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Evaluating the Effectiveness of Early Warning Indicators: An Application of Receiver Operating Characteristic Curve Approach to Panel Data

Yusuf Yildirim*, Anirban Sanyal**

Abstract

Early warning indicators (EWIs) of banking crises should ideally be judged on how well they function in relation to the choice issue faced by macroprudential policymakers. However, the effectiveness of EWIs depends upon the strength of the predicting power, stability, and timeliness of the signal. Using a balanced panel of 6 countries' experience with banking and currency crises in recent times, this paper evaluates the effectiveness of EWIs using Receiver Operating Characteristics. Following the drivers of the banking crisis and currency crisis, the paper evaluates the effectiveness of aggregate credit growth, sectoral deployment of credit along and other macroeconomic indicators generally used as EWI. The paper observes that credit disbursements to non-financial sectors and the central government provides stable signals about systemic risks. Further debt service ratio, interbank rates and total reserves are also found to be useful in predicting these crises. Lastly, the effective EWIs are combined using shrinkage regression methods to evaluate the improvement of signal strength of the combination of EWIs. The predictive power of the combination of EWIs provides better signal strength in predicting the macroprudential crisis.

Keywords: EWIs; ROC; area under the curve; shrinkage regressions.

JEL classification: C40; G01; G21.

1. INTRODUCTION

Global financial instability has resulted from the 2007-2008 financial crisis that began in the USA. World trade considerably shrank, capital flows turned around, and liquidity dried up. Systematically, the shock that began in the US home market and intensified with Lehman Brothers' collapse had a detrimental effect on activity in the world's financial and economic sectors. As a result, it has become imperative for policymakers to recognize the risks and weaknesses that could result in systemic shocks to build their expertise in this area and implement policy at an early stage. Studies on early warning indicators and creating systemic indices have become more important in response to this demand. As a result, several policies

* Department of Economics, University of California, Santa Cruz, United States; e-mail: *yyildiri@ucsc.edu* (corresponding author).
** Department of Economics, University of California, Santa Cruz, United States; e-mail: *ansanyal@ucsc.edu*.

such as counter-cyclical capital buffers have been suggested in the literature and put into practice by macroprudential authorities since that crisis. Most of the proposals have centered on the initial detection of macro-financial imbalances via indicators of excessive credit growth, house price growth, and other vital variables, which are nowadays in depth observed by national authorities (Schularick & Taylor, 2012; Jordà *et al.*, 2015; Tölö *et al.*, 2018). The selection of early warning indicators (EWIs) is difficult, nevertheless. To speed up the time it takes for a policy to respond, EWIs should have the ability to predictably identify any systemic danger well in advance. Beyond the statistical prediction capability, there are a number of other requirements that EWIs must satisfy. To lower any policy cost, for instance, signals must be reliable and dependable. The interpretability of the EWIs and converting them into useful policy actions present yet another significant hurdle in this area.

This study adds to the empirical research on the early detection of financial stress indicators and the effectiveness of those indicators in crisis signaling. The paper uses Receiver Operating Characteristics (ROC) to provide a comprehensive evaluation of the signal strength of domestic and international EWIs of systemic risks in predicting crisis for six countries (Brazil, Russia, Hungary, Turkey, South Africa, and Italy), which recently experienced currency or banking crises and do not have data limitations. As far as we are aware, it is the first work to use the honorable technique of logistic regression with and without shrinkage to produce a linear combination of early warning indicators.

The signaling strategy has been the most popular way to gauge prediction performance in the early-warning model literature. According to this method, when an indicator rises beyond a predetermined threshold, a signal is sent. Then, the signals may be compared in terms of their capacity to generate accurate alerts (True Positive Rate, TPR, or ratio of these signals that accurately foresee the occurrences being studied), as well as the frequency of false alarms (False Positive Rate, FPR). This relates to the statistical ideas of Type I (not signaling a genuine event) and Type II (not indicating a true event) mistakes (issue a wrong positive signal). In this sense, a common metric of predictive performance is the signal-to-noise ratio, which is the TPR divided by FPR. The performance of a model will vary based on the chosen value for this metric, which necessitates the specification of a certain threshold. Additionally, the signal-to-noise ratio is often optimized at high thresholds, resulting in the issuance of few positive signals (Alessi & Detken, 2011). In light of this, the major benefit of the AUROC (Area Under the Receiver Operating Characteristics Curve) assessment is that it takes into consideration all potential threshold values. This metric is now often employed to evaluate classification models across a wide range of industries. One of the most important studies employing AUROC as a criterion for evaluating indicators for the categorization of recessions and expansions in the economics field is Berge and Jordà (2011) work. Several research on early warning signs of financial crises have adopted this metric as a standard (Detken *et al.*, 2014; Drehmann & Juselius, 2014; Giese *et al.*, 2014). For each probability threshold, AUROC specifically evaluates the relationship between the noise ratio (FPR) and the signal ratio (TPR). AUROC serves as a gauge for the likelihood that model predictions are accurate in this situation. It can range from 0.5 to 1, with a value of 1 denoting excellent prediction and a value of 0.5 denoting that the model is unable to outperform predictions made using a random assignment. In this study, AUROC is employed to evaluate how well local and international EWIs capture crisis and non-crisis periods.

The article concludes that loan disbursement to the central government and the private non-financial sector demonstrates a steady signal using local and international data. Both in absolute terms and scaled by GDP, the signal impacts of the credit variables may be seen. Additionally, the banks' credit distribution to private, non-financial industries looks to include strong indicators of systemic hazards. In addition to these, the debt service ratio seems to have a significant signal impact and to have a consistent trend across the forecast horizon. Finally, the total reserve is another encouraging indication that sends out clear signs as the crisis draws closer. Last but not least, the article finds that a linear combining of these EWIs increases signal strength even further.

The other sections of the study are structured as follows: Section 2 provides summaries of significant research on the creation of systemic risk indices and empirical studies on the identification of early warning indicators. Section 3 provides a description of the data sources. The approach is explained in Section 4, and Section 5 presents the empirical findings. The major findings in Section 6 are highlighted in the paper's conclusion.

2. LITERATURE REVIEW

This section provides an overview of the key theoretical research on the development of systemic risk indices as well as empirical works that evaluate the effectiveness of early warning indicators using various methodologies (e.g., signal approach, AUROC).

The Kansas City Financial Stress Index (KCFSI) was developed by Hakkio and Keeton (2009) using eleven market factors that potentially indicate stress in the financial markets. According to reports, KCFSI has consistently done well in anticipating changes in economic activity over the past 20 years, as well as events related to financial stress. Oet *et al.* (2011) developed the Cleveland Financial Stress Index using a number of techniques (dynamic weighting method, principal component method, equal variance weighting method) and the daily published stress indicators of four financial markets (credit, foreign exchange, equity, and interbank markets).

According Lo Duca and Peltonen (2013), a systemic event is one that significantly impairs economic development and welfare by disrupting the financial system's normal operation. For each nation, a composite index is produced, and incidents that surpass the index value's twentieth percentile (which corresponds to the era of economic downturn) are designated as systemic events. The composite index is created using portfolio theory and fifteen daily market variables that represent the money, foreign currency, bonds, and hedging markets as well as the equities and bond markets. Systemic events that are determined by this index are calculated using discrete selection models that take into account both local and global factors as well as their interactions. The model correctly predicted the world financial catastrophe five quarters beforehand (2006 Q2).

Studies undertaken by the central banks of Japan and Germany were also looked at as a model for the early warning system. The Financial Activity Index (FAI) was created by the Bank of Japan (Ishikawa *et al.*, 2012) to track changes in financial activity. The indicators in this index were chosen based on two criteria. Showing that these indicators have a theoretical foundation or are experimentally helpful in the literature is the first of these requirements. The second requirement is the capacity to identify the economic heating brought on by Japan's Heisei bubble in 1990. It aims to catch the collapse of Lehman Brothers in order to examine the indicators for which there is no data for 1990. The definitions of heating and cooling in the economy are +1 standard deviation rise and -1 standard deviation reduction, respectively. The capacity to anticipate the Heisei balloon and/or Lehman Brothers led to the selection of

10 indicators out of the 100 used in the literature. Instead of being blended, these indications are displayed as a heat map and stretch chart with the number of indicators that represent the heating and cooling throughout the pertinent period.

In the study Jahn and Kick (2012) conducted for Germany, a composite indicator is produced primarily to demonstrate banking sector instability. After that, the capacity of macroprudential indicators to forecast this instability is examined using the panel regression approach. The likelihood of bank default, the cost of borrowing money from banks, and the stock returns of publicly traded banks make up the indicator that signals instability.

By using PCA and its adaptations, Arzamasov and Penikas (2014) created a financial stability index for Israel. They suggested that the ideal model includes "Regulatory Capital to Risk-Weighted Assets" and "Return on Assets" as predictors of financial stability.

Using the equal variance weighting approach and principal component analysis, Park and Mercado (2014) created financial stress indices for 25 emerging nations. They used five monthly variables made up of the banking sector, the stock market, the debt market, and the foreign currency market.

Using the equal variance weighting approach, Cardarelli *et al.* (2009) created financial stress indices for seventeen developed nations. They used seven daily market indicators, including data from the securities, foreign currency, and banking sectors. This study uses this index to pinpoint instances of financial unrest and suggests an analytical framework for determining how financial stress affects the actual economy. They highlighted that stress primarily in the securities or foreign currency market is less likely to be linked to severe and prolonged downturns than stress defined by banking difficulty.

The financial stress index for 26 developing economies was created by Balakrishnan *et al.* (2011) using the equal variance weighting approach. They made use of the beta for the banking sector, stock market returns, volatility, sovereign debt spreads, and exchange rate changes.

Yildirim (2021) used main component analysis to create a banking soundness index for Turkey. He made use of the fundamental set of IMF-publication financial soundness measures, such as the capital adequacy ratio and the non-performing loan ratio. They contended that the financial stability reports released by the Central Bank of the Republic of Turkey (CBRT), which contain assessments of the banking sector, are consistent with the calculations used for the banking soundness index.

Using sixteen weekly data sets from the banking, equity, sovereign bond, and stock markets, Grimaldi (2010) created a financial stress index for the Euro area nations using a weighting method based on the inverse of variances.

The financial stability index was proposed by Morales and Estrada (2010) as a function of profitability, liquidity, and default risk. Their findings suggested that the indicator accurately predicts the system's stress level. Additionally, they used macroeconomic data to forecast the financial stability index.

Ekinci (2013) created a daily financial stress index for Turkey. The index is created by adding together the four indices for the banking industry, public sector, stock market, and foreign exchange markets with equal weights. The standard deviation of each variable is divided by its demeaned value (calculated using the arithmetic mean). The total financial stress index for Turkey is calculated by adding these four standardized components. The Turkish economy has been divided into six distinct periods using the financial stress analysis, including (i) the high-stress period, (ii) the normal stress period, (iii) the stress caused by the global financial crisis, (iv) the low-stress period, (v) the increasing stress period, and (vi) the decreasing stress period.

The depth of the connection between the financial sector and macroeconomics is demonstrated by the financial crisis of 2008, according to Camlica and Gunes (2016), who also notes that the structure, intensity, and duration of financial stress can all have an impact on how negatively economic activity is affected. The equal variance weighting approach, principal component analysis, and portfolio theory methodologies are used to create three financial stress indexes for the years 2002 through 2015. The index calculated using the portfolio theory approach gives more consistent results with the preliminary expectations based on the relationship between financial stress and economic activity as a result of the evaluation of the indices in terms of capturing the stress periods historically and accurately reflecting the stress level. Additionally, it is concluded that industrial production responds negatively to financial shocks in normal stress periods, but the reactions are more severe and persistent in high-stress periods as a result of the analysis of the relationship between industrial production and financial systemic stress by linear and nonlinear methods.

Financial Stress Indicator (FSI) was created by Chadwick and Ozturk (2018) using weekly data from April 2005 to December 2016. In order to achieve this, they put together 15 separate FSIs, each of which represented one of five markets: the money market, bond market, foreign exchange market, equities market, or banking sector. Several methods, such as principal component analysis (PCA), fundamental portfolio theory, variance equal weights, and the Bayesian dynamic factor model, were used to combine these five distinct markets. According to their findings, Turkey lacks a straightforward best indication for determining the stress on the financial system. They also emphasized that while certain indicators have a larger link with systemic risk than others, some have a good predicting potential for economic growth.

Frankel and Rose (1996) examine the factors that contributed to exchange rate crises in 100 developing nations between 1971 and 1992. The study's conclusions indicate that direct investment weakness, inadequate reserves, rapid loan expansion, and currency overvaluation are all associated with exchange rate crises. The probit model was used to assess the significance of indicator coefficients because this study did not provide a framework for testing the importance of indicators.

