. In fact in the regular exchanges, the uncertainty is eliminated by fiat money. (Ibid.)

According to Schinasi (2004), finance necessarily involves a certain degree of uncertainty since it includes the human promises of payment in exchange for an investment. And this uncertainty combined with fairly fragile trust can easily turn into financial risks, and create instability.

Indeed, the possibility that not all trades will be settled creates a systemic risk, this is why public authorities regulate and supervise financial activities. Also economists identify five sources of market failure: public goods, externalities, incomplete information, incomplete markets, and a lack of competition. Public authorities play a crucial role in addressing these market failures and regulating financial institutions to ensure financial stability and economic prosperity (Barr, 1998; Stiglitz, 2000; Houben, Kakes, and Schinasi, 2004)

Economists list prerequisites to have a good understanding of financial stability. First, for Schinasi (2004), as we said, finance contains uncertainty which can lead to market instability. For W.A Allen and G. Wood, this uncertainty can lead to financial or banking crises and can have consequences on the entire economic system, not only the financial institutions. (Allen & Wood, 2006 ; Houben, Kakes and Schinasi, 2004)

The public intervention is necessary to maximize the system's capacity, and for Schinasi that is the consequence of the fact that the services generated by finance and the currency – which is, for him, used as a means of payment - are as such a matter for the public as the private sector. Allen and Wood goes beyond that and state that the financial stability is linked to welfare, and the latter should be the objective. They agreed upon that financial stability is a public objective,

they think that it should be a public entity's objective. (Allen, Wood, 2006)

However, according to Schinasi (2004), even if finance can create uncertainty, stability and uncertainty can coexist. A change in the system would not necessarily create instability. That is why he considers that financial stability does not imply the absence of a crisis but rather the system's ability to contain, limit and manage social imbalances before they become a threat to stability. Not all of the imbalances pose a problem for stability. That also implies that the system has not to be at its peak performance to be considered as stable financially. Schinasi defines an important principle, later adopted by many authors, stating that financial stability is not a static condition but occurs along a continuum (Schinasi, 2004).

Following this statement, economics characterize financial stability as a macroeconomic phenomenon. Consequently it would be pointless to suppress all microeconomic phenomena. That's why they will conclude that a financially stable system should be able to absorb shocks at some point and to amplify others. (Houben, Kakes and Schinasi, 2004 ; Schinasi, 2004)

Schinasi (2004) list the ability of a financially stable system :

- Allocate resources efficiently and facilitate the efficiency of others economic process.
- Assess, price, spread and manage the financial risks.

Its final definition is as follows: *Financial stability is a condition in which an economy's mechanisms for pricing, allocating, and managing financial risks (credit, liquidity, counterparty, market, etc.) are functioning well enough to contribute to the performance of the economy (as defined above).* (Ibid.)

Allen and Wood (2006) add that the stability of a system is achieved when a moment of financial instability is unlikely to occur.

1.2 Theories and models of financial stability

1.2.1 Risk Models

1. The liquidity risk

The liquidity risk model is an instrument comprising several ratios that can be used to

monitor financial stability.

It includes liquidity gap and liquidity coverage ratio analyses. This is part of the standards defined by the Basel Committee, which are made up of the guidelines used to define how much capital banks are supposed to keep in reserve according to the level of risk of their assets.

The latest version of these standards is Basel III, which has been reformed in relation to the lessons learned during the 2007 crisis. (Bank for international settlements, 2008)

2. The financial contagion models

There are models relating to financial contagion that make it possible to assess it. Contagion is a phenomenon that occurs when the performance of one institution may impact another or more institutions. This can take place in two forms: direct or indirect. (Wagalath,2018) The effect of contagion in the financial system can be evaluated with several models, we will only explain two of them : the Eisenberg-Noe contagion model and the Gai-Kapadia model.

The **Eisenberg-Noe** model analyzes, from a network of interconnected institutions, the probability of the spread of payment defaults.(Eisenberg and Noe, 2001)

This is represented by the following formula, which models the spread of financial crises in the network:

$$\mathbf{p} = \mathbf{\Pi}^T \mathbf{p} + \mathbf{e}$$

The $\mathbf{\Pi}$ matrix represents the relative responsibilities matrix that is used to determine payments from each node to the others

The \mathbf{p} represents the payment vector and the \mathbf{e} is the operating cash flow vector

Finally, the equation illustrates the search for the payment vector \mathbf{p} that satisfies the general equation of the model, this balance ensures that the obligations between the nodes are balanced by taking into account the operational cash flows and relative liabilities. (Ibid.)

The aim of their analysis is to assess systemic risk in a financial network, through the modelling of interdependencies between institutions.

It helps determine the compensation payments needed to balance financial obligations, it allows interconnections to be analyzed to identify weak points in the network. With this model, stress scenarios can be simulated and this helps inform regulatory policies to

strengthen financial stability. (Ibid. ; Feinstein and Sojmark, 2019)

The second model useful for the analysis of the contagion effect is **the Gai-Kapadia model**. This model illustrates contagion within financial networks.

The model characterizes the financial system as a complex network of financial institutions interacting with each other through their common financial exposures. It demonstrates a link between network connectivity (i.e. the average number of banks connected to each other) and the probability and magnitude of default risk. (Gai and Kapadia, 2010)

The equation of this model is as follows:

$$G_1(y) = \sum_{j,k} \frac{j \cdot p_{jk} \cdot y^k}{\sum_{j,k} j \cdot p_{jk}}$$

$p_{j\mathbf{k}}$ is the probability that a bank has \mathbf{j} neighbors and that among these \mathbf{k} are vulnerable. $\sum_{j,\mathbf{k}} \mathbf{j} \cdot p_{j\mathbf{k}}$ is the sum of all the banks in the network that normalize the distribution of vulnerable neighbors, this allows to take into account the total number of links in the network.

And $\mathbf{Y}^{\mathbf{k}}$ represents a counting variable, which is used to generate the terms of the series for each number of vulnerable neighbors. When $Y = 1$, this represents the sum of all the probabilities. (Gai & Kapadia, 2010)

The purpose of this equation is to model how failures can eventually propagate in the network, the purpose being to calculate the probability that the neighbor, i.e. another bank with which the first bank has a direct link in the financial network, of a vulnerable bank has \mathbf{k} vulnerable neighbors.

In short, it makes it possible to determine the probability that a failing bank will drag its neighbours down with it, and that its neighbours will drag their neighbours down and that this will lead to a cascade of failures in the network. (Ibid.)

Thanks to this equation, it allows us to understand systemic risk in financial networks, it shows how financial shocks can spread depending on the structure of the network.

The conclusion of the model is that the more interconnected the network, the faster the contagion can spread, but on the other hand, a highly connected network can also absorb smaller shocks without widespread contagion.

1.2.2 Methods to Assess Financial Stability

1. Stress tests

The bank stress tests are carried out by European Banking Supervision to assess the level of preparedness of banks for financial and economic shocks. Through these tests, supervisors can identify possible vulnerabilities and be able to remedy them upstream. (European Central Bank, 2024)

There are different types of stress tests conducted by the European Central Bank. There are annual stress tests (which include several types of tests), stress tests as part of comprehensive assessments – assessing the financial health of banks conducted in association with national supervisors – and finally macroprudential stress tests (assessing the financial health of the system and not individual banks). (Ibid.)

The stress test involves crafting multiple scenarios projected for the upcoming year or subsequent ones, then subjecting banks' portfolios to these scenarios to gauge their performance over time. These scenarios make it possible to test not only the risks that could weigh on a particular financial institution, but also the risks weighing on the system as a whole – systemic risks. (La finance pour tous, 2023)

2. Monte Carlo Simulations

Monte Carlo simulations are algorithms used to estimate the probability of occurrence of a scenario in which we take into account random parameters, this technique makes it possible to modelized the uncertainty inherent in economic and financial variables.

This analysis allows us to integrate different models into our research depending on the type of information we are looking for. It allows institutions to better understand and manage the risks around them. (Fastercapital,2024)

3. Financial Stability Indicators (FSI)

And the last framework used to assess financial stability are the FSI. They were developed

by the International Monetary Fund (IMF) in response to the financial market crises of the late 1990s, their aim is to create macro-prudential indicators that assess the domestic financial systems of various countries and make this information accessible to the public. This initiative seeks to enhance the overall transparency of the financial system, particularly in developing countries where such data has been historically scarce. (Bank of Albania)

FSIs were introduced to make information more accessible to everyone. This need arose from the financial complications of the late 1990s and was further highlighted by the subprime crisis, demonstrating the necessity of assessing the soundness and stability of financial systems for several reasons. (San Jose and Georgiou)

By analyzing these indicators, interconnections can be identified and the risk of contagion can be controlled. As highlighted in the previous section, the financial system is highly interconnected, and risk can easily spread from one sector to another. Ultimately, improving the collection of information on the soundness of financial systems has enhanced transparency, risk management, and policy decision-making within financial systems. (Ibid.)

FSIs serve as crucial warning signals, allowing for timely intervention and control of risks when deterioration in certain ratios is observed. Furthermore, FSIs can be associated with other assessment standards, such as evaluations of international codes and standards, to ensure alignment with best practices in financial regulation and supervision. (Craig and Sundararajan, 2003)

FSIs are primarily useful for macroprudential supervision, as we have mentioned, but they are also crucial for monitoring financial stability through various ratios. Regular analysis of FSIs can help detect financial imbalances and manage them promptly.

Additionally, FSIs facilitate simpler comparisons between different financial systems, allowing for effective comparison across countries or regions. This comparative capability enhances the ability to identify and address systemic risks and vulnerabilities on a broader scale. (Craig and Sundararajan, 2003)

In summary, financial stability indicators enable comprehensive monitoring of the financial system, complementing the assessment program known as the FSAP. By leveraging FSIs in regular monitoring and analysis, policymakers and regulators can enhance their ability to safeguard financial stability, promote the soundness of the financial system, and respond effectively to evolving challenges and risks. (Ibid.)

At the practical level, financial stability indicators are measured using financial data from financial institutions and regulators. This is done in several stages: first, the collection of data, which is done on a regular basis from financial institutions. Then there is the calculation of the ratios, we can find the base set as well as the encouraged set in this table. (International Monetary Fund, 2019)

The indicators consist of two parts: (i) the "core set", which includes key indicators for the banking sector and is mandatory for participating countries; and (ii) the "encouraged set", which, in addition to complementary indicators for the banking sector, includes selected indicators for other financial and non-financial institutions, households, market liquidity and the real estate market. (See Appendix A.1)

Once these ratios are calculated, they are analyzed to assess the financial soundness of institutions and the financial system as a whole. Variations in scans may indicate trends, risks, or vulnerabilities within the system.

During the analysis they can be compared to different thresholds, standards as well as to other countries. These analyses are then periodically reported to the regulatory authorities and to the general public to inform them about the health of the financial system analyzed. (International Monetary Fund, 2019)

2 Chapter 2 : financial crisis

2.1 Banking crises

Banking crises are defined by the notation that they include either bank runs, a moment of temporary confusion about the possible unobservable impact of observable aggregate shocks across the banking system that would provoke collective action by bankers, or severe waves of

bank failures, which would result in an aggregate negative net worth of failed banks exceeding 1% of GDP. (Calomiris, 2009)

However, banking crises can manifest themselves in different ways, as mentioned above, by liquidity or solvency concerns that can lead to bankruptcy but also to a loss of confidence among depositors. Indeed, during a crisis, the bank can encounter difficulties in meeting depositors' withdrawal requests, and this is where liquidity problems begin. These can create a domino effect where the failure of a bank triggers a chain reaction of bankruptcy in the banking system. This is how a crisis begins, and it is in these cases that government intervention may be necessary, such as by freezing deposits, or by providing a guarantee to depositors in order to avoid a complete collapse of the banking system. (Beck et al., 2005)

There are two types of banking crises : systemic and non-systemic.

2.1.1 Systemic banking crises

A systemic banking crisis is characterized by an episode where the entire national banking system suffers losses large enough that non-performing loans exceed 10% of the total assets of the banking system. (Beck et al., 2005)

A banking crisis is considered systemic under two conditions:

- There are significant signs of financial distress in the banking system, such as significant bank runs, significant losses in the banking system or bank liquidations.
- A significant banking policy intervention following these significant losses.

For an intervention to be classified as meaningful, at least three of these six measures must be applied:

- The liquidity support must be extended, i.e. to more than 5% of deposits and liabilities to non-residents.
- Bank restructuring costs must be at least 3% of GDP.
- The bank nationalizations must be significant.
- Important safeguards must be put in place.