The banking and balance of payments problems were covered by Kaminsky and Reinhart (1999), who also expanded on prior research. The invention of the "signal" technique, in which the indicators are assessed for importance, is a significant contribution of this work. In this method, it is considered that indicator values over predetermined thresholds indicate a crisis, and the threshold values are chosen to reduce the ratio of false signals to real signals. 105 variables from the financial, real estate, public finance, institutional, structural, and political sectors are used in this study. It is underlined that predicting foreign exchange crises required consideration of a number of factors, including international reserves, real interest rates, loans made to citizens, loans to the public sector, and domestic inflation. The international trade balance, the pace of monetary expansion, real gross domestic product (GDP) growth, and budget deficit are other factors that are proven to be relevant. The research reveals that the statistics on the profile of external debt and the current account deficit are not particularly good at foretelling foreign exchange crises.

The signal technique was employed in research by Berg and Pattillo (1999); Edison (2003); Berg *et al.* (2004), who also used the probit model to forecast the Asian financial crisis. In 2000, Demirgüç-Kunt and Detragiache (2000) used a multivariate logit model to anticipate financial crises and assessed the effectiveness of discrete choice models. This study discovered that when assessing early warning models, policymakers must decide between missing crises (type 1 mistake) and receiving a signal of crises even when there are none (type 2 error). Additionally, it has been demonstrated that choosing threshold values based on the “false signal / true signal” ratio produces less-than-ideal outcomes. Instead, it is suggested that threshold values be chosen by minimizing loss functions in accordance with the policymakers' preference between missing crises (type 1 error) and receiving the signal of crises even when there are none (type 2 error).

In one of the research projects carried out in the wake of the financial crisis, Alessi and Detken (2011) assessed the abrupt rises and falls in asset prices using the signal technique and taking type 1 and type 2 preferences into account. The global credit gap outperformed local factors in this study's analysis of the relevance of global variables in anticipating crises.

Another research on early warning systems undertaken after the global financial crisis by Frankel and Saravelos (2012) looked at 80 papers with the goal of evaluating the claim that indications that can be employed in one crisis may not be adequate to anticipate another. The evolution of central bank reserves and real exchange rates have been shown to be the most helpful indicators for understanding crises in this context, even when various nations and different crises are considered.

Modeling the tradeoff between the cost of type 1 error and the cost of type 2 error and determining the thresholds of the indicators by reducing the overall cost of these errors are two techniques used to assess the performance of early warning indicators. The ROC curve is the second approach used when it is impossible to quantify these expenses precisely. The ROC curve is used in the study undertaken by BIS economists Mathias Drehmann and Mikail Juselius (2014) to assess the effectiveness of early warning signs. The trade-off between type 1 and type 2 mistakes is displayed by the ROC curve. On the horizontal axis of the ROC curve are the false positive signal ratio (type 2 error) and on the vertical axis are the true positive signal ratio (type 1 error/type 1). The quality of the signal is shown by the area under the curve. The area under the curve is utilized in the study to assess and contrast the effectiveness of indicators in the categorization of crises. For two indicators at a specific time before the crisis, the performance of the indicator with a bigger AUROC is seen to be better. Additional considerations are the signal's timeliness and stability. This is because macroprudential policies must be put in place at a specific moment in order to be successful. Taking a signal too early, on the other hand, is not a desirable condition since it costs money to implement policy. To meet the criteria, the indications must appear 1.5 to 5 years before the crisis. Additionally, they consider the consistency of signals as well as their quality. They contend that trends rather than abrupt changes should be taken into account when making judgments, therefore it is also assessed to see if an indicator's signal quality declined as the estimation time shrunk. In other words, this early warning signal is deemed to be steady if the area under the curve grows as the crisis draws near. They also assert that indicators should be simple to comprehend and offer resilience for various samples. The effectiveness of 10 distinct early warning indicators is assessed in the investigation spanning 26 nations from 1980 to 2012. The history of the nation's financial crisis and debt service ratio are included as two new indicators among these ten early warning indicators, which also include indicators from the literature (real credit growth, credit / GDP gap, growth rates of real estate prices, stock prices, and non-core liability ratio). The credit/GDP gap and the debt service ratio are deemed to be the best performing metrics, it is decided.

By collecting data from the years 1970 to 2010, Babecký *et al.* (2011) create an early warning system for the USA and 40 industrialized OECD nations. For the crises examined in the study, a thorough data collection is created. The availability of data is taken into consideration while evaluating a total of 50 macroeconomic and financial indicators. In this study, it was decided that the indicators should have predicted the crisis two years prior, and the dynamic panel logit model was used to examine the model's predictive capacity. The rise in house prices, low credit interest rates, and the expansion of commercial credit are all seen as crucial early warning indications. A high likelihood of a crisis is likewise correlated with a rise in long-term public bond rates. GMM is used to examine the impact of crises on the actual economy in addition to the discrete selection model (Generalized Moment Method). To do this, an index has been created utilizing the dependent variables of GDP growth, unemployment rate, and budget deficit. The model accounts for 37% of the variation in how crises affect the actual economy. The most significant early warning signs are determined to be global variables, notably worldwide GDP, global credit, and oil prices. The cost of housing and debt levels are important local economic indicators. It is discovered that while global factors are significant in the model that assesses the impact of the crisis on the real economy, local economic indicators are significant in the model that assesses the probability of the crisis.

The early warning signs of financial and macroeconomic imbalances in nations of Central and Eastern Europe are explored in a paper by Csortos and Szalai (2014). The real exchange rate, capital flows, and debt level are found to be potential early warning indicators in identifying macroeconomic imbalances as a result of the method based on selecting the most useful variable combinations in terms of missing crisis (type 1 error) and false signal (type 2 error).

Chen and Svirydzenka (2021) looked at the indicators with the best ability to foretell financial crises. They discovered that while equity prices and the output gap are the best leading indicators in advanced markets, these are equity and property prices and credit gap in emerging markets using data from 59 advanced and emerging economies and applying a non-parametric signal extraction approach similar to Kaminsky *et al.* (1998) and AUROC analysis.

In a Markov switching (MS) paradigm, Duprey and Klaus (2017) use a continuous financial stress metric to forecast the stages of the financial cycle. They discovered that although economic mood indicators give signs of a shift to a calm state, the debt service ratio and property market factors signify a change to a high financial stress regime. Additionally, they claimed that the MS model with a regime-dependent mean considerably outperforms the logit model up to two quarters before the high-financial-stress episode, as evaluated by the AUROC.

With the private credit-to-GDP ratio as the dependent variable, Ortiz Vidal-Abarca and Ugarte-Ruiz (2015) presented the Early Warning System Indicator (EWSI) of banking crises based on a credit gap measure calculated by a non-linear (Gompertz curve) panel-data model. They made use of estimations of the private credit ratio's long-term structural level, which are based on the long-term levels of a number of macroeconomic, governmental, and structural factors. They calculated their credit gap variable by deducting the estimated long-term component from the observed credit-to-GDP ratio. By using AUROC analysis, they also contrasted our credit gap measure's efficacy as an early warning signal against other ad hoc measures of excessive private credit level across a sizable sample of industrialized and emerging nations.

Străchinaru (2022) used logit regression to calculate the probability of a financial crisis using the indicators suggested by the European Commission, which reflect vulnerabilities in the macroeconomic environment. They noted that the model had a 90% accuracy rate and a

91% AUROC value, demonstrating a significant ability to distinguish between times of crisis and those without crises.

By employing supervised machine learning models to offer banks with early warnings of liquidity stress using market base indicators, Tarkocin and Donduran (2021) focused on the management of bank liquidity. To train the machine learning model, they used publically accessible data from 2007 to 2021. To gauge market stress, they used the St. Louis Fed Financial Stress Index, and they awarded a red-amber-green (RAG) rating to indicate the amount of risk for each trading day. To provide early warning indications, they combined ensemble classifiers with a random under-sampling approach. They assessed the classification performance using two families of ensemble algorithms (Averaging and Boosting). According to AUROC data, they discovered that "Ensemble – RUSBoost" is the model that performs the best.

To create a collection of indicators that can act as an early warning system on exchange rates, Engeline and Matondang (2016) combined an empirical model from Commerzbank with theoretical models from Candelon, Dumitrescu, and Hurlin. They sought to comprehend how the Fed's normalization would put pressure on central banks to manage volatility, particularly for nations like Indonesia that had significant trade and budget deficits. They showed that lagged binary variables in dynamic logit models (AUROC 77,4%) beat static ones (AUROC 58,7%) and the Commerzbank depreciation index (AUROC 53,4%). Second, by merging the two early warning systems (EWS), we may be able to detect impending currency decline more accurately.

In the context of developing countries, Gersl and Jasova (2018) investigated the function of credit-based variables as early warning indicators (EWIs) of banking crises. From 1987 to 2015, they looked at 36 rising economies' instances of financial crises. They used the ROC curve and computed AUC to evaluate the signal quality. Their findings demonstrate that in virtually all policy-relevant horizon parameters, nominal credit growth and the change in the credit-to-GDP ratio surpass the credit-to-GDP gap and have the highest signaling qualities. These results stand in stark contrast to those found for advanced nations, where the credit-to-GDP gap is the best-performing EWI overall. These findings highlight the need for care when applying statistical methodologies designed for developed markets to developing ones.

Different EWSs are put out by Allaj and Sanfelici (2020) for the purpose of anticipating probable market instability situations, where market instability is defined as significant drops in asset prices. Based on the realized variation (RV) and/or price-volatility feedback rate, they used early warning signs. On the foundation of logit models, they created early warning systems. Using AUROC, they assessed the models' effectiveness in classifying data. According to their findings, the RV is crucial for forecasting future price losses in a given time series, but the EWI using the price-volatility feedback rate can further enhance prediction.

Based on the Random Forest Modelling Approach, one of the machine learning algorithms well suited for capturing the potential non-linear relationship between financial development, financial imbalances, and the likelihood of a financial crisis, Ponomarenko and Tatarintsev (2020) established an early warning system for financial crises. In addition to traditional imbalance metrics, they employed a unique set of predictors that includes financial development indicators (such as the levels of loan to GDP ratio) (e.g., the credit gaps). Utilizing AUROC analysis, the EWSs' predictive power is evaluated. The findings showed that integrating financial imbalances and financial development indicators helps to increase the early warning system's accuracy outside of samples.

An EWS was suggested by Casabianca *et al.* (2019) to forecast the escalation of systemic financial crises. Their publications used supervised machine learning (ML) and conventional discrete choice models to pinpoint the macroeconomic causes of banking crises. Additionally, they used anticipated probabilities to gauge how much a country was exposed to systemic threats. They provided the AUROC, a common metric used to assess the prediction effectiveness of any binary classification models, for each specification. Their findings suggested that ML algorithms can execute predictions more accurately than logit models. In the concluding years of the sample for the advanced nations, all models give rising projected probabilities, cautioning against the potential accumulation of pre-crisis macroeconomic imbalances.

Pietrzak (2021) investigated ways to improve the usefulness of Financial Soundness Indicators (FSIs) in financial monitoring. They developed many EWI models by utilizing various approaches, including signal extraction, decision trees, discriminant analysis, support vector machines, k-nearest neighbors, naive bayes, and logistic regression. Using AUROC statistics, they assessed the models' performance. They discovered that FSIs provide signals that may reliably predict the emergence of financial distress, which is gauged by tight financial circumstances, with a lead time of 4 to 12 quarters.

Alessi *et al.* (2015) examined the effectiveness of nine different models for forecasting banking crises developed by the Macroprudential Research Network (MaRs), a project of the European System of Central Banks. By comparing the ratios of false alarms and missed crises, they assessed the relative utility of the models. They concluded that multivariate models, in all their manifestations, had a significant potential advantage over straightforward signaling models.

Martinez and Oda (2021) investigated how several early warning indicators (EWIs), such as the conventional banking credit-to-GDP gap and the ratio of real bank credit to its historical trend, were calculated. They began by outlining the local peculiarities and problems that relate to the characteristics of the Chilean economy and other quirks. They used a variety of filtering techniques, including the Baxter and King (BK), Cristiano and Fitzgerald (CF), and Hodrick and Prescott (HP) filters, to extract the cyclical features of the data. Following the estimation of the cycle, they used AUROC analysis to assess their capacity to forecast episodes of financial instability. They concluded that a good "single" choice for completing the BCBS-proposed credit-to-GDP gap indicator is the ratio of real bank credit to its historical trend.

3. EWIs AND DATA

We test if a variety of EWIs meet the discussed policy requirements in the rest of the study. Rather than considering a broad range of potential indicators, we concentrate on those that have a clear economic meaning, are available across time and nations, and have been proven to be effective in prior studies. We look at ten different variables in all.

3.1 EWIs

We choose our global variables that have support in the literature. In addition to this, we also gather local indicators depending on each country's specific crisis history, that is to say, we analyze the economic reasons of banking crisis each country experienced different periods of time.

We first present the papers providing the basis for global indicators. Drehmann *et al.* (2011) looked at a wide range of possible indicators, including macroeconomic factors, banking sector indicators, and market indicators. They discovered that the last two groupings perform poorly as EWIs in systemic banking crises. As a result, we concentrate on a small number of global macroeconomic indicator variables that have a better chance of capturing the accumulation of financial vulnerabilities.

Excessive credit and asset price boom indicators, according to Drehmann *et al.* (2011), perform well as EWIs. The credit-to-GDP gap, which measures credit-to-GDP deviations from a long-run trend, is the single best indicator, according to the authors. According to the Basel Committee, this variable also serves as a starting point for talks about the level of countercyclical capital buffer charges (2010). Reinhart and Rogoff (2009); Gourinchas and Obstfeld (2012); Jordà *et al.* (2015), among others, agreed that the substantial changes in credit conditions are important. As a result, the credit-to-GDP gap and the change in real credit are included in the analysis. We also incorporate changes in actual residential property and equity prices, as well as their corresponding gaps, in the research as alternative indications of such financial booms.

Real credit growth in different forms such as 'Credit to Non-financial sector from All sectors at Market value - Percentage of GDP', 'Credit to Non-financial sector from All sectors at Market value - US dollar', 'Credit to Non-financial sector from All sectors at Market value - Domestic currency', 'Credit to Private non-financial sector from All sectors at Market value - US dollar' is also included in the research due to the fact that it is used as a business cycle indicator. Lending to the private sector grows rapidly during booms and slows or contracts during credit crunches, so credit growth deviations from the trend could be a useful indicator.

The aggregate debt service ratio (DSR) was proposed by Drehmann and Juselius (2012) as a valuable early warning indicator. The DSR is a measure of interest payments and obligatory principal repayments as a percentage of income for the private non-financial sector as a whole, and it can be used as a proxy indicating the incoming liquidity limitations of private sector borrowers. When DSRs are high, it means that people and businesses are overextended, and even minor revenue gaps hinder them from moderating consumption or investing. Larger gaps could lead to an increase in defaults and, eventually, a crisis.

According to Hahm *et al.* (2012), loan booms can only last as long as banks can fund assets with non-core liabilities, such as wholesale and cross-border funding, because traditional retail deposits (core liabilities) adjust only slowly. They discovered that the ratio of non-core liabilities to core obligations is the most effective EWI for crises. In our study, we incorporate this variable as the non-core liability ratio, which is in line with their findings. To identify the local variables, we start by examining Hungary's crisis episode, which lasted from October 2008 to March 2009, to hit local EWIs. Witte (2012) investigated whether the 2008 currency crisis in Hungary was self-inflicted or a result of the current global financial crisis. He found that both factors are influential in the depreciation of Hungarian forint. Current account deficits, high inflation, and low levels of reserves negatively impacted the exchange rate. This effect was amplified by the severity of the crisis, as measured by the TED spread, which is the difference between the 3-month LIBOR rate and Treasury Bill interest rate. Then, we analyze the Turkey currency crisis episode that occurred in August 2018. From the start of the global financial crisis to August 2018, the value of its currency fell by approximately 40% against the US dollar. Interest rates in advanced economies were at historic lows following the 2008-2009 global financial crisis. International investors increasingly turned to emerging markets to seek higher rates of return on their investments. Turkey was an appealing destination due to early-2000s economic reforms, strong growth (6.9% annually on average between 2010 and 2017, compared to 3.8% globally), and a large domestic market (80 million population). Turkish banks and large corporations borrowed heavily from foreign investors, usually in US dollars. Turkey's large annual current account deficits (a broad measure of trade balance), which averaged 5.5% of GDP per year between 2010 and 2017, were among the largest in the world. Turkey's reliance on external financing exposed it to the exchange rate and rollover risks. Turkey's borrowing costs rose as the Federal Reserve of the United States (Fed) began raising interest rates (Nelson, 2018). Next, we discuss the financial crisis episode of Russia. Russia entered a financial crisis in November 2014 as a result of a sharp devaluation of the Russian ruble. Three types of factors contributed to the crisis: market factors, political factors, and structural factors. Investors' loss of confidence in the Russian economy resulted in a decline in the value of the Russian ruble, sparking fears of a financial crisis. The lack of confidence in the Russian economy stemmed from at least two primary sources. The first is the roughly 50% decline in the price of oil, which is Russia's primary export product, throughout 2014. The second is the result of international economic sanctions imposed on Russia in the aftermath of its illegal occupation of Crimea and military intervention in Ukraine (Viktorov & Abramov, 2020). Another country we included in the analysis is Italy. During November 2011, Italy was involved in an economic and political crisis. That crisis was caused by both cyclical and structural conditions, as well as national and international forces, resulting in a complicated phenomenon, whose causes and origins are difficult to trace back to their source. The differential between the 10-year Treasury Bond yields in Italy and Germany was 574 basis points at the start of November 2011, but it was 400 basis points lower at the beginning of the same year. This alarming dynamic was self-sustaining, producing a vicious cycle of negative self-fulfilling assumptions about the health of Italy's public finances, which exacerbated the situation further. The Sovereign Debt Crisis first started in Greece and was triggered by Greece's reckless handling of public finances. However, as Baldwin and Giavazzi (2015) show, this crisis was not caused solely by unsustainable national debt, but rather by rising and undeniable imbalances that accumulated over time in the European Monetary Union (EMU) since its foundation. The deepening of the crisis brought to light the defective nature of the EMU, which had been constructed in an insufficiently thorough manner. The EMU lacked the adequate tools at the European level to contain the spillover. When the issues in the Greek economy erupted, the financial markets immediately became concerned about the resilience of other national economies, which for a variety of reasons appeared to be less prepared to withstand the negative shock that was spread throughout the Eurozone as a result of the decline in the economy. In addition to this, the Italian economy has been dragged down for a long time by structural problems that all governments have struggled to solve or even just to address. Italy is one of the countries with the highest level of value-added tax (VAT) avoidance in Europe, and it has long struggled with the problem of widespread tax evasion. Together with its massive black economy, this phenomenon depletes significant income sources of the public budget, increasing the country's fiscal sustainability problems. International investors are scared off by the inefficiency of its bureaucracy and judiciary system, as well as the high level of corruption, while national investors are discouraged by the uncertainty caused by its prolonged political instability. Italy requires public investment because a lack of investment dampens productivity growth. However, the government cannot step in due to tight budgetary constraints. Individual euro-zone countries are, by definition, unable to use exchange rate or monetary policy to address competitiveness issues or stimulate growth on an individual basis because they are members of a currency union. This implies that the common monetary policy can only deal with shocks that affect the entire union, whereas the response to idiosyncratic shocks is left to the discretion of national policies. Even if these national policies are insufficient, the Eurozone lacks union-wide stabilizers: labor and capital mobility between member countries has been limited, fiscal coordination throughout the union has been incomplete, and the EMU lacks common fiscal capacity. As the Greek experience of 2010-2011 revealed, a significant national shock can quickly become systemic in such an environment (Romano, 2021). The only country which we examine from Latin America is Brazil. Brazil experienced currency crisis in March 2015. It is explained by two major factors: First of all, the worsening of the European crisis and the resulting uncertainty in the international environment, along with a reduction in international commodity prices and Brazilian exports, exacerbated the Brazilian economy's recession, which had already begun in 2013. Brazil is the world's biggest producer of sugar, coffee, and soybeans. It also ranks near the top in iron ore and oil. China is its largest commercial partner, although its growth slowed significantly in 2015. As a result, demand for Brazilian commodities fell, forcing prices to plummet. While several oil-producing countries, including Brazil, struggled with declining energy prices, the country was forced to deal with yet another challenge. Petrobras, Brazil's state-owned oil firm, was probed by prosecutors for funneling bribes to President Rousseff's election campaigns and legislators in her Workers' Party. Second, the changes in the conduct of domestic macroeconomic policy plummeted the currency. To be more precise, the government shifted from the Macroeconomic Tripod, which combines a primary surplus with inflation targeting and a floating exchange rate regime, to the New Economic Matrix, which was interpreted as a combination of the Brazilian economy's real interest rate being set at high levels combined with an appreciated exchange rate (Vartanian & Garbe, 2019). Finally, we trace out the crisis episodes for South Africa. South Africa suffered a more recent currency crisis in 2015. The upswing in the US economy and expectations of Federal Reserve rate rises in the subsequent quarters were two major variables influencing Rand value. Any rate rise hurt developing countries such as Turkey, South Africa, Thailand due to the reversal of short-term capital flows to developed economies. Another factor for the devaluation was China's adaptable foreign policy. Because the Rand is one of the currencies most vulnerable to changes in Chinese foreign policy, any changes in Chinese foreign policy directly influence the Rand. After the People's Bank of China devalued the Yuan by 2% in mid-2015, the Rand lost about 26% of its value over the next six months. In addition to these reasons, China's economy weakened significantly in 2015. Reduced demand from China harmed the Rand since China is South Africa's largest trading partner and a substantial source of foreign money. Another aspect influencing currency value is investor confidence. South Africa's government made adjustments at the ministerial level that impacted investor confidence. The fact that the Finance Minister was replaced three times within a short period amplified the loss in value of the Rand. To make matters worse, monetary policy did little to support the sliding Rand. In November 2015, a 25 basis point (bps) increase failed to make much difference (Deloitte, 2016).

3.2 Data

We examine quarterly time series data from six different countries. The sample starts in 2000Q1 for most countries, and at the earliest available date for the rest. It ends in 2021Q2. Table no. 1 summarizes the global and local variables. For the paper's main section, we build a balanced sample, which means we only employ a subsample with all indicator variables present. Furthermore, before any crisis is included in the sample, we confirm that all variables exist for the whole five-year projection horizon, so that the predicted temporal profile of AUCs does not change due to differences in the number of countries. We also remove the crisis quarter and the next two years because binary EWIs become skewed when the post-crisis period is taken into account.

Table no. 1 – EWIs

Local Variables	Global Variables
M3	GDP by Expenditure
Total Reserves	DSR
Interbank Rate	Credit-to-GDP Ratio
Current Account Balance of GDP	Share Prices
	Credit to Non-Financial Sector from All Sectors
	Credit to General Government Sector
	Credit to on Financial Sector from Banks

We acquire macroeconomic variables from national data sources and the International Monetary Fund's International Financial Statistics (IMF-IFS). We employ a measure of total credit to the private non-financial sector collected from a new BIS database (Dembiermont *et al.*, 2013), a significant data-related component of our research. Historically, the literature has relied on proxies for this indicator, such as bank loans to the private-non-financial sector provided in the IMF-IFS. This, however, can be misleading because it ignores crucial sources of credit, such as bond markets and cross-border loans. This new database includes more detailed information, such as the amount of total credit from all sectors or from banks extended to consumers, businesses, and governments available in nominal value, percentage of GDP, and currency.

We compute gap measures by subtracting the level of a series from the trend of a one-sided Hodrick-Prescott filter. This is performed by iteratively extending the sample by one period and retaining the difference between the real value of the variable and the trend value at the new point. We only examine the EWIs individually, but we also explain the reasons of not combining them at the end of the paper. In terms of identifying banking crises, existing influential research on banking crises offer a variety of definitions based on the performance of selected variables against defined thresholds, expert assessments, extensive literature reviews, and so on – for a detailed discussion of alternative definitions, see Babecký *et al.* (2014). We depend on Harvard Business School Global Crises Data (2022), which covers banking, exchange rate, and stock market crises for more than 70 countries from 1800-present. Crisis dates across the countries in question are displayed in Table no. 2.

Table no. 2 – Crisis Dates Across Countries

Country	Crisis Date	Type
Brazil	Nov-15	Currency
Turkey	Aug-18	Currency
Italy	Nov-11	Banking
Hungary	Oct-08	Currency
Russia	Nov-14	Currency
South Africa	Mar-15	Currency

4. METHODOLOGY

4.1 ROC Curve and AUROC

The framework used in this paper for comparing the prediction performance of standalone EWI indicators follows ROC, used for signal extractions and the methodology is used since World War II. The ROC curve is used in this paper to identify the quality of the signal of each EWI for predicting a crisis. The methodology used in this paper broadly follows Drehmann and Juselius (2014) but differs in terms of variable selection and combination of the selected variables. Before getting into the discussion of the results, a brief description of ROC method is provided below.

The choice of appropriate early warning indicators poses challenges to policymakers in terms of the stability and persistence of the signal emanated by the indicators during good times and bad times. Policymakers face the dilemma of their choices of suitable policy actions given different states of the economy. The choice become crucial given that the utility of the policymakers is broadly unknown. Each policy bears a trade-off between implementing a policy against the backdrop of the cost of the policy action. Further, the timing of the policy action also become crucial given the business cycle variations in the economy. Against this backdrop, any suitable early warning indicators should provide valuable input to assess the transition to crisis well before the crisis occurs. The ROC curve analysis provides a threshold of the signal to differentiate the crisis point from the normal times. The choice of threshold strikes a balance between true positive and false positive rates.