- Asset purchases must be significant and represent at least 5% of GDP.
- A freeze on deposits and/or bank holidays must have taken place. (Laeven and Valencia, 2010)

A systemic crisis occurs when many banking institutions simultaneously encounter solvency or liquidity problems. These worries can be caused by an external shock – affecting all banks – or because of a failure of one or more banks which then spreads to other institutions in the system. In terms of consequences, a systemic crisis can lead to a sharp increase in non-performing loans as well as the near-total depletion of global bank capital. It may also experience depreciation in asset prices (e.g., equities or real estate), a rise in real interest rates, and a slowdown or reversal of capital flows. (Feneir, 2016)

The panic associated with the lack of liquidity creates a fear of not being able to access means of payment, which leads to a rush to the base currency and withdrawal of external credit lines. In a systemic crisis, the chain of events can change rapidly, banking conditions can quickly worsen and the asymmetry of information due to limited and outdated information from banks creates a systemic banking crisis. (Hoelscher and Quintyn, 2003)

2.1.2 Non-systemic banking crises

Since non-systemic banking crises do not affect the entire banking system significantly, they are limited to certain institutions or sectors. In fact, they do not require government intervention. (Beck and al., 2005)

The causes of this type of crisis are varied, they can be due to mismanagement or fraud in certain banks or localized economic shocks that affect a certain part of the financial sector. (Boyd and al., 2003)

Obviously, the consequences are less extensive. The negative effects are more limited, short-term and focused on the financial institutions concerned, policy interventions are less costly. (Ibid.)

2.2 Currency Crises

According to Eichengreen, Rose and Wyplosz (1994), an currency crisis is defined as a sudden drop in confidence in a specific currency, corresponding to a sharp depreciation of that currency.

Indeed, a currency crisis occurs when investors flee a currency for fear that it will be devalued. These crises are characterized by: a sudden depreciation of the national currency, significant losses of central bank foreign exchange reserves, and/or sharp increases in domestic interest rates. (Burnside, Eichenbaum and Rebelo, 2016)

In general, a currency crisis is when a nominal depreciation of 25% or more, which is at least 10% higher than the depreciation of the previous year, is observed. (Glick and Hutchison, 2011) Currency crises can have several causes, including fundamental macroeconomic imbalances, domestic financial vulnerabilities and international market dynamics. Market factors may also play a role, such as a sudden loss of investor confidence, or a sudden reduction in foreign capital flows. (Ibid.)

Currency crises can be explained by different point of view, which is why they are classified into two categories :

2.2.1 First generation crises : Krugman's model

In this model, Krugman aims to demonstrate that expansionary fiscal and monetary policies, combined with a fixed exchange rate, will lead to a loss of foreign exchange reserves, and once these are exhausted, to a devaluation or currency crisis. (Flood and Marion, 1998)

Flood and Marion (1998) explain Krugman's model as follows :

In this model, it is assumed that a country sets the exchange rate of its currency based on a larger foreign partner. The equilibrium of the national money market is defined as follows:

$$m - p = \alpha(i), \quad \alpha > 0$$

where M is the national supply of money with high purchasing power, P is the domestic price level, and i is the domestic interest rate.

The model is composed of :

- Domestic money supply which is supported by domestic credit (d) and international reserves (r), with $m = d + r$.
- Price level (p) follows purchasing power parity, $p = p^* + s$, where p^* is the foreign price level and s is the exchange rate.
- Interest rate parity, $i = i^* + s'$, where i^* is the foreign interest rate.

2.2.2 Second generation crises : Obstfeld's model

This model tends to explain crises by investor expectations combined with certain political choices, it takes into account the non-linear behavior of economic agents and integrate market perceptions that can lead to a crisis. The Obstfeld model introduce the concept of multiple equilibria, concluding that the economy can face different stable situation depending on the initial conditions and the agents' behavior. (Flood and Marion, 1998)

Flood and Marion (1998) explains the Obstfeld's mathematical model as follows :

It is then assumed that the government seeks to minimize its loss function, defined as follows:

$$L(.) = (y - y^*)^2 + \beta\epsilon^2 + C(\epsilon)$$

where:

- y is the actual production,
- y^* is the target production,
- ($\epsilon = e_t - e_{t-1}$ is the change in the exchange rate,
- β is a weight,
- ($C(\epsilon)$ represents the cost of changing the exchange rate.

To this equation, we will integrate the Phillips curve – in order to demonstrate the relationship between inflation and unemployment. The function then becomes:

$$L = [(y - y^*) + \alpha(\epsilon - \epsilon^e - u)]^2 + \beta\epsilon^2$$

where:

- α is a coefficient related to the Phillips curve,
- ϵ^e is the anticipation of the change in the exchange rate,
- u is a negative supply shock.

To minimize this function, we derive L with respect to ϵ and solve to obtain

$$\epsilon = \frac{\alpha(y^* - y + u) + \alpha^2\epsilon^e}{\alpha^2 + \beta}$$

Indeed if $y^* > y$, it means there is an incentive to devalue because $\epsilon > 0$.

The model concludes with 3 equilibria depending on the shocks (u):

- **Equilibrium I :**

$$E(\epsilon) = \frac{\alpha}{\alpha^2 + \beta}[y^* - y + \alpha\epsilon^e]$$

- **Equilibrium II :**

$$E(\epsilon) = \left(\frac{\mu - u}{2\mu}\right) \left(\frac{\alpha}{\alpha^2 + \beta}[y^* - y + \alpha\epsilon^e] + \frac{\mu - u}{2}\right) + \left(\frac{-u^2 - u^2}{4\mu}\right)$$

- **Equilibrium III :**

$$E(\epsilon) = \frac{\alpha}{\alpha^2 + \beta}(y^* - y + \alpha\epsilon^e)$$

$$E(u) = 0$$

In short, the second-generation model emphasizes the importance of understanding the complex dynamics, the non-linear behaviors of economic agents, and emphasizing the perceptions and expectations of the market in the occurrence of monetary crises.

2.3 Debt Crises

According to Manasse, Roubini and Schimmelpfennig (2003), a debt crisis can be identified by several criteria:

- First, a country is classified as defaulting by Standard Poor's if its government is unable to meet interest or principal payments on its external obligations by the maturity date.

- A country is also considered to be in debt crisis if it receives a large non-concessional loan from the IMF, defined as access exceeding 100% of the quota.
- In order to characterize a debt crisis, "incipient" defaults are also taken into account, which correspond to defaults that could have occurred but were avoided thanks to financial support from the IMF.

A debt crisis can be caused by different factors. These include macroeconomic imbalance, which is the most common cause of debt crises, with high levels of foreign debt relative to capacity to pay, or a concern for illiquidity due to high short-term debts relative to foreign reserves. (Manasse, Roubini and Schimmelpfennig, 2003)

Developments in international financial markets, including the growing importance of bond markets, may also play a role in the occurrence of debt crises. (Pescatori and N.R Sy, 2004)

However, macroeconomic variables can be used as predictors of debt crises, and this can be done a year in advance. These are variables that reflect solvency and liquidity factors, including:

- A high level of foreign debt relative to a measure of capacity to pay – GDP – will increase a country's probability of default;
- Illiquidity measures, such as short-term debt versus foreign exchange reserves. They indicate the impact of liquidity constraints on the occurrence of crises;
- An important feature is debt repayment capacity in crisis prediction, as measured by debt-servicing obligations. (Ibid.)

These variables serve as early warning signals of sovereign debt crises, allowing policymakers to adjust their economic policies. (Pescatori and N.R Sy, 2004)

2.4 Balance of paiement crises

Balance of payments crises occur when the central bank can no longer maintain a fixed exchange rate, due to a persistent balance of payments deficit. This situation led to a flight of speculators from domestic currency, who then acquired a large part of the central bank's foreign exchange reserves. (Obstfeld, 1983)

They are therefore characterized by a massive loss of central bank foreign exchange reserves, as well as a speculative attack as speculators will flee domestic currency, which will aggravate the pressure on the central bank's reserves. In order to calm the situation, the central bank will then allow the exchange rate to float before re-evaluating it and transitioning to a new fixed rate. (Ibid.)

A balance of payments crisis can also lead to an increase in inflation, as the devaluation of the national currency can lead to an increase in the prices of imported goods, which would lead to an increase in inflation. (Kulkarni and Kamaiah, 2015)

These crises can be caused not only by a persistent balance of payments deficit, which would then have depleted the central bank's foreign exchange reserves, but also by expectations coming from economic agents. Indeed, if they expect a significant devaluation, it can lead them to withdraw their capital and then cause a crisis. Of course, inappropriate fiscal and monetary policies can also increase the pressure on the balance of payments and foreign exchange reserves. (Obstfeld, 1983)

Beyond a devaluation of the national currency, a balance of payments crisis can have other consequences. The loss of confidence in the currency, combined with rising interest rates, can lead to economic recessions. The situation could be worsened by a massive flight of capital, which would reduce investment. Finally, all these consequences could lead the IMF to intervene in order to stabilize the economy. (Chui, 2002)

Empirical Research

In this section, our aim is to answer our research question by means of an econometric analysis.

We will carry out two regressions and forecasting in order to identify the extent to which FSIs can be used to measure banking stability during crises.

3 Methodology

First, we'll define the geographical scope of our models.

In order to carry out a fairly global analysis, we have selected 13 countries from different geographical zones, with developed or undeveloped economies. These are: Argentina, Brazil, Canada, China, India, Nigeria, the Republic of Korea, South Africa, Greece, Germany, Spain, the UK and, finally, the USA.

We had also selected Japan for a more global analysis, but as financial data on FSIs was not available, we removed it from our analysis.

In terms of time-frame, our timeline runs from 2005 to 2022. We cover 3 major financial crises: the global financial crisis (2007-2009), the European sovereign debt crisis (2010-2012) and the Covid-19 pandemic (2020).

We also wanted to cover the Asian crisis of 1997. Unfortunately, due to the lack of information available on FSIs and on the overall health of financial statements prior to the Basel accords, we had to restrict our scope.

Once we've described our variables we'll be using for all our different analyses in the following sections, we'll run a GAM regression, which will be explained in the corresponding section. This model will enable us to run two regressions: a non-crisis model and a crisis-centric model. This has enabled us to make a comparative analysis of our results and to measure the impact of crises. Next, we will carry out forecasting using the ARIMA model, which will enable us to forecast our data over five years in order to analyze the behavior of FSIs over longer periods.

All our models, analyses and graphs have been made in RStudio.

4 Dataset

Our dataset comprises five core financial stability indicators, two macroeconomic variables, and a measure of overall financial stability. All our data, including a binary variable defining the years of economic crisis, spans the period from 2005 to 2022.

The first part of our data, on FSIs, comes from the IMF database¹ and published reports. Macroeconomic indicators come either from the Federal Reserve Bank of St. Louis (FRED)² or the World Economic Outlook Database from the International Monetary Fund (WEO)³.

Given that financial stability indicators were only introduced in the 2000s, but implemented later for a good number of countries, we had difficulty gathering a relevant and comprehensive data set for our analyses. This is one of our limitations.

To overcome this considerable lack of information, we used the “MICE” function (Multivariate Imputation by Chained Equations) on RStudio.

This method is used to deal with gaps in a dataset, reducing bias and proposing results that preserve the relationships between variables, thus improving the quality of subsequent analyses. We are aware that this does create some bias in our analysis, and we will take this into account when interpreting the results, but it was an effective solution for completing our analysis. We applied this method to the data from each country, which allowed us to create a new dataset used for all subsequent models.

¹IMF database: <https://data.imf.org/>

²FRED website: <https://fred.stlouisfed.org/>

³WEO website : <https://www.imf.org/en/Publications/WEO/weo-database/2024/April>

5 Variables

In this section, we describe the different variables that have enabled us to build our database and our model.

All variables have been taken on an annual and percentage basis, in order to facilitate comparative analysis.

5.1 Financial Soundness Indicators

5.1.1 Tier 1 Capital Ratio

The Tier 1 capital ratio is our chosen measure of equity capital.

It is the ratio of a bank's Tier 1 capital to its risk-weighted assets. It includes common shares, retained earnings, cumulative total income and regulatory adjustments. (Investopedia, 2023)

It is used to measure a bank's financial strength. Since Tier 1 capital is the most robust and solid, this ratio is favored by regulators to measure its ability to reflect a bank's immediate financial strength. (Ibid.)