Given any signal S, the true positive and false positive rates are defined as $\boldsymbol{TPR_{it}} = \boldsymbol{P(S > \theta | Crisis)}$ and $\boldsymbol{FPR_{it}} = \boldsymbol{P(S > \theta | No\ crisis)}$. The mapping between TPR and FPR provides the ROC. The choice of threshold values is determined by point on the ROC curve which equates the marginal rate of substitution of policy action between good and bad states i.e., the suitable threshold corresponds to the indifference points on the ROC curve. However, the indifferent point is difficult to identify without proper assessment of the cost function of the policymakers. The seminal work by Drehmann and Juselius (2012) reflected on the trade-off of different policy actions with suitable approximation of cost and benefit of each policy action. In the absence of suitable parameterization of the cost function, the optimal choice of threshold is derived from the quality of signal derived by the Area Under the Curve (AUC). AUC is defined as the area under the ROC curve for the full spectrum of the choice of $\boldsymbol{\theta}$. The thresholds which give an area estimate of more than 0.5, is considered as the informative signal and thresholds having AUC value below 0.5 are considered as weak signals. The area estimates are generated following Pepe *et al.* (2009) and Janes *et al.* (2009). The bootstrap standard error is derived using Janes *et al.* (2009) to eliminate any serial auto correlations among the observations.

Though the choice of suitable threshold provides an assessment of signal quality, the timing and stability of the signal become crucial for reducing the risk of unnecessary policy actions. The timing part of EWI is challenging, particularly in the context of macroprudential policies. The macroprudential policies work at longer lags which means that the underlying conditions starts deteriorating well before the crisis emerges. Hence, the EWI's should transmit stable signals well before the crisis occurs. However, the signal should not emerge too early before the crisis as the cost of implementing the policy can be significant. Following the recommendation of Basel III capital buffer framework and recent works by Caruana

(2010) and Fernández de Lis and Garcia-Herrero (2012), the timing assumption is considered by allowing the transmission time of Following Drehmann and Juselius (2014), AUC is estimated over 5 years horizon before the crisis and the EWI is selected if signal is informative for any horizon between 6 – 20 quarters prior to crisis. Apart from the timing assumption, the stability of the signal is also factored in to isolate EWIs exhibiting the trend component of the underlying data generating process. The monotonic increasing property of the AUC at different horizon is considered to suitable for identifying the stability of the signal quality. More specifically, the signal should be informative, and the signal quality should stay informative over the forecast horizon.

Combining the timing and stability, EWI's should satisfy following conditions:

Condition 1: $\boldsymbol{AUC\left(S_i^h\right) > 0.5}$ for at least one $\boldsymbol{h} \in [\boldsymbol{-20, -6}]$

Condition 2: $\boldsymbol{AUC\left(S_i^{-6-l}\right) \leq AUC\left(S_i^{-6}\right) \leq AUC(S_i^{-6+k})}$ for j = 1(1)14 and k = 1(1)5

4.2 Combining indicators

Early warning indicators can be selected based on their signal strength and thereby can be used for predicting any elevation in the systemic risk. However, the main drawback of single EWI based screening is that the EWIs only highlight risks emanating from certain sectors while it ignores evolving scenarios emerging in other dimension. For instance, any credit boom is generally accompanied with greater chances of default and thereby debt servicing should go up. Hence it may be optimal to combine suitable indicators for getting a holistic assessment about the overall systemic risk. However, combining indicators can become tricky as we could not satisfy the interpretability requirement of an ideal EWIs. Any EWI signals should be easy to interpret and translate into policy actions. Combination of indicators lacks this interpretability as the structural interpretation is lost in combination process.

In this paper, we validate the combination of indicators using regression based approach. Combination of indicators is done using linear combinations i.e. $\sum_i \theta_i EWI_{it}$ as it has a natural interpretability due to linear additivity of the indicators. Su and Liu (1993) proposed an optimal linear combination of indicators to generate highest AUC across horizons which also coincides with the separating hyper-plane derived using linear discriminant analysis. One can also use logit/probit model to come up with the linear combinations. However, adding lagged values leads to an exponential increase in parameter space. To avoid the curse of dimensionality, we propose to use logit/probit models with shrinkage regressions to eliminate lesser important lags of indicators. Our proposed framework follows logit/probit model with different shrinkage mechanism which can be illustrated as follows.

$$\mathbf{P}(\boldsymbol{I_{il}} = \mathbf{1}) = \boldsymbol{\alpha_0} + \sum_{\boldsymbol{i=1}}^{\boldsymbol{I}} \boldsymbol{\alpha_{il} EWI_{i,l-l}} + \boldsymbol{\lambda_1} \sum_{\boldsymbol{i=1}}^{\boldsymbol{I}} |\boldsymbol{\alpha_{il}}| + \boldsymbol{\lambda_2} \sum_{\boldsymbol{i=1}}^{\boldsymbol{I}} \boldsymbol{\alpha_{il}^2} + \boldsymbol{\epsilon_{il}} \quad \forall \boldsymbol{l} = \mathbf{1(1)20} \quad (1)$$

where λ_1 and λ_2 are penalizing parameters for L_1 and L_2 norms of parameters and these parameters will be used for restricting the size of the parameter space. Further, I is the number of indicators shortlisted, L is the lag selection. We consider all possible lags of the indicators from L quarters to 20 quarters prior to crisis. The shrinkage method helps us to include only the relevant lags of the selected indicators. The linear combination of selected indicators, derived from the logit/probit model, can be used to define the linear combination of the EWIs.

5. EMPIRICAL RESULTS

5.1 Pre-crisis variations in EWIs

Before starting out the analysis, we first applied unit root tests in three forms (no-drift and no-trend, drift and no-trend, both drift and trend) to investigate whether the series are stationary or not. The list of abbreviations used to label the indicator and the unit root test results are presented in Appendices A1 and A2. Most variables are non-stationary. Therefore, we calculate cyclical component by subtracting the level of a series from a one-sided Hodrick-Prescott filtered trend. The Hodrick-Prescott filter computation requires using a critical smoothing parameter, which is λ. Borio *et al.* (2010) proposed that the smoothing parameter should be proportional to the duration of the financial cycle, with a λ of 400,000 corresponding to a financial cycle that is approximately four times the duration of the business cycle. Therefore, the smoothing parameter (λ) is set to 400,000. To ensure that trends are sufficiently stable, we require a ten-year window length. The results are displayed in Appendix A3. We look at the time profile for all indicator variables around systemic banking crises before conducting our statistical tests. The behavior of the indicators is summarized in Figure no. 1 - during a period of 20 quarters prior to and 12 quarters following the onset of a crisis (time 0). The median (solid line), as well as the 25th and 75th percentiles (dashed lines) of the distribution, are shown for each variable across episodes. We use the variable's median value from previous periods as a benchmark (red vertical dashed line). In the following paragraphs, EWIs are classified into major categories to analyze the pre-crisis trends in these variables over different horizons.

Credit to non-financial sector (NFS) as percentage of GDP appears to be increasing steadily before the crisis quarters. The variation in credit supply to NFS is also narrow, implying that the credit supply relaxes prior to the crisis period. However, as the crisis approaches, the variation in credit supply increased visually. This may point to the fact that different countries started adopting different liquidity restrictions before the crisis become eminent. The median path of credit to NFS remains elevated before the crisis and starts easing out after the crisis. The lead and lag in the credit disbursement points towards the transmission time of the crisis and transmission of macroprudential measures after the policy actions were adopted (refer to Figure no. 1).

Unlike the non-financial sector, total credit disbursement remains benign prior to the crisis. Credit to all sectors grows modestly compared to the GDP growth. The variation in the credit to GDP ratio is also found to be tight. The total credit value (in US dollars and domestic currency) also follows similar pattern before and after the crisis (refer to Figure no. 2). The credit disbursement from the banks to non-financial sectors increased before the crisis. The increase is found to be short-lived in nature. As the crisis approaches, the credit boom marginalized (refer to Figure no. 3). Comparing Figure no. 1 and no. 3, it is evident that the credit disbursement remained elevated to the non-financial sectors but the disbursements from banks remained lower. This points to the ease of lending from non-banks before the crisis.

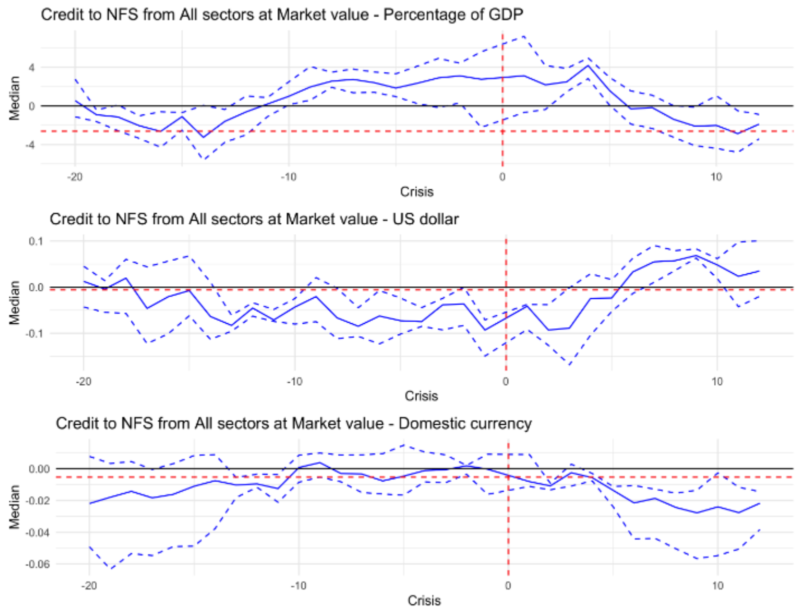

Figure no. 1 – Credit Indicators Around Crises

Figure no. 2 – Credit Indicators around crises

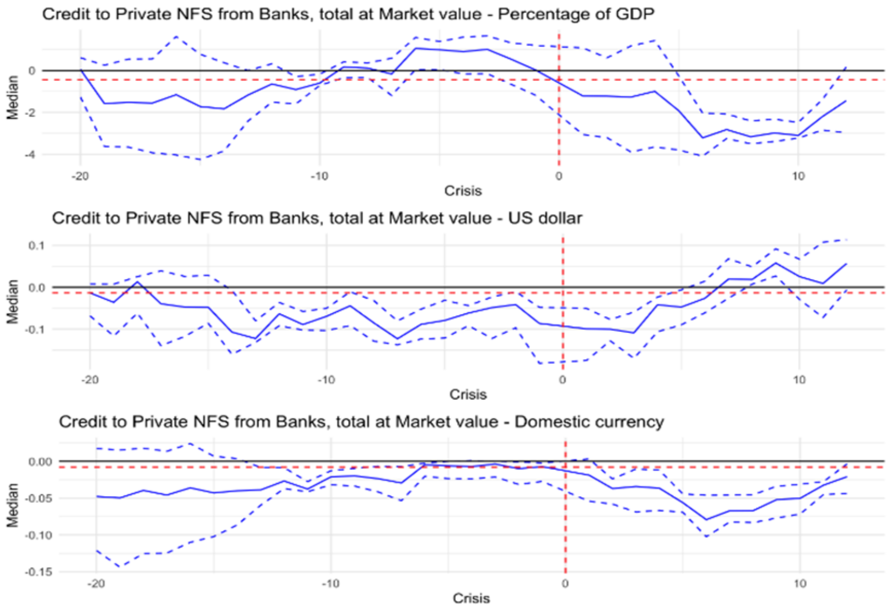

Figure no. 3 – Credit Indicators around crises

Looking at the macro indicators of credit, total credit to GDP ratio remained elevated before the crisis. The elevation started since 10 quarters before the crisis and the variation in the credit-GDP ratio remained tight for some quarters, but it started widening as the crisis approached. The debt servicing ratio also remained elevated during this time. However, unlike the total credit disbursement, the debt service ratio increased steadily over period before the crisis which underlines the increasing burden of the non-financial firms toward servicing their existing debt. The debt burden remained elevated after the crisis and then, it gradually moderates as the transmission from macroprudential policies kicks in. The equity market, proxy by the share prices, does not show similar pattern. Share prices increases for brisk period before the crisis and then dies down (refer to Figure no. 4).

Following Figure no. 5, the interest rate also remained high prior to the crisis periods. This signifies the possibility of pass through of debt servicing burden on the bank balance sheet on the inter-bank lending market. As the firms start experiencing the debt burden, the stress asset burden also increases on the bank balance sheet, resulting in higher interest rate and tighter liquidity conditions in the inter-bank markets. The current account balance as per cent of GDP also increased prior to the crisis. But unlike the credit variables, the offtake in the current account balance started late (refer to Figure no. 5).

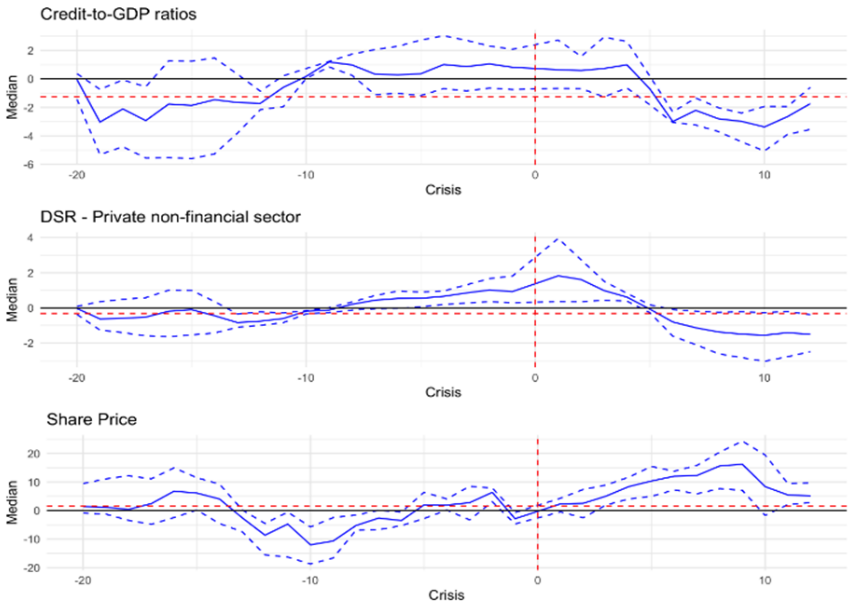

Figure no. 4 – Credit and Equity Market around the Crisis period

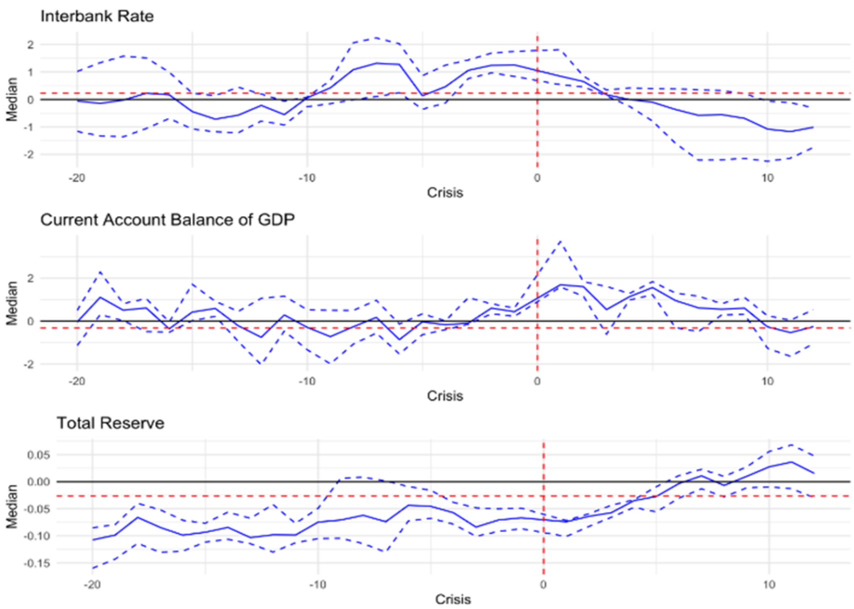

Figure no. 5 – Interest rate and external sector around the crisis period

5.2 The signalling quality of different standalone EWIs

The findings of assessing whether proposed EWIs meet the two statistical requirements are presented in this section. We estimate ROC curves non-parametrically, as described in Section 4.1. When computing the AUC values, we utilize trapezoid approximations to smooth the estimated curves and bootstraps with 1,000 replications to calculate standard errors.

The key results are summarized in Figures no. 6 – no. 12 (the AUC estimates with confidence band are also provided numerically in the Appendix). For all indicator variables and prediction horizons, the graph shows the computed AUCs and associated 95 percent confidence intervals (shaded region). The red vertical line corresponds to horizon 6 quarters before the crisis. The black horizontal line marks the threshold of 0.5. As indicated previously, the strength of the signal of indicators is assessed with respect to the AUC threshold value of 0.5. Hence, a higher value of AUC above the black line, therefore, supports better strength in the signal of the indicators. On the contrary, the AUC value below the threshold signifies a lack of signal strength of the indicators ahead of the crisis horizon. Lastly, ROC curve estimates for horizons of 8 quarters before crisis and AUC values for all horizons are shown in Appendix A4.

First, we evaluate the signal strength of credit variables. Following Figure no. 6, the credit to non-financial sectors showcases a consistent signal prior to 6 quarters of crisis as the AUC estimates of these variables stayed above the threshold value. Further, the strength of signal also remained steady up to 20 quarters before the crisis period with marginal slips around 10^{th} and 17^{th} quarter prior to crisis. The credit to non-financial sectors, scaled by the domestic GDP, remained strong given the robustness and stability criteria listed in methodology section. On the other hand, absolute credit disbursement in dollar terms as well as in domestic currency, also remained strong prior to crisis. However, the dollar value of total credit disbursement to non-financial sectors satisfies the robustness and stability criteria near the threshold of 6 quarters before crisis.

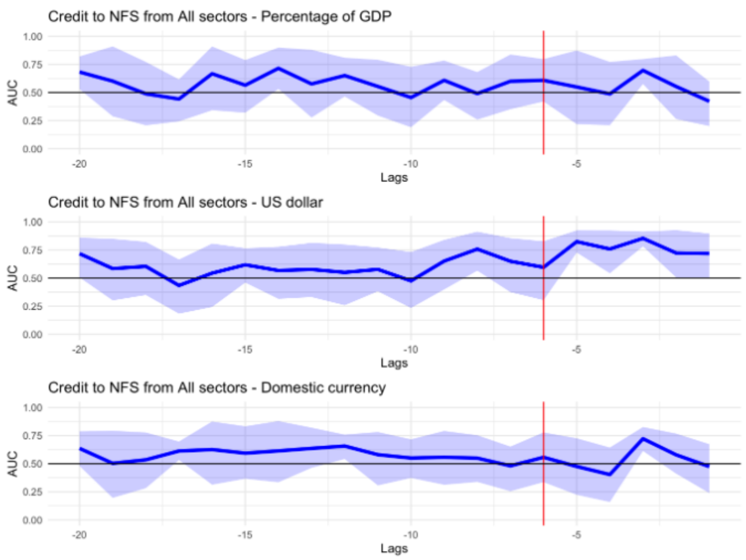

Figure no. 6 – EWIs and policy requirements – AUCs over time

The signal strength of credit to private non-financial sector also demonstrated similar signal strength. The credit to private non-financial sector scaled by GDP and dollar denominated credit value to private non-financial sector showed better signal strength among other components. The signal strength increased before the crisis which implies that strong credit disbursement to private non-financial sector remained a major driver of crisis across these countries. The signal strength remained strong after 6 quarters also. Given the stability of the signal, credit to private non-financial sector considered as EWI for predicting the crisis (following Figure no. 7).

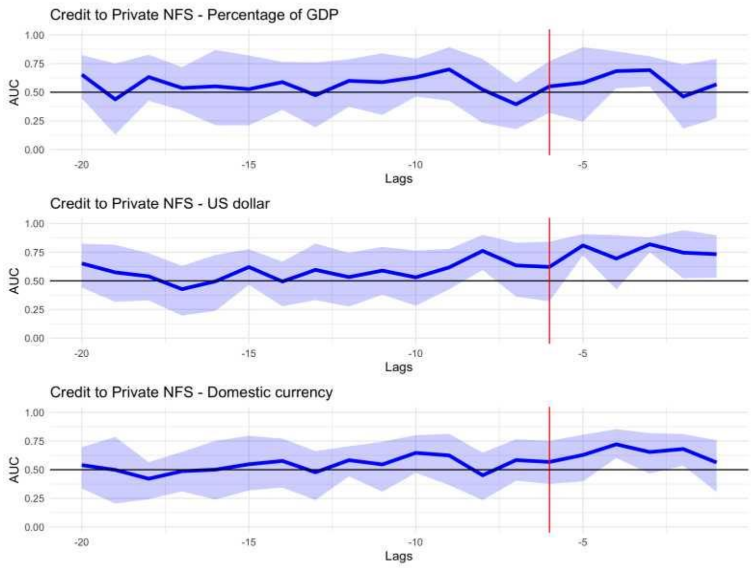

Figure no. 7 – EWIs and policy requirements — AUCs over time

The credit disbursement to private non-financial sector from banks also showed strong signal prior to the crisis. The credit disbursed by the banks as percentage of nominal GDP exhibit better stability and robustness over the prediction horizons, prior to 6 quarters of the crisis. The absolute credit value also remained stable in terms of its signal strength. Unlike the total credit disbursed to non-financial sectors, the bank credit to private non-financial sector in local currency, demonstrated strong signal strength. The credit amount in US dollars also signaled a strong information effect and the effect started elevating within 10 quarters of the crisis (refer to Figure no. 8).

Next, we analyze the signal strength of credit to the central government. The signal strength of the absolute value of credit to government in dollar terms and in domestic currency displayed lesser stability over prediction horizons. The credit disbursement to the government, scaled by nominal GDP, remained relatively more stable and robust over the horizon of 6-20 quarters prior to crisis period (from Figure no. 9).

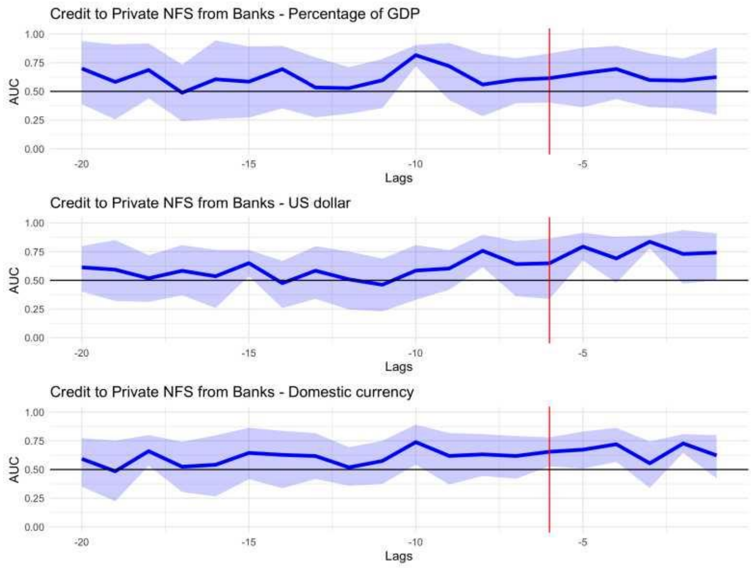

Figure no. 8 – EWIs and policy requirements — AUCs over time

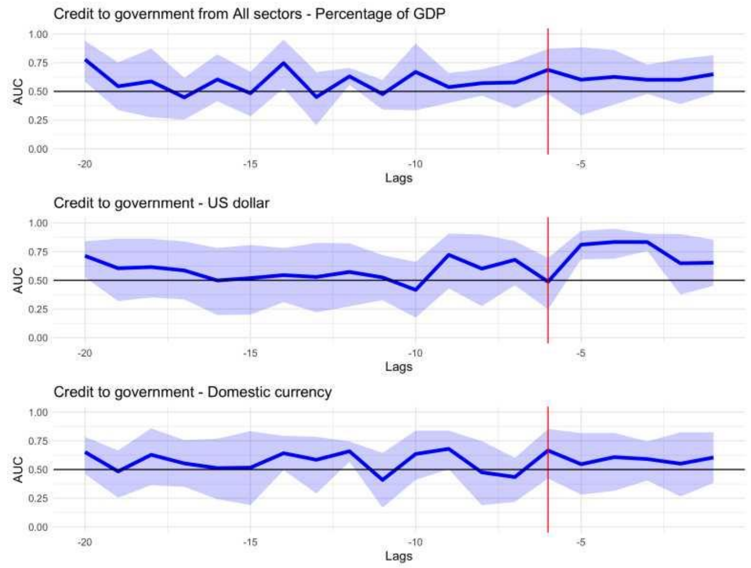

Figure no. 9 – EWIs and policy requirements — AUCs over time

Among other indicators, the debt servicing ratio provided a strong prediction power prior to the crisis. The signal strength marginally dipped below the threshold during 6-7 quarters ahead of crisis. Nevertheless, the signal strength remained robust prior to 7 quarters of crisis and remained stable before 20 quarters of crisis. On the other hand, signal strength of credit-to-GDP ratio and output gap remained unstable before the crisis (refer to Figure no. 10). Share price provided a mixed signal around prediction horizon of 16-20 quarters. However, the signal strength improved after that. The signal of inter-bank rate also remained stable over the prediction horizon. However current account balance (as % of GDP) remained unstable in signal strength (refer to Figure no. 11). Lastly, the total reserve appeared to be better indicator of systemic risk compared to money supply (refer to Figure no. 12).