Since the Basel III accords, it has been decided that banks should maintain a ratio above 6% to ensure that they can withstand financial turbulence. But the greater the ratio is, the better. (Ibid.)

$$\text{Tier 1 Capital Ratio} = \frac{\text{Tier 1 Capital}}{\text{Total Risk-Weighted Assets}}$$

5.1.2 Non Performing Loans

The non-performing loans ratio is used to measure a bank's level of credit risk and the quality of its outstanding loans. Non-performing loans can be the source of considerable losses, and influence the bank's earnings strength. (Capital, 2024)

A high ratio indicates a higher risk of loss for the bank if it fails to collect amounts due, while a lower ratio indicates that outstanding loans represent a low risk for the bank. (Ibid.)

A higher ratio may prevent banks from lending to businesses and households. Finally, non-performing loans can have a negative impact on the economy as a whole. (Ibid.)

To compensate for the credit risk, the bank estimates the expected loss on the non-performing loan and establishes a corresponding provision. The portion of the non-performing loan covered

by the provision is referred to as the bank's non-performing loan coverage (NPL Coverage). (Ibid.)

The ratio then compares the total amount of non-performing loans to the total amount of loans granted by the bank. (Ibid.)

$$\text{NPL Ratio} = \left(\frac{\text{Total Non-Performing Loans}}{\text{Total Gross Loans}} \right) \times 100$$

5.1.3 Return On Assets

Return on asset measures a company's profitability in relation to its total assets. It measures the efficiency with which a company uses its assets to generate profits.

A high ROA indicates good resource management, while a low ROA points to opportunities for improvement. It is useful for comparing the performance of different companies in the same sector. This indicator takes into account both assets and liabilities. (Investopedia, 2024)

$$\text{ROA} = \left(\frac{\text{Net Income}}{\text{Total Assets}} \right) \times 100$$

5.1.4 Interest Margin to Gross Income

The interest margin to gross income ratio measures the proportion of a company's gross income represented by the net interest margin. It indicates how much of a company's revenue is generated by its interest activities compared with its total gross revenue.

This profitability ratio measures the proportion of net interest income (received - paid) to gross income. (IMF)

$$\text{Interest Margin to Gross Income} = \frac{\text{Net Interest Income}}{\text{Gross Income}}$$

5.1.5 Liquidity Coverage Ratio (LVR)

The LVR is the liquidity ratio we have chosen for our analysis, representing the proportion of highly liquid assets that financial institutions must hold to ensure they can meet their short-term obligations and weather financial disruptions. It is designed to anticipate large-scale shocks and ensure that institutions can overcome them. It is imposed by the Basel agreements. (Investopedia, 2024)

$$\text{LVR} = \frac{\text{High-quality liquid assets (HQLA)}}{\text{Total net cash flows}}$$

Where:

- High-quality liquid assets (HQLA): The amount of liquid assets that can be quickly converted into cash.
- Total net cash flows: The net cash outflows expected over a 30-day stress period.

5.2 Gross Domestic Product (GDP)

Gross domestic product (GDP) is the total value of goods and services produced by a country over a given period. It also includes all final goods produced in the country, regardless of the nationality of the producers. However, it only takes into account production carried out within the country (unlike Gross National Product). When GDP increases, we speak of economic growth, if it is continuous; then the country is expanding. Conversely, when a prolonged period of contraction occurs, the country is in recession. (Britannica, 2024)

For the purposes of our analyses, we have chosen to use real gross domestic product (at constant national prices). We have taken real GDP so that it can be corrected to eliminate the effects of inflation (since we also take inflation into account in our macroeconomic variables), real GDP uses fixed prices of a base year to ensure an accurate comparison of economic output over different periods. (Investopedia, 2024)

This choice enables us to make a simpler comparison between different crisis and non-crisis periods, as well as between different countries, since they have all followed the same criterion, namely “Millions of 2017 U.S. Dollars”.

$$\text{Real GDP} = \frac{\text{Nominal GDP}}{1 + \text{Inflation Rate}}$$

Where :

$$\text{Nominal GDP} = C + G + I + \text{NX}$$

Where :

C = Consumption

G = Government Spending

I = Investment

NX = Net Exports (Exports - Imports)

5.3 Inflation Rate

The consumer price index measures changes in the prices of goods and services purchased by households, which use them directly or indirectly to satisfy their needs and desires. (International Monetary Fund)

This index is calculated on the basis of a typical basket of goods and services (known as the “consumer basket”), which represents consumer spending. The basket covers a range of categories, including food, housing, transport and healthcare.(Investopedia, 2024)

One of the most common measures of inflation, this index also helps manage monetary policy. But it is also used to adjust salaries, pensions and social incomes to compensate for the possible loss of purchasing power due to inflation. This indicator is crucial for assessing economic trends and living conditions.(Ibid.)

$$\text{CPI} = \left(\frac{\text{Cost of Basket in Current Period}}{\text{Cost of Basket in Base Period}} \right) \times 100$$

5.4 Z-Score

The Z-Score is a measure used to assess the financial health of banking institutions. It is an approximation of the indicator reflecting a bank’s distance from the default threshold, but is based on historical balance sheet information.

It is an interesting indicator for assessing the financial strength of the banking sector. (World Bank Group, 2024)

It is therefore the measure, in number of standard deviations, of the fall in the bank rate of return leading to full absorption of equity capital. As we have taken this indicator by country, it is used here to assess the overall financial stability of the country’s banking sector.(BCL, 2014)

A high Z-score indicates a low probability of default, while a Z-score close to zero or negative indicates an increased risk of default, suggesting financial instability. (Ibid.)

$$Z\text{-Score} = \frac{k + \mu}{\sigma} \tag{1}$$

where:

k represents the capital adequacy ratio (equity to total assets ratio),

μ is the average return on assets (ROA),

σ is the standard deviation of the return on assets (volatility of ROA).

5.5 Crisis indicator variables

5.5.1 Crisis

We've incorporated a binary variable into our model, which equals "1" when it's a crisis year. We have defined several years as years of economic crisis. Here are the three periods we take into account in our models :

1. Global Financial Crisis : From 2007 to 2009
2. The European sovereign debt crisis : From 2010 to 2012
3. The Covid-19 pandemic : From 2020 to 2021

5.5.2 Crisis variables

In order to focus on certain variables and make it easier to analyze and compare crisis years, we have incorporated variables that have been adjusted for crises.

All our financial stability indicators have been crisis-adapted for our second model. Our macroeconomic indicators (GDP, Inflation) have also been adapted, although for the first model.

They have all been multiplied by the crisis variable and are therefore equal to 0 in non-crisis periods.

6 Additive Generalized Regression Model (GAM)

We decided to use an additive generalized regression model (GAM), which enabled us to capture non-linear relationships between the independent variables and the dependent variable. A GAM will combine aspects of a linear model and non-parametric methods to model complex relationships in the data. Each independent variable will be associated with its smoothing

function, a non-parametric function that captures non-linear relationships between each independent variable and the dependent variable.

Our objective in using this model is to assess the applicability of financial stability indicators (FSI) to measure the financial stability of banks in times of crisis.

Using this regression model, we can analyze the non-linear relationship between the financial stability indicator (FSIs), the Z-score as well as macroeconomic variables (GDP, CPI).

To do this, we first built a first model that uses the above-mentioned variables outside times of economic crisis. In order to make a comparative analysis, we built a second model, which follows the same logic, but with variables modified to take account of crises.

By proceeding in this way, we are able to understand which part of our dependent variable (Z-Score) is then explained by FSIs during crises.

6.1 Presentation of the models

6.1.1 Non-Crisis Model

1. Dependent Variable

- Z-Score

2. Independent Variables

- Tier 1 Capital to Risk-weighted assets ("ICR")
- ("Tier 1")
- Non-performing Loans Ratio ("NPL")
- Returns on assets ("ROA")
- Interest Margin to Gross Income
- Liquidity Coverage Ratio ("LVR")
- Gross Domestic Product ("GDP")
- Consumer Price Index ("Inflation")

We also included variables specific to period of crisis ("GDP_Crise", "Inflation_Crise") as well as a binary variable indicating the presence of a crisis ("Crise").

3. Equation

This is the equation of our model :

$$\begin{aligned}
 Z = & \beta_0 + \beta_1 \text{Crise} + f_1(\text{TIER1}) + f_2(\text{NPL}) + f_3(\text{ROA}) \\
 & + f_4(\text{LVR}) + f_5(\text{ICR}) + f_6(\text{GDP}) + f_7(\text{Inflation}) + f_8(\text{GDP_crise}) \\
 & + f_9(\text{Inflation_crise}) + \epsilon
 \end{aligned} \tag{2}$$

where:

- β_0 is the intercept.
- β_1 is the coefficient associated with the Crise variable.
- $f_i(\cdot)$ represents the smoothing functions for the continuous variables, capturing non-linear relationships.
- ϵ is the residual error.

6.1.2 Crisis Model

1. Dependent Variable

- Z-Score

2. Independent Variables

- Tier 1 Capital to Risk-weighted assets * Crise ("ICRCrise")
- Liquidity Coverage Ratio * Crise ("LVRCrise")
- Non-performing Loans Ratio * Crise ("NPLCrise")
- Gross Domestic Product * Crise ("GDP_Crise")
- Returns on assets * Crise ("ROACrise")
- Consumer Price Index * Crise ("Inflation_Crise")
- Interest Margin to Gross Income *

We also include a binary variable ("Crise") to indicate the period of crisis.

3. Equation

This is the equation of our model :

$$\begin{aligned}
Z = & \beta_0 + \beta_1 \text{Crisis} + f_1(\text{Tier1Crisis}) + f_2(\text{NPLCrisis}) + f_3(\text{ROACrisis}) \\
& + f_4(\text{LVR Crisis}) + f_5(\text{ICRCrisis}) + f_6(\text{GDP_crisis}) + f_7(\text{Inflation_crisis}) + \epsilon
\end{aligned} \tag{3}$$

where:

- β_0 is the intercept.
- β_1 is the coefficient associated with the Crisis variable.
- $f_i(\cdot)$ represents the smoothing functions for the continuous variables, capturing non-linear relationships.
- ϵ is the residual error.

6.2 Model comparison

6.2.1 Parametric coefficients

1. Non-Crisis Model

β_0 : The intercept is 13.6266, which is therefore equivalent to the value of Z when all variables are zero.

This value is significant and reflects a base effect or intrinsic level of financial stability, not explained solely by the variables we have chosen to include in our model.

It suggests that there is a significant level of financial stability, even without the influence of the variables present in our model.

β_1 : The coefficient for the crisis variable is 2.0264.

It is not significant (p-value = 0.588). We can therefore conclude that in the presence of the influence of the other variables, the binary variable Crisis does not have a strong linear effect on the Z-Score ; the impact of this crisis can be captured in other ways through interactions with other variables.

2. Crisis Model

β_0 : The intercept is 36.40.

This indicates that the average value of Z is 36.40. This value is significant, and as for the non-crisis model, it indicates that financial stability, or in this case instability, is not

explicable by our variables only, and that a certain level of financial stability (of Z) exists even when our variables are at 0.

β_1 : The coefficient of the crisis variable is -49.45.

In contrast to the first model, this indicates that this variable is significant. This means that, when the crisis is present (if the Crisis variable is equal to 1), the response variable Z decreases by 49.45 units on average compared to when there is no crisis, taking into account the other variables in the model. So the presence of a crisis affect significantly and negatively the Z-Score variable. The significance of this variable indicates that crisis periods modify Z.

6.2.2 Model Quality Measurement

1. Non-Crisis Model

- R-squared (adj): 0.647

Our model explains around 64.7% of the variance in our dependent variable. We can therefore say that 64.7% of the variations observed in the Z-score can be attributed to the variables included in our model.

Indeed, our model captures a good proportion of the variability in Z.

However, it still leaves 35.3% unexplained by our variables. We have to take into account the fact that we have chosen only 5 financial stability factors.

- Deviance Explained

Our explained deviance covers 72.1% of the total deviance, indicating that our model has a strong ability to explain variations in the data.

2. Crisis Model

- R-squared (adj): 0.212

Our model explains around 21.2% of the dependent variable. This means that only 21.2% of the variance within financial stability during crises is explained by our model. We can therefore conclude that the unexplained proportion is quite substantial during crises.

- Deviance Explained

Our model explains 27.3% of the total deviance, which means that our model has a low capacity to explain variances.

6.2.3 Multicollinearity

Table 1: Variance Inflation Factors (VIFs)
- Non-Crisis Model

Variable	VIF
TIER1	2.147
NPL	1.471
ROA	2.396
LVR	3.038
ICR	1.579
GDP	4.327
Inflation	1.789
GDP_crisis	4.586
Inflation_crisis	1.980
Crisis	2.485

Table 2: Variance Inflation Factors (VIFs)
- Crisis Model

Variable	VIF
Tier1Crisis	22.265
NPLCrisis	1.912
ROACrisis	2.676
LVRCrisis	18.023
ICRCrisis	20.655
GDP_crisis	1.347
Inflation_crisis	1.714
Crisis	33.521

The high VIFS of our second model indicates a significant increase in multicollinearity when interactions with the binary “crisis” variable are included.