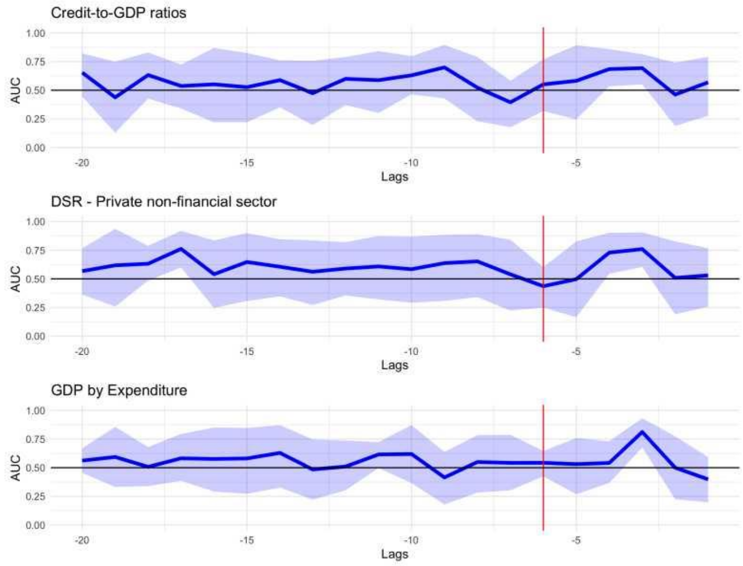

Figure 10. EWIs and policy requirements – AUCs over time

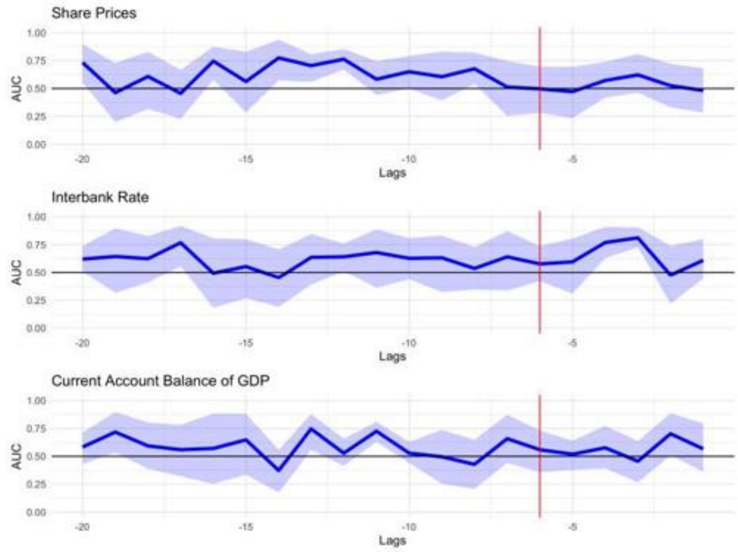

Figure no. 11 – EWIs and policy requirements — AUCs over time

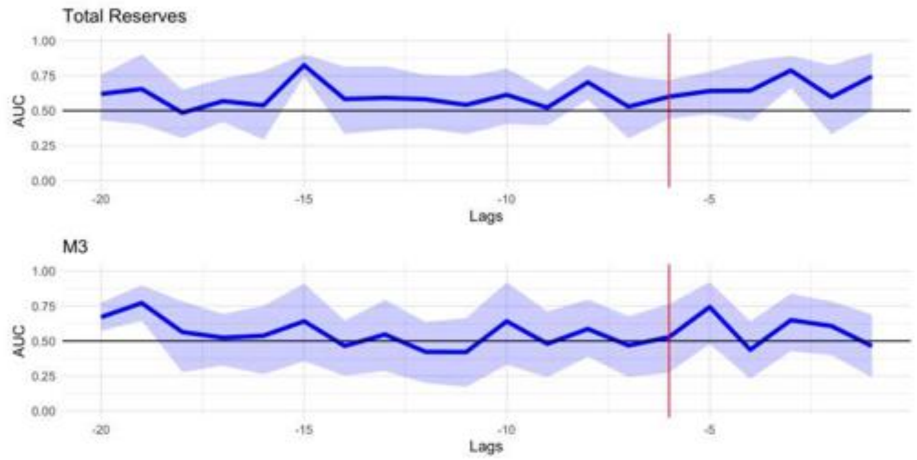

Figure no. 12 – EWIs and policy requirements — AUCs over time

The signal strength appears to be varying over the prediction horizon. These indicators provide a greater signal in predicting systemic risk and the significance of these indicators also signifies various aspects of systemic risk faced by these countries. First, our analysis looks at a balanced panel of countries starting from 2001 onward. Most of the selected countries experienced noticeable influence from global economies prior to the global crisis period. The credit disbursement increased significantly during this period. The elevated level of credit boom led to greater systemic risk for these countries. Naturally, the prominence of credit channels strengthens the signal strength of credit indicators before the crisis. Second, the selected countries also experienced greater integration with the global economy which led to greater credit disbursement within countries (IMF, 2010). As credit availability increased, the disbursement accelerated leading to greater credit supply to private non-financial sectors and government. It also leads to higher debt services for the local financial systems leading to greater systemic risk. The dollar dominance in lending also appears to impart significant influence on the systemic risk from credit disbursement. The dollar-denominated credit indicators appear to be stronger in signaling compared to their domestic currency counterparts. The variation of the exchange rate may be pinned as the plausible reason behind its contribution in systemic risk prediction. Foreign reserve accumulation, thereby, appears to be a strong predictor of systemic risk. Greater foreign reserve accumulation leads to better stabilization of exchange rate fluctuations. Following the logic, the prominence of credit channel and external interconnectedness remains two major source of systemic crisis in these countries. However, in absence of such safety nets, the risk of crisis remains significant. Unlike the findings of Drehmann and Juselius (2014), we don't observe any single indicator dominating in signal strength over short and medium horizon prior to crisis. This happens since the increase in systemic risk was reflected across these major indicators at the same time. Hence the signal strength of these selected indicators remained strong well before the crisis. The strict prominence of short-term signaling vis-a-vis the medium term signaling, thereby cannot be established for any indicator. However, it is worth noting that the signal strength is derived from the ROC analysis of the indicators, measured by the deviation from long term trend. The limitations in form of data availability of these indicators, infuses volatility in the estimates.

The lack of absolute supremacy of any indicator in terms of signal strength, rules out the possibility of single indicator-based monitoring of systemic risk. Rather, it advocates for a combination of indicators to predict the systemic risk episodes. However, any combination of these indicators does not necessarily provide the optimal solution as the policy instrument should be interpreted clearly. Hence, we combine these indicators in a meaningful way to provide a framework for the risk monitoring under macroprudential policy.

5.3 Combination of EWIs

We start with the selected EWIs namely (i) credit to the non-financial sector (in US dollar) (ii) credit to the non-financial sector (per cent to GDP) (iii) credit to the private non-financial sector (in US dollar) (iv) credit to the private non-financial sector as per cent of GDP (v) credit to the non-financial sector from banks (per cent to GDP) (vi) credit to the non-financial sector from banks (in the dollar) (vii) credit to the non-financial sector from banks (in local currency) (viii) credit to the central government as per cent of GDP, (ix) DSR and (x) Total reserves. However, these EWIs exhibit optimum signal strength across different prediction horizons. Hence, we combine these indicators in a meaningful way to strengthen the signal strength further. As indicated earlier, an ideal combination of these indicators can be thought of as a separating hyper-plane where the linear combination of these indicators separates out the classes (here, there are classes namely crisis and non-crisis). We estimate the hyper-plane using logit and pro-bit model with shrinkage. We use logistic regression with and without shrinkage to obtain linear combination of early warning indicators.

The combination of EWIs using logit model yields improvement of signal strength over all horizons. In particular, the signal of the EWI combinations remains at an elevated position compared to the threshold value of 0.5. However, the parameter space remains unrestricted in the logit regression due to lack of any shrinkage. Next, we restrict the parameter space using shrinkage approach. One of the benefits of using these shrinkage methods is that the important indicators are only considered. Though multiple indicators based early warning system provides a holistic approach of monitoring any emergence of systemic risks, it is often difficult to monitor many indicators at the same time. Here the shrinkage approach provides a better evaluation of the signal strength by looking only for the relevant indicators. Among the shrinkage models, the signal strength remains robust and stable over the prediction horizon (refer to Figure no. 13).

Next, we compare the signal strength of individual EWIs with the combined indicators. The variation in signal strength of individual indicators is plotted against the prediction horizon using box plot. The signal strength of combined EWI, derived from logit regression, remains at an elevated position compared to the variation of individual EWIs on average which implies strengthening of signal using combination of EWIs (refer to Figure no. 14).

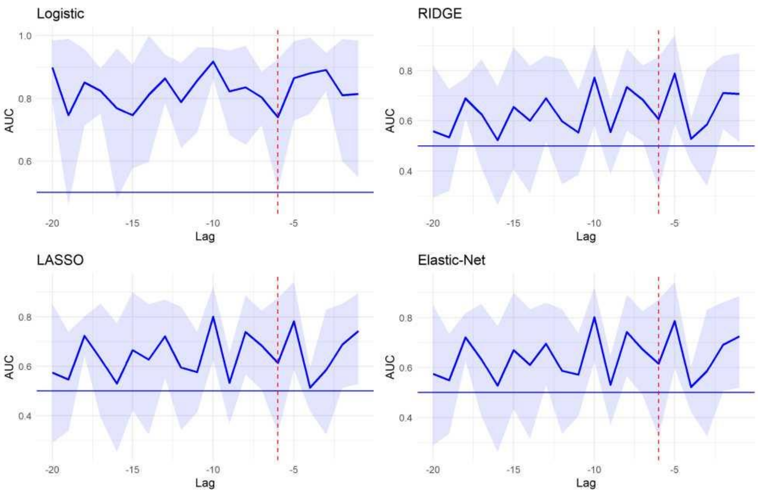

Figure no. 13 – Signal assessment of EWI combinations

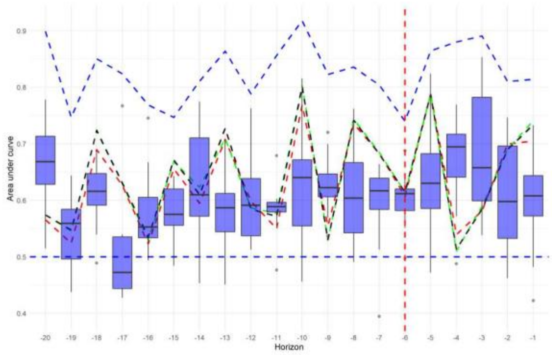

Figure no. 14 – Comparison of signal strength*

Note: Here, the blue line corresponds to logistic regression, the red line is the Ridge regression, the green line is for the Lasso, and the black one is for Elastic-net.

6. CONCLUDING REMARKS

This paper tries to analyze the effectiveness of EWIs in capturing and predicting banking and currency crises in cross-country set up using ROC analysis. However, the choice of early warning indicators poses challenge for the policymakers due to the cost involved in macroprudential policy. Targeting larger early warning indicators results in better management of systemic risks but the cost involved in false positive scenario leads to macroeconomic costs. Using a selection of emerging market economies, the paper analyzes the effectiveness of EWIs over 6 to 20 quarters horizon prior to the crisis. The indicators were selected to cover any systemic risks emerging from the banking sector and external sector. The paper observes that credit disbursement to private non-financial sector, credit disbursement to the central government, debt service ratio and foreign reserve appears to have better signal in predicting banking and external sector crisis. Further, the signal strength of the selected EWIs were found to be robust and stable over prediction horizon. However, the time profile of the EWIs remained varying and no unique EWI appeared to have dominating prediction power in short and medium horizon.

Next, we assess the prediction performance of combination of individual EWIs. The linear combination of EWIs is carried out using logistic regression. Further, shrinkage models are used to restrict the parameter space and avoid overfitting. Using three different types of shrinkage, the paper creates combination of EWIs using logistic regression, Ridge, Lasso and Elastic Net regression. The signal strength improves after combination of EWIs. Further, the signal remains stable and robust which underlines the importance of EWIs combination as an optimum policy instrument.

The limitation of the paper is mainly on account of data limitations. The framework requires longer time span data to determine the long-term trend. Also, the ROC analysis requires balanced panel of observations. The choice of emerging market economies restricts the data availability and thereby, may impact the stability of results. One cannot overcome the data limitations due to data availability issues. In view of the limitations, the paper attempts to address the concern using different choice of smoothing parameters and EWI combination models. The paper provides detailed evaluation of the EWIs at aggregate and disaggregated level and highlights the sectoral heterogeneity in identifying the EWIs. This approach can be generalized and extended to other countries. However, the banking and financial system of different countries are heterogeneous in nature and one has to consider the country level factors which triggered crisis. Further work involves the extension of the EWIs into country-level analysis so that the sectoral weaknesses can be identified.

ORCID

Yusuf Yildirim http://orcid.org/0000-0001-9556-6653
Anirban Sanyal http://orcid.org/0000-0002-3093-001X

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APPENDIX

A1 – List of abbreviations used

- A= Credit to Non-financial sector from All sectors at Market value - Percentage of GDP - Adjusted for breaks
- B = Credit to Non-financial sector from All sectors at Market value - US dollar - Adjusted for breaks
- C = Credit to Non-financial sector from All sectors at Market value - Domestic currency - Adjusted for breaks
- D = Credit to General government from All sectors at Nominal value - Percentage of GDP - Adjusted for breaks
- E = Credit to General government from All sectors at Nominal value - US dollar - Adjusted for breaks
- F = Credit to General government from All sectors at Nominal value - Domestic currency - Adjusted for breaks
- G = Credit to Private non-financial sector from All sectors at Market value - Percentage of GDP - Adjusted for breaks
- H= Credit to Private non-financial sector from All sectors at Market value - US dollar - Adjusted for breaks
- I = Credit to Private non-financial sector from All sectors at Market value - Domestic currency - Adjusted for breaks
- K = Credit to Private non-financial sector from Banks, total at Market value - Per¬centage of GDP - Adjusted for breaks
- L = Credit to Private non-financial sector from Banks, total at Market value - US dollar - Adjusted for breaks
- M = Credit to Private non-financial sector from Banks, total at Market value - Do¬mestic currency - Adjusted for breaks
- O = Credit-to-GDP ratios (actual data) - Credit from All sectors to Private non- financial sector
- P = DSR - Private non-financial sector
- Q = Gross Domestic Product by Expenditure in Constant Prices: Total Gross Domestic Product, Index 2015=100, Quarterly, Seasonally Adjusted
- R = Share Prices
- S = Interbank rate
- T = Current balance as per cent of GDP
- U = Total reserves (excl. Gold)
- V = M3

A2 – Unit root test

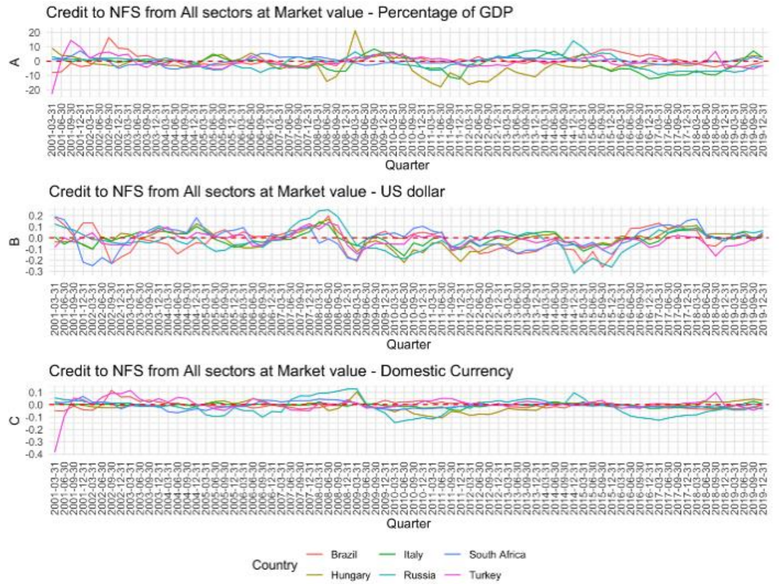
Country	Variable	No-drift No-Trend	Drift-No Trend	Drift-Trend
Brazil	A	0.98	0.99	0.92
Brazil	B	0.89	0.61	0.62
Brazil	C	0.99	0.99	0.98
Brazil	D	0.87	0.92	0.97
Brazil	E	0.98	0.99	0.92
Brazil	F	0.90	0.59	0.48
Brazil	G	0.99	0.99	0.99
Brazil	H	0.99	0.98	0.38
Brazil	I	0.85	0.62	0.75
Brazil	K	0.99	0.99	0.62

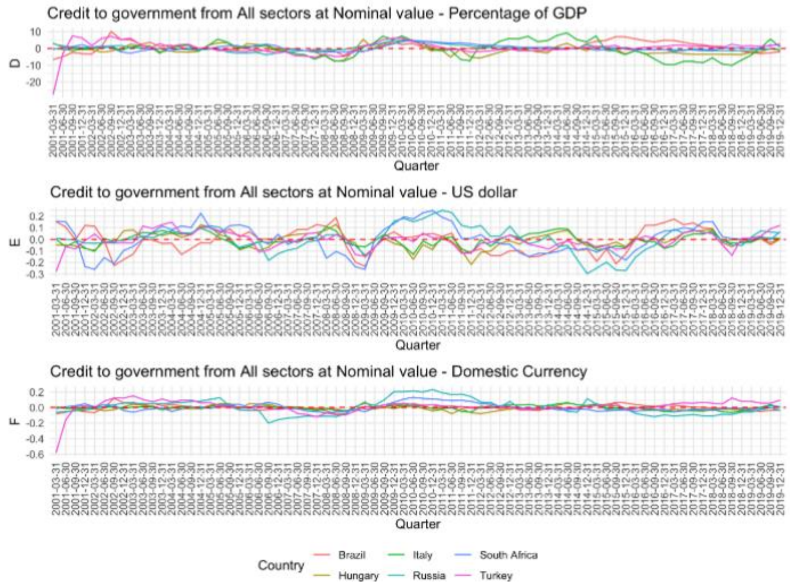
Country	Variable	No-drift No-Trend	Drift-No Trend	Drift-Trend
Brazil	L	0.94	0.70	0.73
Brazil	M	0.74	0.57	0.91
Brazil	O	0.99	0.98	0.38
Brazil	P	0.36	0.08	0.30
Brazil	Q	0.93	0.26	0.98
Brazil	R	0.96	0.92	0.64
Brazil	S	0.16	0.31	0.05
Brazil	T	0.06	0.14	0.04
Brazil	U	0.71	0.52	0.98
Brazil	V	0.99	0.99	0.28
Turkey	A	0.65	0.36	0.03
Turkey	B	0.92	0.31	0.94
Turkey	C	0.99	0.99	0.98
Turkey	D	0.01	0.01	0.12
Turkey	E	0.65	0.36	0.03
Turkey	F	0.69	0.02	0.27
Turkey	G	0.99	0.99	0.99
Turkey	H	0.97	0.84	0.12
Turkey	I	0.90	0.58	0.96
Turkey	K	0.99	0.99	0.99
Turkey	L	0.93	0.69	0.76
Turkey	M	0.84	0.60	0.96
Turkey	O	0.97	0.84	0.12
Turkey	P	0.44	0.25	0.04
Turkey	Q	0.99	0.93	0.55
Turkey	R	0.90	0.73	0.01
Turkey	S	0.01	0.01	0.01
Turkey	T	0.15	0.02	0.11
Turkey	U	0.77	0.29	0.93
Turkey	V	0.99	0.99	0.99
South Africa	A	0.97	0.98	0.01
South Africa	B	0.95	0.45	0.47
South Africa	C	0.99	0.99	0.60
South Africa	D	0.93	0.99	0.44
South Africa	E	0.97	0.98	0.01
South Africa	F	0.98	0.91	0.35
South Africa	G	0.99	0.99	0.99
South Africa	H	0.72	0.39	0.74
South Africa	I	0.89	0.22	0.68
South Africa	K	0.98	0.98	0.06
South Africa	L	0.71	0.32	0.82
South Africa	M	0.85	0.17	0.67
South Africa	O	0.72	0.39	0.74
South Africa	P	0.52	0.08	0.28
South Africa	Q	0.98	0.01	0.91
South Africa	R	0.97	0.84	0.21
South Africa	S	0.16	0.15	0.10
South Africa	T	0.17	0.05	0.24
South Africa	U	0.98	0.50	0.94
South Africa	V	0.97	0.97	0.30
Russia	A	0.85	0.84	0.37
Russia	B	0.85	0.66	0.29
Russia	C	0.98	0.99	0.53

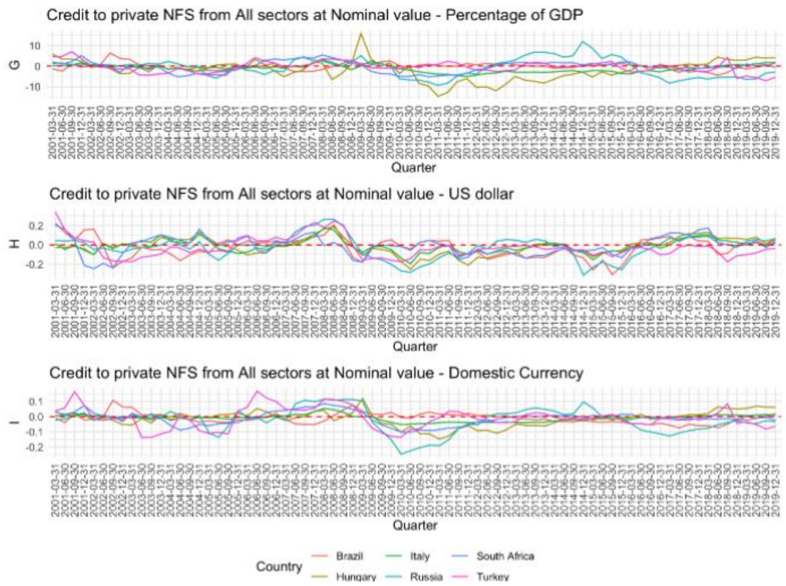
Country	Variable	No-drift No-Trend	Drift-No Trend	Drift-Trend
Russia	D	0.01	0.01	0.01
Russia	E	0.85	0.84	0.37
Russia	F	0.76	0.67	0.45
Russia	G	0.99	0.99	0.67
Russia	H	0.94	0.60	0.49
Russia	I	0.83	0.64	0.35
Russia	K	0.96	0.98	0.47
Russia	L	0.95	0.38	0.78
Russia	M	0.77	0.58	0.51
Russia	O	0.94	0.60	0.49
Russia	P	0.60	0.42	0.29
Russia	Q	0.56	0.01	0.01
Russia	R	0.92	0.79	0.32
Russia	S	0.01	0.03	0.21
Russia	T	0.03	0.01	0.01
Russia	U	0.77	0.43	0.66
Russia	V	0.99	0.99	0.43
Hungary	A	0.76	0.41	0.98
Hungary	B	0.81	0.11	0.73
Hungary	C	0.99	0.36	0.82
Hungary	D	0.76	0.42	0.96
Hungary	E	0.76	0.41	0.98
Hungary	F	0.89	0.08	0.54
Hungary	G	0.99	0.83	0.03
Hungary	H	0.70	0.50	0.96
Hungary	I	0.75	0.23	0.78
Hungary	K	0.99	0.31	0.88
Hungary	L	0.62	0.63	0.84
Hungary	M	0.67	0.31	0.69
Hungary	O	0.70	0.50	0.96
Hungary	P	0.41	0.79	0.90
Hungary	Q	0.98	0.95	0.88
Hungary	R	0.93	0.86	0.68
Hungary	S	0.05	0.50	0.01
Hungary	T	0.05	0.37	0.16
Hungary	U	0.64	0.47	0.92
Hungary	V	0.99	0.99	0.97
Italy	A	0.95	0.50	0.91
Italy	B	0.87	0.08	0.61
Italy	C	0.99	0.15	0.94
Italy	D	0.91	0.81	0.55
Italy	E	0.95	0.50	0.91
Italy	F	0.91	0.16	0.25
Italy	G	0.99	0.92	0.44
Italy	H	0.80	0.02	0.99
Italy	I	0.76	0.14	0.77
Italy	K	0.86	0.01	0.95
Italy	L	0.61	0.29	0.99
Italy	M	0.71	0.18	0.89
Italy	O	0.80	0.02	0.99
Italy	P	0.56	0.52	0.87
Italy	Q	0.67	0.18	0.32
Italy	R	0.33	0.15	0.41