This multicollinearity may make our model unstable and more difficult to interpret, but is due to the combination of the original variables with the binary variable, which introduces additional interaction effects and amplifies multicollinearity.

6.2.4 Smoothing functions

In order to analyze the results of the smoothing functions, we’ll first point out that the significance threshold is at $p < 0.05$.

1. Non-Crisis Model

Variable	EDF	Ref.df	F-value	p-value
$s(TIER1)$	5.008	5.912	0.908	0.484404
$s(NPL)$	8.504	8.881	4.324	9.55×10^{-5}
$s(ROA)$	5.311	6.352	4.452	2.59×10^{-4}
$s(LVR)$	8.021	8.446	14.428	$< 2 \times 10^{-16}$
$s(ICR)$	4.662	5.718	11.587	$< 2 \times 10^{-16}$
$s(GDP)$	8.222	8.805	4.242	5.83×10^{-5}
$s(Inflation)$	1.000	1.000	0.322	0.570950
$s(GDP_crise)$	1.000	1.000	6.078	0.014676
$s(Inflation_crise)$	2.715	3.341	1.117	0.323679

Table 3: Approximate Significance of Smooth Terms in the GAM Non-Crisis Model

We will analyze the relationship between the Z-Score and the various independent variables. (See appendix for graphical illustrations : section B)

- Tier 1 to risk-weighted assets

Since the p-value is not significant, we conclude that tier 1 to risk-weighted assets has no clear, non-linear relationship with Z in the data we were able to observe.

Still, we observe a high EDF (effective degree of freedom), suggesting that the relationship between the two variables is non-linear. However, this relationship remains statistically insignificant for our analyses.

- Non-performing loans ratio

We find that the non-performing loan ratio and the financial stability measure have a highly significant relationship. Since the EDF is very high, we also observe that this relationship is not linear.

We can therefore say that the effects of non-performing loans on financial stability are not constant. They vary according to the level of financial stability. And, given their very high p-value, this also means that changes in non-performing loans are strongly associated with changes in financial stability (of Z). So this relationship reveals complex dynamics with important implications for risk management and regulatory policy.

- Return on Assets

The relationship between ROA and financial stability (Z) is significant and easier to interpret. The EDF indicates a non-linear relationship. And the p-value tells us that ROA is strongly linked to financial stability. In short, ROA will have a significant impact on financial stability, so good asset management will be reflected in ROA, which in turn will be reflected in the Z-score.

- Liquidity Coverage Ratio

We observe that the relationship between the liquidity coverage ratio and the Z-Score is highly significant, implying that a change in the LVR will be very strongly associated with a change in financial stability.

This is why effective management of this ratio is essential to ensure financial resilience, and the level of LVR must remain optimal to remain stable in the face of possible financial shocks.

The EDF of this ratio is very high, indicating a complex relationship. Indeed, as the LVR level changes, the impact on financial stability may vary.

- Interest Coverage Ratio

The impact of the interest coverage ratio on financial health is highly significant, due to its p-value. This indicates that it plays a crucial role in assessing financial stability.

However, the EDF is not as high as for other variables, which may mean that there are non-linear interactions within the relationship that influence financial stability, but they are not as complex as for the Liquidity Coverage Ratio, for example.

- Gross Domestic Product

The high statistical significance proves that GDP is a key indicator for assessing financial stability.

Variations within it have a significant and measurable impact on financial stability.

What's more, the EDF indicates a fairly complex relationship. It's a relationship that can involve non-proportional effects as well as complex variations.

- Inflation

The relationship between inflation and financial stability is not significant, meaning that there is no evidence that inflation has a measurable effect on financial stability. Furthermore, the EDF indicates a linear relationship between the two variables.

- Gross Domestic Product * Crise

The results indicate that GDP growth during a crisis is a factor to watch, as it can influence financial stability in a predictable and proportional way since their relationship is linear.

- Inflation * Crise

The relationship between inflation during a crisis and financial stability is statistically non-significant and indicates a non-linear relation.

Crisis Model

Variable	EDF	Ref.df	F-value	p-value
$s(\text{Tier1Crisis})$	1.000	1.000	1.176	0.279458
$s(\text{NPLCrisis})$	1.000	1.000	2.841	0.093474
$s(\text{ROACrisis})$	1.326	1.547	0.150	0.733810
$s(\text{LVRCrisis})$	7.062	8.028	4.011	1.96×10^{-4}
$s(\text{ICRCrisis})$	3.424	4.260	4.273	0.001413
$s(\text{GDP_crisis})$	1.000	1.000	5.673	0.018172
$s(\text{Inflation_crisis})$	1.000	1.000	1.052	0.306340

Table 4: Approximate Significance of Smooth Terms in the GAM Model for Crisis Data

Comparison : significant variables

Non-Crisis Model

- Liquidity Coverage Ratio (LVR)
- Non-Performing Loans Ratio (NPL)
- Return on Assets (ROA)
- Gross Domestic Product (GDP)
- Interest Coverage Ratio (ICR)
- Inflation * Crisis
- GDP * Crisis

Crisis Model

- Liquidity Coverage Ratio * Crisis (LVRcrisis)
- Interest Coverage Ratio * Crisis (ICRCrisis)
- Gross Domestic Product * Crisis (GDPcrisis)
- Non-Performing Loans * Crisis (NPLCrisis)
- Return on Assets * Crisis (ROACrisis)
- Inflation * Crisis (Inflationcrisis)

In short, we see similarities between our two models. The three most significant ratios in terms of impact on financial stability are: Liquidity Coverage Ratio (LVR), Non-Performing Loans Ratio (NPL), and Gross Domestic Product (GDP) in the Non-Crisis Model.

However, we find significant differences in the EDF, which interprets the linearity of our variables. For some variables, such as Tier 1 and ROA, this may be due to the multicollinearity present in our model.

Nevertheless, the results obtained for LVR are very similar across both models, which can be concluded as the fact that this variable does, indeed, even in times of crisis, tend to have a more complex relationship than the others.

Despite this, we can see a higher EDF for LVR in times of crisis, indicating that this indicator will be more to watch than the others in times of crisis.

6.3 Results

Our non-crisis model indicates that several indicators are effective tools for assessing financial stability:

Liquidity Coverage Ratio (LVR) has a complex non-linear relationship with Z-Score, suggesting that liquidity adjustments can have a significant impact on bank resilience.

Gross Domestic Product (GDP) shows a significant and slightly non-linear relationship, suggesting that GDP contributes positively to financial stability.

Finally, Non-Performing Loans Ratio (NPL) shows a significant and highly non-linear relationship, underlining its importance in risk management and assessing an institution's financial health.

Our crisis model shows a sharp decline in the explanatory power of FSIs. With an adjusted R-squared of just 21.2%, we see that FSIs lose predictivity during crises. However, a few features are worth noting:

As mentioned above, the multicollinearity of the crisis model indicates that the variables interact with each other in complex ways, making the analysis of the individual effects of FSIs on financial stability more complex, which in turn makes the results less reliable and difficult to interpret.

In short, in times of crisis, FSIs are no longer as effective in assessing bank financial stability. However, some indicators remain relevant, but the increased complexity and multicollinearity governing them indicate that they are no longer sufficient to explain financial stability.

7 ARIMA Forecasts

In this section, we aim to forecast financial stability indicators (FSIs) during periods of economic crisis using ARIMA models.

This is an essential analysis in order to answer our research question and understand how FSIs such as the TIER1 ratio, non-performing loans (NPLs), return on assets (ROA), liquidity coverage ratio (LVR) and interest coverage ratio (ICR) behave during major crises such as the three we have chosen to analyze. Understanding how these indicators react in times of crisis is crucial to assessing the financial stability of banks.

ARIMA models are designed to analyze and forecast time series by capturing past trends and cycles, and are then applied to FSIs to forecast future periods. ARIMA is able to capture trends and cycles in historical data, making it useful for forecasting financial variables that exhibit

recurring temporal patterns. By applying these models to FSI data, we seek to identify patterns in FSI variations and extrapolate these patterns to make forecasts for future periods.

As FSIs can fluctuate significantly during crises, the challenge is to be able to forecast these variations in order to manage risk. FSI forecasts can provide valuable insights into banks' resilience to economic shocks, enabling better preparation and more effective response.

The use of ARIMA models to generate these forecasts is based on the idea that past trends and cycles in financial data can offer clues to future developments. By applying these models to the FSIs time series for each country, we aim to anticipate fluctuations in indicators during crises, which can help identify early signs of financial deterioration or increased stability.

The process begins by extracting and modeling the FSIs time series for each country we have decided to analyze. The ARIMA models are then fitted to these series to generate short-term forecasts, over 5 years in our case. We analyze the quality of our forecasts by analyzing forecast errors, which are calculated by comparing forecasts with actual observed values, enabling us to assess the accuracy of the ARIMA models and their ability to capture variations in FSIs during crises.

This provides valuable insights into how FSIs behave during economic crises, and helps improve forecasting tools to better anticipate future variations in banks' financial stability.

7.1 Forecasts

We will now analyze the forecasts by indicator. We'll start with TIER1 (see appendix table 5).

7.1.1 TIER1

We'd just like to point out that we didn't have enough data collected for Germany to make any relevant forecasts.

Let's take a look at the different trends in this indicator by country. Argentina shows a continuous upward trend in the TIER1 ratio, ending up with 44.92 in 2027. Confidence intervals are becoming wider and wider, leading to growing uncertainty in long-term forecasts.

A few countries are showing fairly stable forecasts, notably Brazil and Canada. Also China and

Korea.

For India, forecasts are relatively stable, and we also note tighter confidence intervals, indicating a gradual reduction in uncertainty.

On the other hand, although Spain and South Africa show a slight upward trend, we also note improved predictability thanks to narrower confidence intervals. The same is true of the USA, where forecasts have fallen slightly.

Conversely, Greece shows stable forecasts, but with a significant variation in confidence intervals, indicating increased uncertainty, and we note the same trends in Nigeria.

The United Kingdom shows an upward trend, with fairly stable confidence intervals.

7.1.2 NPL

For the non-performing loans indicator, we see a similar trend for Argentina. The indicator is improving, with a downward trend and stable values over the years, but despite this the confidence intervals are widening. This indicates that, although forecasts are stable, there is considerable uncertainty which needs to be monitored. We observe the same trend for Brazil, the USA and the UK, with stable rates and widening confidence intervals. (See appendix : table 6)

For China, we see a stable progression in indicators and a very slight increase in confidence intervals, suggesting financial stability with a slight expected volatility.

In India, we note a fairly stable but very high rate (4.81%). What's more, the confidence intervals are relatively wide, demonstrating the volatility that creates uncertainty. For Greece, we see the same problems. Indeed the confidence intervals are negative and even wider, leading us to conclude that the Greek banking system is not very resilient to potential crises.

For Germany, we can see stability in both rates and ranges, suggesting relative stability. We have the same conclusion for Korea: the rates are stable and fairly low, and the confidence intervals are getting closer and closer, indicating a reliable forecast.

In Spain, the NPL rate rises until 2024, but then stabilizes. However, we observe constant confidence intervals once the rate has stabilized, which leads us to conclude that forecasts are fairly stable, but that asset quality is uncertain.

For South Africa, both rates and intervals are trending downwards, indicating improved loan management and growing confidence in financial stability.

In Nigeria, NPL rates are very high (9.73%), albeit constant. Intervals are similarly wide and

constant, indicating a high degree of uncertainty and potential risk.

7.1.3 ROA

In terms of ROA , we note a stable trend for Argentina, Canada, China, Spain and South Africa. This indicates that these countries are managing to maintain a certain balance in their asset management.(See appendix : table 7)

While the USA, Germany and South Korea show a slight improvement in ROA, reflecting good resource management.

However, for India, the UK and Brazil, we note a downward trend. This suggests either economic challenges or necessary economic adjustments.

On the other hand, we note very wide confidence intervals for Greece and Nigeria, reflecting a high degree of economic uncertainty.

Even if the indicator is fairly stable for Nigeria, widening confidence intervals show only instability.

7.1.4 Liquidity Coverage Ratio

In terms of the liquidity coverage ratio, we see stable forecasts for China, Spain, Korea and Nigeria. (See appendix : table 8)

On the other hand, we see a downward trend for Canada, the UK, India, Brazil and South Africa. As for the other indicators, Greece and Nigeria show very wide confidence intervals, indicating a degree of uncertainty.

On the other hand, the ratio for the United States is trending upwards.

Argentina's ratio is fairly stable, but with wide confidence intervals, indicating forecast uncertainty.

We didn't have enough data on Germany's ratio to make any forecasts.

7.1.5 ICR

Finally, for our last indicator, we first note the same trends for Argentina. Argentina's ICR remains constant over the five years, but the confidence intervals are widening, demonstrating growing uncertainty. The same applies to Spain.(See appendix : table 9)

Brazil has a fairly stable ratio trend, but is also experiencing an increase in the uncertainty that goes with it. Canada is experiencing the same trend, as is Germany.

South Africa remains stable in terms of its confidence interval, with a slight increase in the indicator. The same applies to Nigeria.

In the same vein, Greece has a high but stable ICR, with a very high risk of volatility, reflecting uncertainty about financial stability.

China, on the other hand, has a very high ratio associated with very little uncertainty about its forecasts. The same applies to India.

Korea also has a very good ratio, but on the other hand, it also has growing uncertainty, rising from 17.25 in 2023 to 38.57 in 2027.

The United States, on the other hand, remains fairly constant in terms of its ratio, despite a slight decline in 2023, and has a fairly low confidence interval, which is a good sign.

The UK is experiencing an upward trend in the ICR ratio, with a fairly constant confidence interval. However, we note that the UK's ICR ratio is lower than the other major economies.

7.2 Means errors

In order to measure the quality of our forecasting results, we will now analyze the error parameters obtained for each FSI analyzed. (See appendix : table 10)

We have also calculated the mean errors of each indicator for each country. For reasons of clarity, we will not analyze them, but we have indicated them (for information purposes) in our appendices. (See tables 11 to 23)

7.2.1 TIER 1

In order to measure the quality of our forecasting results, we will now analyze the error parameters obtained for each FSI analyzed.

First, for TIER1, we have a positive mean error of 0.1223, indicating a tendency to overestimate forecasts.

We also find a high RMSE (root mean square error) and MAE (mean absolute error), indicating significant variability in forecast errors for this indicator.

The absence of data for the other indicators is due to the lack of data for Germany, which biases the analysis.

7.2.2 NPL

The average error for the ratio of non-performing loans is negative, indicating a tendency to underestimate results. With a fairly high MAPE, this indicates large relative errors in forecasts.

The ACF1 (autocorrelation of errors at one lag) close to 0 indicates a lack of correlation between forecast errors.

7.2.3 ROA

Return on assets also shows a negative mean error, and therefore a tendency to underestimate forecasts. In addition, the high MAPE indicates forecast inaccuracy.

7.2.4 Liquidity Coverage Ratio

The liquidity coverage ratio shows a positive mean error, indicating a tendency to overestimate. Lack of data prevents calculation of other statistics.

7.2.5 ICR

The ICR also shows a tendency to underestimate, but only slightly. But the high RMSE and MAE indicate a lot of variability and significant errors.

8 Limitations

The first limitation we faced during our analysis was the lack of data. Indeed, the publication of FSIs for each country is not systematic.

For Germany, for example, we lacked a great deal of data. This considerably biases our results. As mentioned earlier, in order to carry out a global geographical analysis, we wanted to include Japan in our analysis, but this was not possible as the country does not publish its FSIs.

We must also bear in mind that certain ratios were introduced after the global financial crisis, under the Basel III accords, which were published in 2010 and implemented between 2012 and 2019.

This limitation led to the next one, which is our time frame. We have chosen to take data from 2005 to 2022, incorporating only three financial crises. Due to the late introduction of the FSIs and the publication of these reports, data was not available prior to this. This considerably reduces the scope of our analysis.

One of the limits we had to face was the shape of our database. First of all, we wanted to

forecast using the VAR model, but this required our data to be stationary, and despite numerous attempts, we were unable to make them stationary. We were also afraid that modifying them too much would skew our results. We therefore opted for the ARIMA model, although it was less suited to our analysis.

We also created a bias by introducing only five FSIs into our model, and two macroeconomic variables. We could have chosen to introduce more, but this was becoming impractical due to the scarcity of data.

9 Conclusion

The assessment of the applicability of financial stability indicators in analyzing the financial stability of banks during crises has revealed significant results. Our analytical models, using an additive generalized regression (GAM) model, were able to highlight complex linear relationships between FSIs, macroeconomic variables and financial stability.

In the no-crisis model, several indicators - such as the liquidity coverage ratio, GDP and NPL - demonstrated a robust ability to explain financial stability, highlighting their importance in risk management and bank resilience. On the other hand, our crisis model showed a marked decline in the explanatory capacity of FSIs, with an adjusted R-squared of just 22.8%, leading us to conclude that these indicators lose their predictability during crises.

As for our forecasts, we are aware of the biases they may contain. It should be noted that FSIs are indicators based on the past.

Nevertheless, our analysis allows us to conclude that the predictive performance of FSIs is significantly impacted by unstable market conditions. We have noted a high degree of uncertainty in our indicators.

However, the presence of multicollinearity in our crisis model complicated our analysis, making it difficult to interpret the individual effects of FSIs on financial stability. Nevertheless, we note that some indicators, such as the LVR, remain relevant even in times of crisis, while their relationship with financial stability (Z-Score) becomes more volatile and less predictable.

In conclusion, although FSIs are essential tools for assessing financial stability in normal times. According to our analysis, their effectiveness is compromised in times of crisis. However, our results also indicate the importance of incorporating more variables into this analysis in order to achieve a more comprehensive and accurate assessment of financial stability in times of crisis.

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Appendix

A Financial Stability

A.1 FSIs

Table 1	
Financial soundness indicators: the core and encouraged sets	
Core Set	
Deposit takers	
<i>Capital adequacy</i>	Regulatory capital to risk-weighted assets Regulatory Tier 1 capital to risk-weighted assets Non-performing loans net of provisions to capital
<i>Asset quality</i>	Non-performing loans to total gross loans Sectoral distribution of loans to total loans
<i>Earnings and profitability</i>	Return on assets Return on equity Interest margin to gross income Non-interest expenses to gross income
<i>Liquidity</i>	Liquid assets to total assets Liquid assets to short-term liabilities
<i>Sensitivity to market risk</i>	Net open position in foreign exchange to capital
Encouraged set	
Deposit takers	Capital to assets Large exposures to capital Geographical distribution of loans to total loans Gross asset position in financial derivatives to capital Gross liability position in financial derivatives to capital Trading income to total income Personnel expenses to non-interest expenses Spread between reference lending and deposit rates Spread between highest and lowest interbank rate Customer deposits to total (non-interbank) loans Foreign currency denominated loans to total loans Foreign currency denominated liabilities to total liabilities Net open position in equities to capital
Other financial corporations	OFCs' financial assets to total financial assets OFCs' financial assets to GDP
Non-financial corporations sector	Total debt to equity Return on equity Earnings to interest and principal expenses Net foreign exchange exposure to equity Number of applications for protection from creditors
Households	Household debt to GDP Household debt service and principal payments to income
Market liquidity	Average bid-ask spread in the securities market ¹ Average daily turnover ratio in the securities market ¹
Real estate markets	Residential real estate prices Commercial real estate prices Residential real estate loans to total loans Commercial real estate loans to total loans

¹ Or in other markets that are most relevant to bank liquidity, such as foreign exchange markets.

Figure A.1: Core and encouraged set

B GAM

B.1 Non-Crisis Model

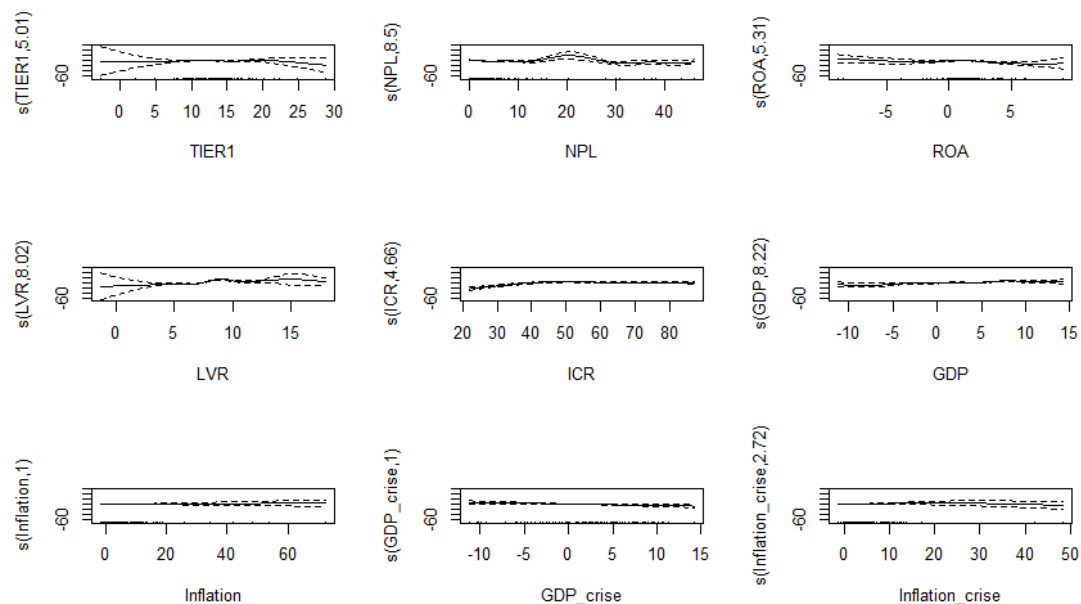


Figure B.1: Smoothing Functions for Independent Variables in the GAM Non-Crisis Model

B.2 Crisis Model

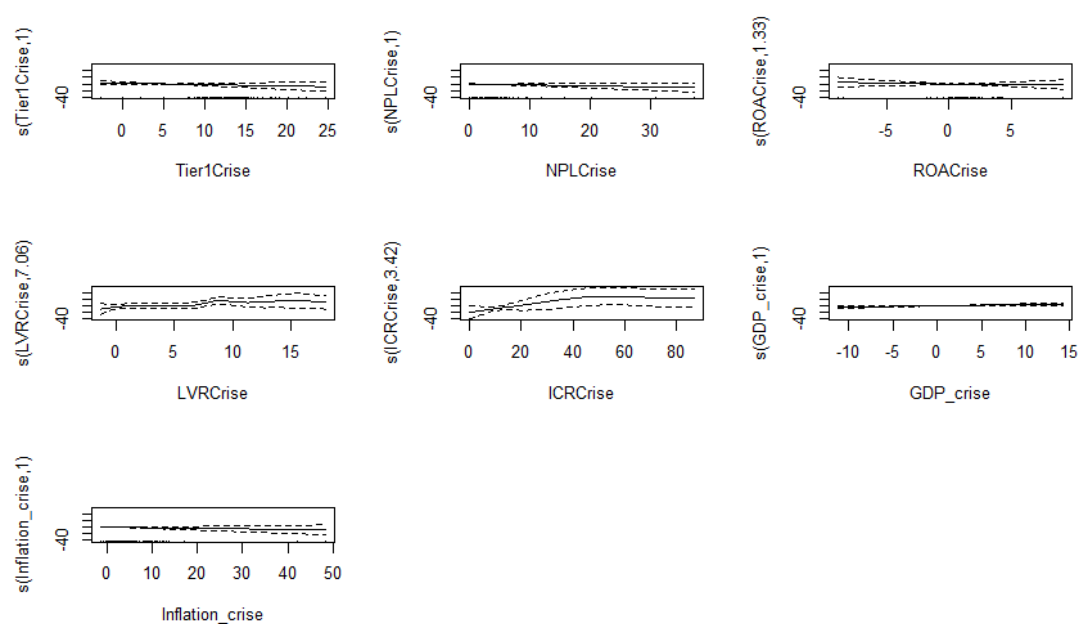


Figure B.2: Smoothing Functions for Independent Variables in the GAM Crisis Model

C ARIMA

C.1 Forecast

C.1.1 TIER 1

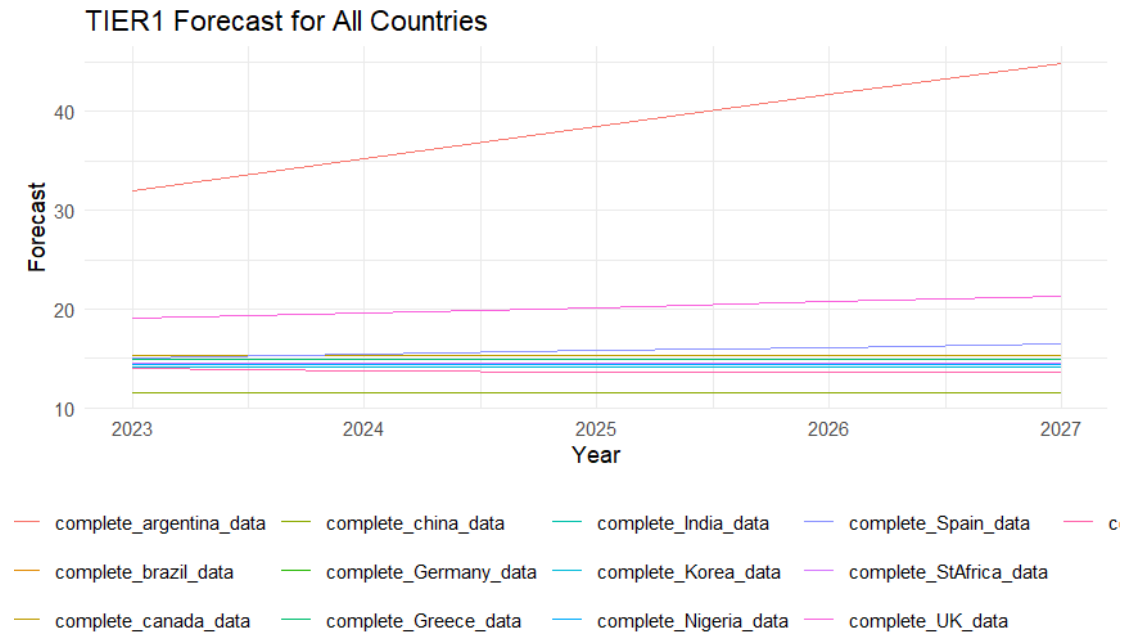


Figure C.1: Forecasts for TIER1 Indicator for Various Countries

Table 5: Forecasts for TIER1 Indicator for Various Countries

Country	Year	Point Forecast	Lo 80	Hi 80
Argentina	2023	32.02890	29.25320	34.80460
	2024	35.25171	30.53493	39.96850
	2025	38.47452	31.70805	45.24100
	2026	41.69733	32.72680	50.66787
	2027	44.92015	33.58621	56.25409
Brazil	2023	15.33044	14.25871	16.40217
	2024	15.33044	13.81479	16.84609
	2025	15.33044	13.47415	17.18673

Country	Year	Point Forecast	Lo 80	Hi 80
	2026	15.33044	13.18698	17.47390
	2027	15.33044	12.93398	17.72690
Canada	2023	15.34934	14.19702	16.50167
	2024	15.34934	13.71971	16.97898
	2025	15.34934	13.35346	17.34523
	2026	15.34934	13.04469	17.65400
	2027	15.34934	12.77266	17.92603
China	2023	11.58421	10.99796	12.17046
	2024	11.58421	10.75513	12.41329
	2025	11.58421	10.56880	12.59962
	2026	11.58421	10.41172	12.75670
	2027	11.58421	10.27333	12.89509
India	2023	14.37028	12.34064	16.39991
	2024	14.37028	11.49994	17.24062
	2025	14.37028	10.85484	17.88571
	2026	14.37028	10.31100	18.42955
	2027	14.37028	9.83187	18.90868
Greece	2023	14.97586	8.56954	21.38218
	2024	14.97586	5.91596	24.03576
	2025	14.97586	3.87980	26.07193
	2026	14.97586	2.16323	27.78849
	2027	14.97586	0.65090	29.30082

Country	Year	Point Forecast	Lo 80	Hi 80
Germany	2023	NA	NA	NA
	2024	NA	NA	NA
	2025	NA	NA	NA
	2026	NA	NA	NA
	2027	NA	NA	NA
USA	2023	14.03580	12.97703	15.09458
	2024	13.78925	12.59912	14.97939
	2025	13.66269	12.44029	14.88509
	2026	13.59772	12.36695	14.82848
	2027	13.56436	12.33140	14.79732
UK	2023	19.05964	17.33240	20.78688
	2024	19.62367	17.18098	22.06636
	2025	20.18770	17.19603	23.17937
	2026	20.75173	17.29725	24.20621
	2027	21.31576	17.45353	25.17799
Spain	2023	15.00263	14.20283	15.80242
	2024	15.38497	14.25389	16.51605
	2025	15.76732	14.38203	17.15260
	2026	16.14966	14.55007	17.74925
	2027	16.53201	14.74361	18.32040

Country	Year	Point Forecast	Lo 80	Hi 80
South Africa	2023	14.51123	13.05100	15.97147
	2024	14.51123	12.44615	16.57632
	2025	14.51123	11.98203	17.04044
	2026	14.51123	11.59076	17.43171
	2027	14.51123	11.24604	17.77642
Korea	2023	14.12046	13.36771	14.87321
	2024	14.12046	13.05591	15.18501
	2025	14.12046	12.81666	15.42427
	2026	14.12046	12.61496	15.62597
	2027	14.12046	12.43726	15.80367
Nigeria	2023	14.45567	8.28619	20.62516
	2024	14.45567	8.28619	20.62516
	2025	14.45567	8.28619	20.62516
	2026	14.45567	8.28619	20.62516
	2027	14.45567	8.28619	20.62516

C.1.2 NPL

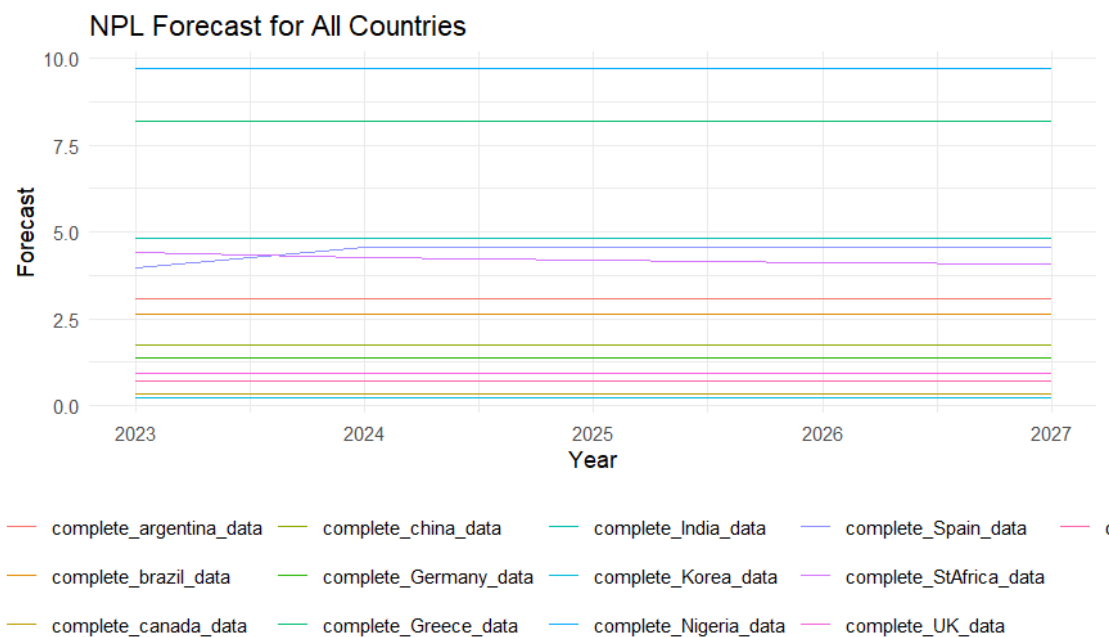


Figure C.2: Forecasts for NPL Indicator for Various Countries

Table 6: Forecasts for NPL Indicator for Various Countries

Country	Year	Point Forecast	Lo 80	Hi 80
Argentina	2023	3.082099	1.770029	4.394168
	2024	3.073839	1.477291	4.670387
	2025	3.068112	1.351526	4.784698
	2026	3.064142	1.292752	4.835531
	2027	3.061389	1.264253	4.858525
Brazil	2023	2.641233	1.942014	3.340453
	2024	2.641233	1.652387	3.630079
	2025	2.641233	1.430149	3.852317
	2026	2.641233	1.242794	4.039672
	2027	2.641233	1.077731	4.204736
Canada	2023	0.3426102	0.102123380	0.5830970

Country	Year	Point Forecast	Lo 80	Hi 80
	2024	0.3426102	0.002510475	0.6827099
	2025	0.3426102	-0.073925195	0.7591456
	2026	0.3426102	-0.138363445	0.8235839
	2027	0.3426102	-0.195134684	0.8803551
China	2023	1.744355	1.543977	1.944733
	2024	1.744355	1.460977	2.027732
	2025	1.744355	1.397290	2.091419
	2026	1.744355	1.343599	2.145110
	2027	1.744355	1.296296	2.192413
India	2023	4.811885	2.68159230	6.942177
	2024	4.811885	1.79919637	7.824573
	2025	4.811885	1.12211015	8.501659
	2026	4.811885	0.55130007	9.072469
	2027	4.811885	0.04840629	9.575363
Greece	2023	8.17432	-3.564607	19.91325
	2024	8.17432	-8.427030	24.77567
	2025	8.17432	-12.158098	28.50674
	2026	8.17432	-15.303534	31.65217
	2027	8.17432	-18.074719	34.42336
Germany	2023	1.360459	0.66361546	2.057302
	2024	1.360459	0.37497344	2.345944
	2025	1.360459	0.15349062	2.567427
	2026	1.360459	-0.03322803	2.754146
	2027	1.360459	-0.19773047	2.918648
USA	2023	0.7160736	-0.3887481	1.820895

Country	Year	Point Forecast	Lo 80	Hi 80
	2024	0.7160736	-0.8463802	2.278527
	2025	0.7160736	-1.1975337	2.629681
	2026	0.7160736	-1.4935698	2.925717
	2027	0.7160736	-1.7543828	3.186530
UK	2023	0.9470246	-0.3414303	2.235479
	2024	0.9470246	-0.8751257	2.769175
	2025	0.9470246	-1.2846446	3.178694
	2026	0.9470246	-1.6298851	3.523934
	2027	0.9470246	-1.9340480	3.828097
Spain	2023	3.967128	2.034177	5.900079
	2024	4.557779	2.250308	6.865249
	2025	4.557779	2.250308	6.865249
	2026	4.557779	2.250308	6.865249
	2027	4.557779	2.250308	6.865249
South Africa	2023	4.430230	3.462940	5.397519
	2024	4.276353	3.141298	5.411409
	2025	4.181878	2.989693	5.374063
	2026	4.123873	2.910850	5.336895
	2027	4.088259	2.867474	5.309045
Korea	2023	0.2421666	0.15585153	0.3284817
	2024	0.2421666	0.12009866	0.3642345
	2025	0.2421666	0.09266452	0.3916687
	2026	0.2421666	0.06953646	0.4147967
	2027	0.2421666	0.04916024	0.4351730
Nigeria	2023	9.727927	-0.9136759	20.36953

Country	Year	Point Forecast	Lo 80	Hi 80
	2024	9.727927	-0.9136759	20.36953
	2025	9.727927	-0.9136759	20.36953
	2026	9.727927	-0.9136759	20.36953
	2027	9.727927	-0.9136759	20.36953

C.1.3 ROA

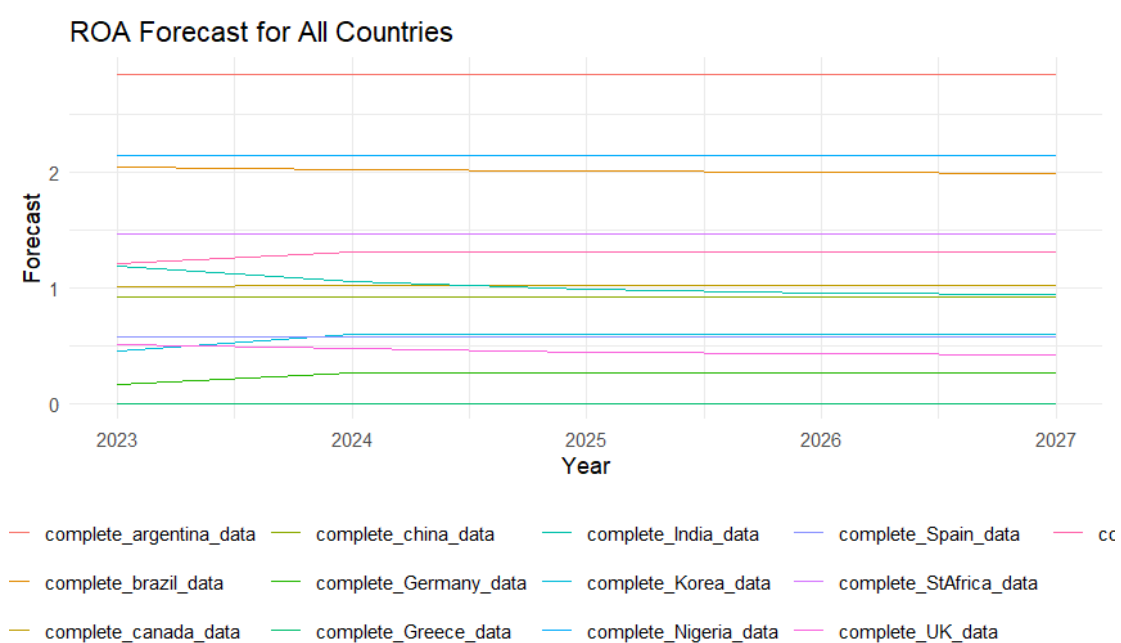


Figure C.3: Forecasts for ROA Indicator for Various Countries

Table 7: ROA Forecasts

Country	Year	Point Forecast	Lo 80	Hi 80
Argentina	2023	2.845893	1.43852625	4.253260
	2024	2.845893	0.85557571	4.836211
	2025	2.845893	0.40826203	5.283525
	2026	2.845893	0.03115916	5.660628
	2027	2.845893	-0.30107515	5.992862

Country	Year	Point Forecast	Lo 80	Hi 80
Brazil	2023	2.042357	1.662749	2.421965
	2024	2.020675	1.558716	2.482634
	2025	2.005638	1.508912	2.502365
	2026	1.995211	1.482602	2.507819
	2027	1.987979	1.467905	2.508053
Canada	2023	1.009424	0.8062080	1.212641
	2024	1.018835	0.7750133	1.262657
	2025	1.018835	0.7750133	1.262657
	2026	1.018835	0.7750133	1.262657
	2027	1.018835	0.7750133	1.262657
China	2023	0.9235361	0.8118699	1.035202
	2024	0.9235361	0.7656162	1.081456
	2025	0.9235361	0.7301246	1.116948
	2026	0.9235361	0.7002037	1.146869
	2027	0.9235361	0.6738429	1.173229
India	2023	1.1869790	0.7349097	1.639048
	2024	1.0532059	0.5475858	1.558826
	2025	0.9861929	0.4680023	1.504383
	2026	0.9526230	0.4313255	1.473921
	2027	0.9358064	0.4137321	1.457881

Country	Year	Point Forecast	Lo 80	Hi 80
Greece	2023	0	-3.003163	3.003163
	2024	0	-3.003163	3.003163
	2025	0	-3.003163	3.003163
	2026	0	-3.003163	3.003163
	2027	0	-3.003163	3.003163
Germany	2023	0.1643094	-0.09266727	0.4212861
	2024	0.2651397	-0.02700738	0.5572868
	2025	0.2651397	-0.02700738	0.5572868
	2026	0.2651397	-0.02700738	0.5572868
	2027	0.2651397	-0.02700738	0.5572868
USA	2023	1.205621	0.7980075	1.613235
	2024	1.306101	0.8417123	1.770490
	2025	1.306101	0.8417123	1.770490
	2026	1.306101	0.8417123	1.770490
	2027	1.306101	0.8417123	1.770490
UK	2023	0.5015154	0.200474714	0.8025562
	2024	0.4681022	0.102559372	0.8336450
	2025	0.4450873	0.052633006	0.8375417
	2026	0.4292349	0.024638335	0.8338314
	2027	0.4183158	0.008084246	0.8285474
Spain	2023	0.5741052	-0.01315878	1.161369
	2024	0.5741052	-0.01315878	1.161369

Country	Year	Point Forecast	Lo 80	Hi 80
	2025	0.5741052	-0.01315878	1.161369
	2026	0.5741052	-0.01315878	1.161369
	2027	0.5741052	-0.01315878	1.161369
South Africa	2023	1.467591	1.141424	1.793758
	2024	1.467591	1.141424	1.793758
	2025	1.467591	1.141424	1.793758
	2026	1.467591	1.141424	1.793758
	2027	1.467591	1.141424	1.793758
Korea	2023	0.4531177	0.2513646	0.6548707
	2024	0.5964896	0.3544793	0.8384998
	2025	0.5964896	0.3544793	0.8384998
	2026	0.5964896	0.3544793	0.8384998
	2027	0.5964896	0.3544793	0.8384998
Nigeria	2023	2.145638	-2.120293	6.411569
	2024	2.145638	-2.120293	6.411569
	2025	2.145638	-2.120293	6.411569
	2026	2.145638	-2.120293	6.411569
	2027	2.145638	-2.120293	6.411569

C.1.4 Liquidity Coverage Ratio

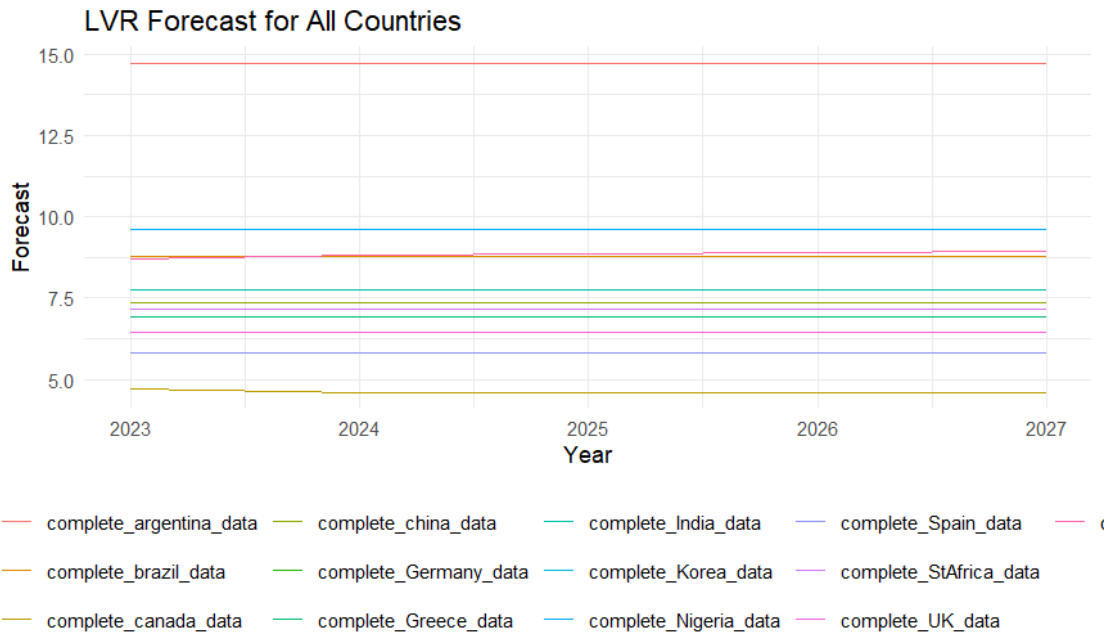


Figure C.4: Forecasts for LVR Indicator for Various Countries

Table 8: LVR Forecasts

Country	Year	Point Forecast	Lo 80	Hi 80
Argentina	2023	14.73519	13.11159	16.35879
	2024	14.73519	12.43908	17.03130
	2025	14.73519	11.92304	17.54734
	2026	14.73519	11.48800	17.98238
	2027	14.73519	11.10472	18.36566
Brazil	2023	8.762979	7.768878	9.75708
	2024	8.762979	7.357108	10.16885
	2025	8.762979	7.041146	10.48481
	2026	8.762979	6.774778	10.75118
	2027	8.762979	6.540102	10.98586

Country	Year	Point Forecast	Lo 80	Hi 80
Canada	2023	4.691338	4.432683	4.949993
	2024	4.604650	4.299815	4.909485
	2025	4.604650	4.299815	4.909485
	2026	4.604650	4.299815	4.909485
	2027	4.604650	4.299815	4.909485
China	2023	7.373235	6.928191	7.818279
	2024	7.373235	6.928191	7.818279
	2025	7.373235	6.928191	7.818279
	2026	7.373235	6.928191	7.818279
	2027	7.373235	6.928191	7.818279
India	2023	7.75638	6.838502	8.674257
	2024	7.75638	6.458305	9.054454
	2025	7.75638	6.166570	9.346189
	2026	7.75638	5.920625	9.592134
	2027	7.75638	5.703944	9.808815
Greece	2023	6.923333	3.49596104	10.35070
	2024	6.923333	2.07629714	11.77037
	2025	6.923333	0.98695071	12.85972
	2026	6.923333	0.06858919	13.77808
	2027	6.923333	-0.74050355	14.58717
Germany	2023	NA	NA	NA

Country	Year	Point Forecast	Lo 80	Hi 80
	2024	NA	NA	NA
	2025	NA	NA	NA
	2026	NA	NA	NA
	2027	NA	NA	NA
USA	2023	8.711970	8.390412	9.033527
	2024	8.806422	8.413089	9.199754
	2025	8.872958	8.448490	9.297426
	2026	8.919829	8.480729	9.358929
	2027	8.952847	8.506664	9.399030
UK	2023	6.459698	5.549984	7.369412
	2024	6.459698	5.173169	7.746228
	2025	6.459698	4.884028	8.035369
	2026	6.459698	4.640271	8.279126
	2027	6.459698	4.425516	8.493880
Spain	2023	5.82558	5.288566	6.362595
	2024	5.82558	5.288566	6.362595
	2025	5.82558	5.288566	6.362595
	2026	5.82558	5.288566	6.362595
	2027	5.82558	5.288566	6.362595
South Africa	2023	7.167614	6.391064	7.944164
	2024	7.167614	6.069406	8.265822
	2025	7.167614	5.822589	8.512639

Country	Year	Point Forecast	Lo 80	Hi 80
	2026	7.167614	5.614513	8.720715
	2027	7.167614	5.431194	8.904034
Korea	2023	7.146836	6.650485	7.643187
	2024	7.146836	6.650485	7.643187
	2025	7.146836	6.650485	7.643187
	2026	7.146836	6.650485	7.643187
	2027	7.146836	6.650485	7.643187
Nigeria	2023	9.624688	4.492767	14.75661
	2024	9.624688	4.492767	14.75661
	2025	9.624688	4.492767	14.75661
	2026	9.624688	4.492767	14.75661
	2027	9.624688	4.492767	14.75661

C.1.5 ICR

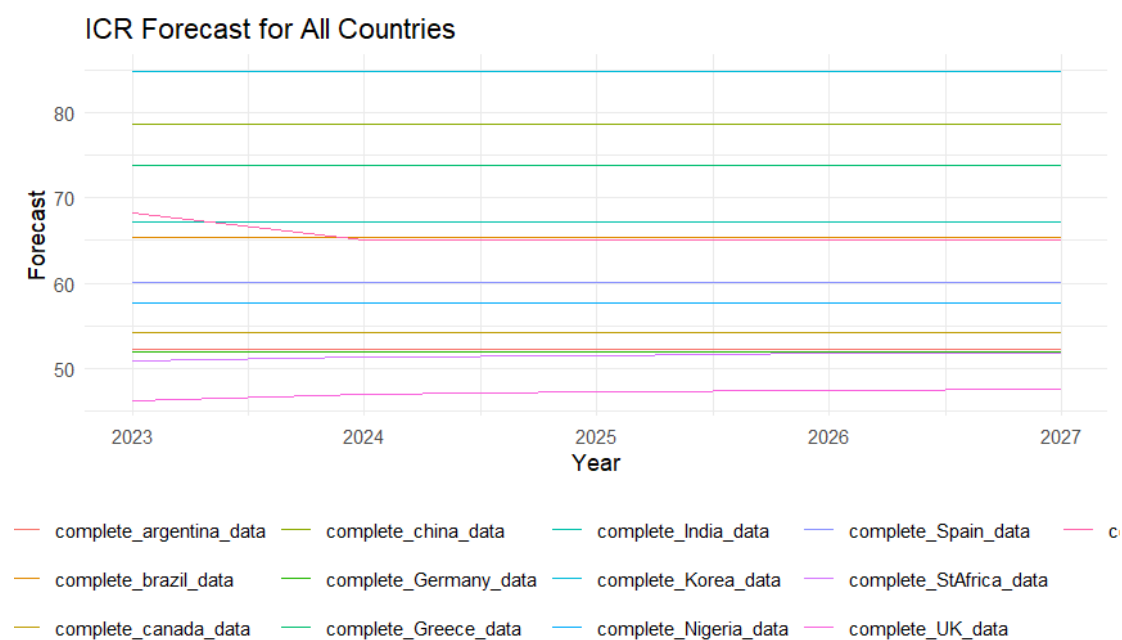


Figure C.5: Forecasts for ICR Indicator for Various Countries

Table 9: ICR Forecasts

Country	Year	Point Forecast	Lo 80	Hi 80
Argentina	2023	52.1541	43.11008	61.19812
	2024	52.1541	39.36393	64.94428
	2025	52.1541	36.48940	67.81881
	2026	52.1541	34.06606	70.24215
	2027	52.1541	31.93106	72.37715
Brazil	2023	65.38806	60.83912	69.93699
	2024	65.38806	58.95489	71.82122
	2025	65.38806	57.50907	73.26705
	2026	65.38806	56.29018	74.48593
	2027	65.38806	55.21632	75.55979

Country	Year	Point Forecast	Lo 80	Hi 80
Canada	2023	54.22215	49.40729	59.03701
	2024	54.22215	47.41290	61.03139
	2025	54.22215	45.88256	62.56174
	2026	54.22215	44.59242	63.85188
	2027	54.22215	43.45579	64.98851
China	2023	78.67086	76.28956	81.05216
	2024	78.67086	76.28956	81.05216
	2025	78.67086	76.28956	81.05216
	2026	78.67086	76.28956	81.05216
	2027	78.67086	76.28956	81.05216
India	2023	67.17315	62.62776	71.71855
	2024	67.17315	62.62776	71.71855
	2025	67.17315	62.62776	71.71855
	2026	67.17315	62.62776	71.71855
	2027	67.17315	62.62776	71.71855
Greece	2023	73.86166	58.67662	89.0467
	2024	73.86166	58.67662	89.0467
	2025	73.86166	58.67662	89.0467
	2026	73.86166	58.67662	89.0467
	2027	73.86166	58.67662	89.0467
Germany	2023	51.83506	44.48261	59.18751

Country	Year	Point Forecast	Lo 80	Hi 80
	2024	51.83506	41.43712	62.23300
	2025	51.83506	39.10024	64.56988
	2026	51.83506	37.13015	66.53997
	2027	51.83506	35.39447	68.27564
USA	2023	68.25349	65.55465	70.95233
	2024	65.02198	61.63096	68.41299
	2025	65.02198	61.63096	68.41299
	2026	65.02198	61.63096	68.41299
	2027	65.02198	61.63096	68.41299
UK	2023	46.21900	41.81445	50.62354
	2024	46.88902	41.90396	51.87407
	2025	47.24417	42.10781	52.38053
	2026	47.43242	42.25434	52.61050
	2027	47.53221	42.34247	52.72195
Spain	2023	60.1381	54.55903	65.71717
	2024	60.1381	52.24811	68.02809
	2025	60.1381	50.47487	69.80133
	2026	60.1381	48.97996	71.29623
	2027	60.1381	47.66292	72.61327
South Africa	2023	50.84163	48.36772	53.31554
	2024	51.22749	48.21020	54.24478
	2025	51.49691	48.24748	54.74633

Country	Year	Point Forecast	Lo 80	Hi 80
	2026	51.68503	48.32824	55.04181
	2027	51.81638	48.40848	55.22428
Korea	2023	84.9546	76.32929	93.57991
	2024	84.9546	72.75658	97.15263
	2025	84.9546	70.01513	99.89407
	2026	84.9546	67.70399	102.20521
	2027	84.9546	65.66783	104.24137
Nigeria	2023	57.72578	50.38878	65.06279
	2024	57.72578	50.38878	65.06279
	2025	57.72578	50.38878	65.06279
	2026	57.72578	50.38878	65.06279
	2027	57.72578	50.38878	65.06279

C.2 Interpreting Forecasts Results

C.2.1 Means errors for each FSIs

Table 10: Mean Errors for Each Financial Stability Indicator

Indicator	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
TIER1	0.1223	1.5000	1.0269	NaN	NaN	NaN	NA
NPL	-0.0557	1.9199	1.4245	-12.1212	27.6699	0.9488	0.0463
ROA	-0.0573	0.6956	0.4294	10.2304	79.5104	0.8025	0.0157
Liquidity Coverage Ratio	0.0465	0.9230	0.6952	NaN	NaN	NaN	NA
ICR	-0.0145	4.5910	3.3950	-0.4619	5.7405	0.9355	-0.0201

C.2.2 Means Errors for each country

1. Argentina

Table 11: Forecast Errors for Argentina

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Tier 1	0.4679	1.9772	1.3733	1.9805	8.8577	0.8501	-0.1874
NPL	-0.1149	0.9653	0.7516	-14.6318	28.2158	1.0329	-0.0234
ROA	0.4359	17.9703	15.1827	-1.5332	11.6272	0.8511	-0.0393
LVR	0.3053	1.2312	0.8898	1.8133	8.9103	0.9450	0.0444
ICR	1.5547	6.8583	5.1660	3.1378	11.8318	0.9447	-0.1289

2. Brazil

Table 12: Forecast Errors for Brazil

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Tier 1	0.0507	0.8127	0.6526	0.1712	4.6413	0.9456	0.1760
NPL	-0.0489	0.5302	0.4107	-3.2662	14.6995	0.9449	-0.3086
ROA	-0.0225	0.2793	0.2507	-3.4073	13.4532	0.9649	0.0521
LVR	-0.0692	0.7538	0.5109	-1.0550	5.4788	0.9455	-0.1580
ICR	-0.6346	3.4495	2.1626	-1.0106	3.0324	0.9463	-0.1892

3. Canada

Table 13: Forecast Errors for Canada

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Tier 1	0.2311	0.8738	0.6274	1.4832	5.1271	0.9454	0.0585
NPL	-0.0087	0.1824	0.1207	-4.9232	17.7148	0.9447	0.3767
ROA	0.0014	0.1495	0.1012	-3.0512	12.0066	0.6293	-0.0597
LVR	0.0020	0.1903	0.1506	-0.1347	3.3194	0.8365	-0.0260
ICR	0.4076	3.6512	1.9724	0.5788	3.6109	0.9457	-0.1974

4. China

Table 14: Forecast Errors for China

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Tier 1	0.0542	0.4446	0.3526	0.4031	3.2615	0.9460	-0.2871
NPL	0.0276	0.1520	0.0952	1.1243	7.4564	0.9451	0.2693
ROA	-0.0112	0.0847	0.0650	-1.4168	6.1809	0.9454	0.1382
LVR	-1.4803e-16	0.3375	0.2910	-0.2141	3.9953	1.0193	0.2760
ICR	-2.5264e-14	1.8058	1.5451	-0.0525	1.9636	1.0725	0.2597

5. India

Table 15: Forecast Errors for India

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Tier 1	0.2989	1.5391	0.9543	1.6629	8.4354	0.9449	-0.0491
NPL	0.0230	1.6154	1.3353	-5.2434	27.2498	0.9446	0.0697
ROA	-0.0071	0.3326	0.2630	-129.9974	152.6360	0.8973	0.0293
LVR	0.1407	0.6960	0.4916	1.6619	7.1797	0.9450	-0.2475
ICR	-1.1841e-15	3.4469	2.9361	-0.2695	4.4241	0.8220	0.1544

6. Greece

Table 16: Forecast Errors for Greece

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Tier 1	0.2209	4.8580	2.9983	37.5149	49.4198	0.9446	-0.3379
NPL	-0.2053	8.9019	6.8099	-23.7702	56.5552	0.9445	0.1621
ROA	-0.7705	2.3434	1.2928	100.0000	100.0000	0.6779	0.0739
LVR	0.1402	2.5990	1.8517	35.9986	54.1227	0.9446	-0.2028
ICR	-3.6712e-14	11.5151	9.1510	-3.1057	14.1225	0.7711	-0.0120

7. Germany

Table 17: Forecast Errors for Germany

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Tier 1	0	0	0	0	0	NaN	NA
NPL	-0.1492	0.5284	0.4063	-9.6102	20.3078	0.9450	-0.0277
ROA	-0.0025	0.1891	0.1182	2.0049	45.5784	0.6645	-0.0546
LVR	0	0	0	0	0	NaN	NA
ICR	-0.9116	5.5755	3.5073	-1.8643	5.1519	0.9455	-0.2553

8. USA

Table 18: Forecast Errors for USA

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Tier 1	0.0161	0.7789	0.5051	-0.2394	3.8334	1.0099	0.0417
NPL	-0.2037	0.8378	0.5730	-15.1940	26.6993	0.9448	0.0481
ROA	-0.0023	0.2999	0.2215	-20.8645	35.4622	0.8378	0.0519
LVR	-0.0183	0.2366	0.1873	-0.2734	2.0918	1.1171	0.2352
ICR	-0.0370	1.9855	1.6615	-0.1622	2.5675	0.9357	0.1198

9. UK

Table 19: Forecast Errors for UK

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Tier 1	0.0005	1.2707	0.9220	-0.2893	7.1849	0.7990	-0.3652
NPL	-0.0025	0.9771	0.6241	-10.0096	30.5873	0.9445	-0.3571
ROA	-0.0297	0.2215	0.1670	-97.9153	216.4657	1.0621	-0.0996
LVR	0.1248	0.6899	0.5173	1.2743	10.9754	0.9449	-0.3133
ICR	-0.0858	3.2403	2.8250	-0.6337	5.8717	0.9417	-0.0717

10. Spain

Table 20: Forecast Errors for Spain

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Tier 1	0.0004	0.5884	0.4057	-0.1953	3.7221	0.7364	-0.3431
NPL	-0.0407	1.4220	1.0939	-10.4716	26.8857	0.8621	-0.0875
ROA	-0.0000	0.4453	0.3001	320.7767	320.7767	0.7252	-0.0624
LVR	0.0000	0.4072	0.3133	-0.5694	5.7256	0.9735	0.2386
ICR	-0.3876	4.2307	2.6694	-0.8627	4.4991	0.9458	-0.4157

11. South Africa

Table 21: Forecast Errors for South Africa

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Tier 1	0.0804	1.1073	0.7932	0.2495	5.8301	0.9453	-0.3254
NPL	0.0179	0.7116	0.5679	-2.5608	14.0953	0.9421	0.2711
ROA	-0.0000	0.2473	0.1587	-4.6841	14.0428	0.7827	0.1781
LVR	-0.0211	0.5889	0.4387	-0.6951	6.4523	0.9453	-0.1254
ICR	-0.0988	1.8200	1.4792	-0.3210	2.8963	1.0573	0.2438

12. Korea

Table 22: Forecast Errors for Korea

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Tier 1	0.1692	0.5708	0.4283	1.2431	3.4675	0.9458	-0.2420
NPL	-0.0182	0.0655	0.0472	-5.8860	11.1347	0.9451	-0.1063
ROA	0.0045	0.1484	0.1209	-5.6449	21.8820	0.7055	-0.0671
LVR	-0.0000	0.3764	0.2701	-0.3065	3.9249	0.8589	0.1416
ICR	0.0047	6.5407	4.7747	-0.4085	6.8389	0.9454	0.0404

13. Nigeria

Table 23: Forecast Errors for Nigeria

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Tier 1	-0.0000	4.6784	3.3367	-36.9804	54.8243	0.9078	0.1922
NPL	-0.0000	8.0697	5.6826	-53.1332	78.1066	0.9936	0.3148
ROA	0.0000	3.2349	1.6936	-22.2169	70.0408	0.5960	-0.0992
LVR	-0.0000	3.8916	3.1256	-38.5694	61.0697	1.2167	0.3586
ICR	-0.0000	5.5638	4.2844	-1.0303	7.8162	0.8882	0.1903

Abstract :

Financial stability analysis is an important concept for maintaining global economic health and preventing financial crises. Financial stability indicators are essential tools for assessing bank resilience.

However, their effectiveness can vary according to economic conditions, particularly during periods of crisis.

The aim of this thesis is to understand the limits within which FSIs can assess the financial stability of banks during periods of crisis.

In addition, this thesis serves to evaluate the effectiveness of FSIs as tools for measuring the financial stability of banks during periods of crisis.

This study analyzes the limitations of financial variables in assessing financial stability during crises using a statistical Generalized Additive Model (GAM). The aim is to determine how these relationships may vary in times of crisis, and what impact they may have on financial stability.

The model distinguishes between crisis periods and normal periods to assess differential effects. The results indicate that variables such as the liquidity coverage ratio and the NPL ratio have a significant impact on financial stability, with clear non-linear relationships.

During crises, different financial ratios may show more complex effects, with a general decrease in the predictability of financial stability indicators.

Our study also highlights the difficulty of making forecasts with financial stability indicators, which are significantly impacted by market conditions and therefore by crises. They are also characterized by a high degree of uncertainty.

The results highlight the importance of adjusting risk management policies to specific economic conditions. Crisis periods modify the relationships between financial variables and stability, requiring special attention to maintain institutional resilience.

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