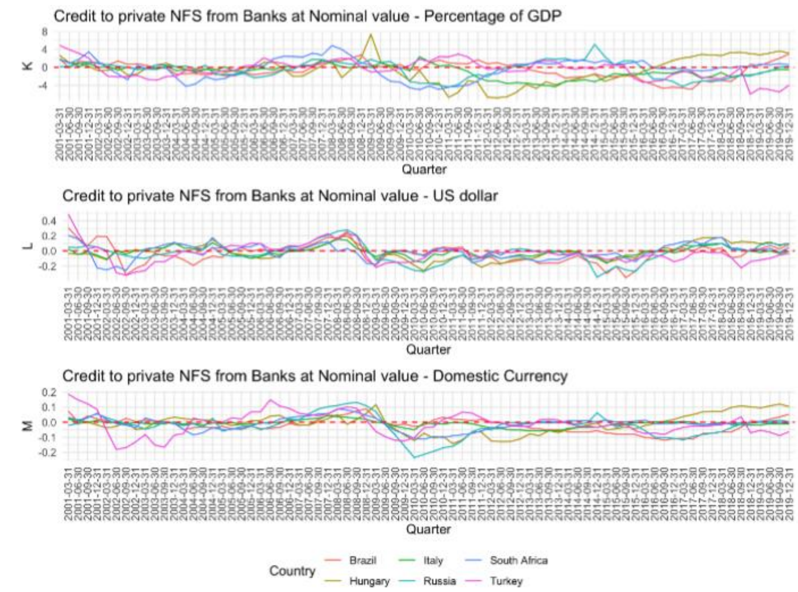
Country	Variable	No-drift No-Trend	Drift-No Trend	Drift-Trend
Italy	S	0.01	0.33	0.13
Italy	T	0.37	0.75	0.55
Italy	U	0.95	0.70	0.64
Italy	V	0.99	0.50	0.49

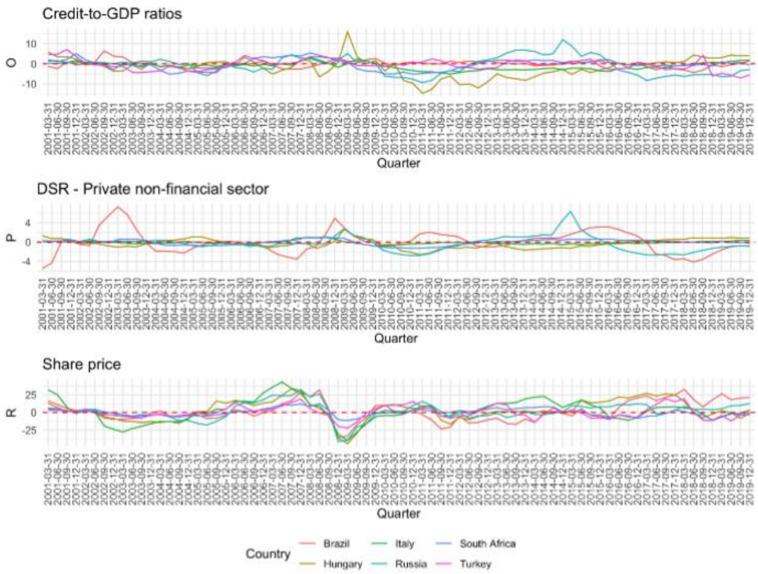
A3 – Detrending

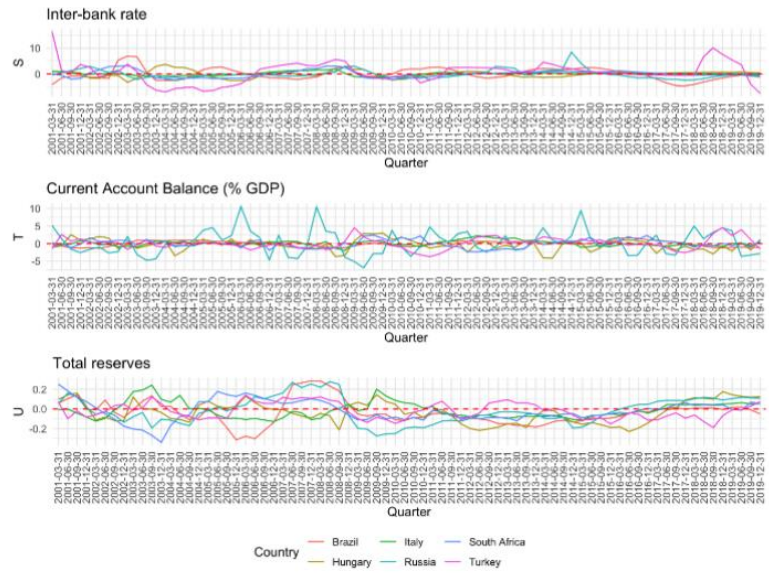


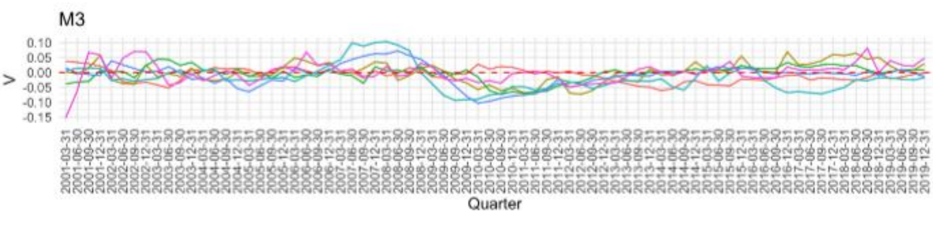



Credit to private NFS from All sectors at Nominal value - Percentage of GDP
G
Quarter
Credit to private NFS from All sectors at Nominal value - US dollar
H
Quarter
Credit to private NFS from All sectors at Nominal value - Domestic Currency
I
Quarter
Country
Brazil
Hungary
Italy
Russia
South Africa
Turkey

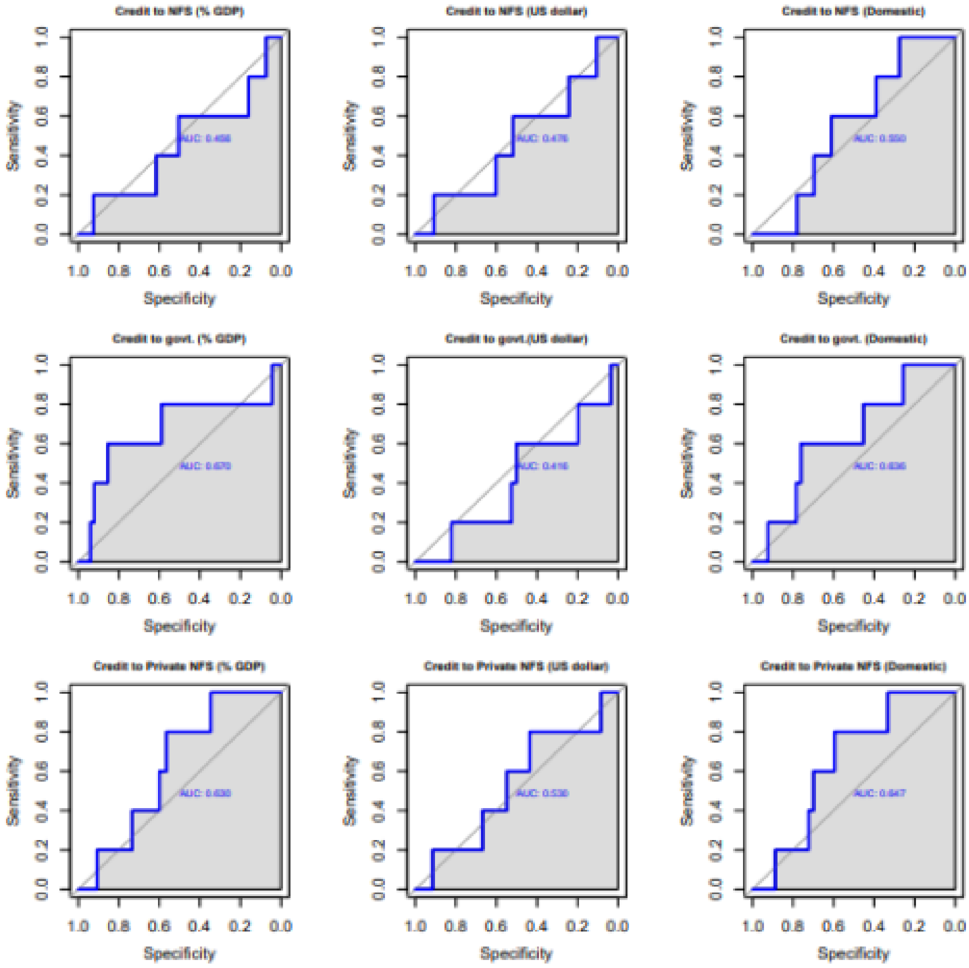

Credit to private NFS from Banks at Nominal value - Percentage of GDP
K
Quarter
Credit to private NFS from Banks at Nominal value - US dollar
L
Quarter
Credit to private NFS from Banks at Nominal value - Domestic Currency
M
Quarter
Country
Brazil
Hungary
Italy
Russia
South Africa
Turkey

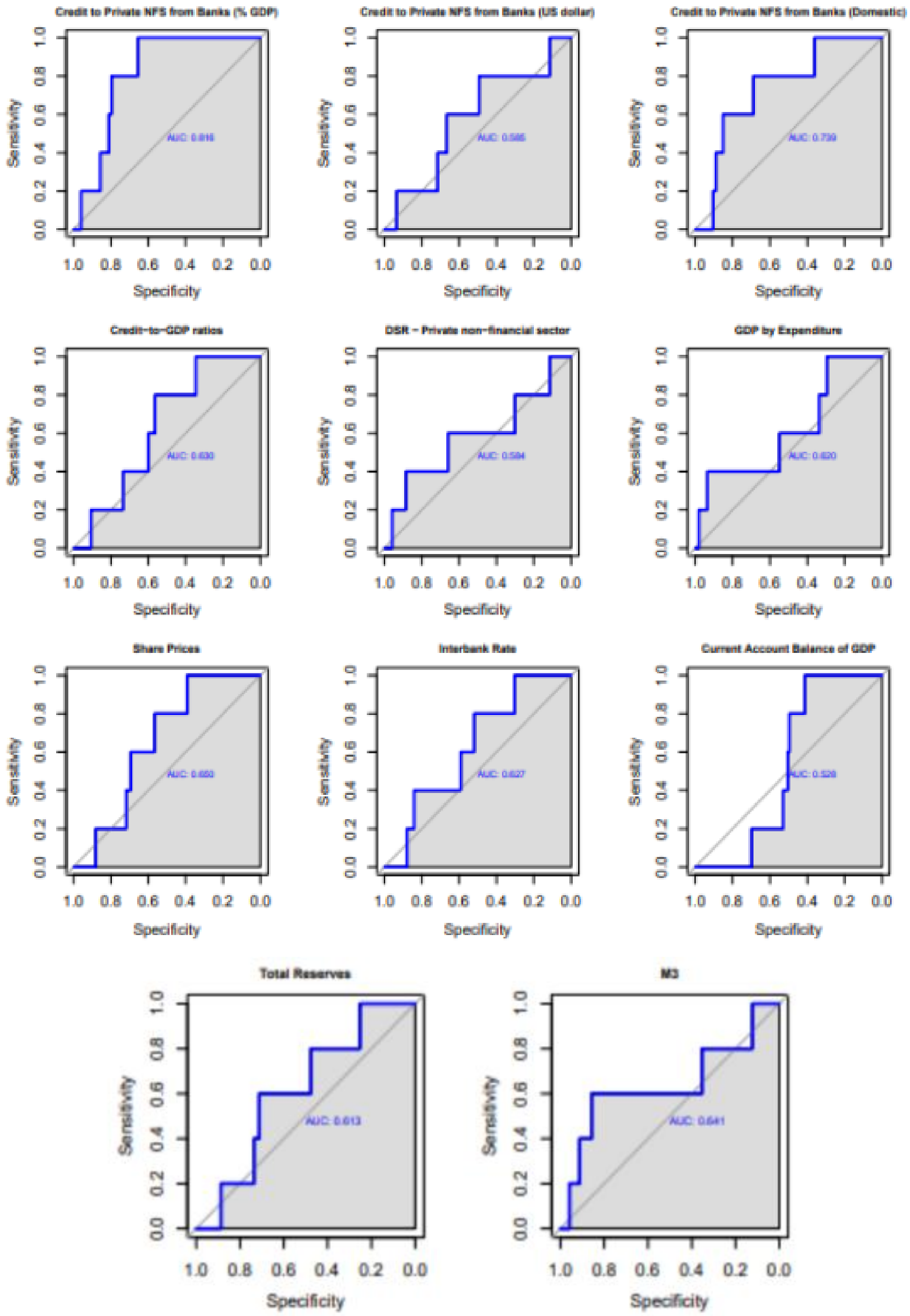

Credit-to-GDP ratios
DSR - Private non-financial sector
Share price
Quarter
Country
Brazil
Hungary
Italy
Russia
South Africa
Turkey


Inter-bank rate
Current Account Balance (% GDP)
Total reserves
Quarter
Country
Brazil
Hungary
Italy
Russia
South Africa
Turkey


M3
Quarter

A4 – ROC curves for horizon -8 and AUCs for different horizons




Credit to Private NFS from Banks (% GDP)
Credit to Private NFS from Banks (US dollar)
Credit to Private NFS from Banks (Domestic)
AUC: 0.739
Credit-to-GDP ratios
AUC: 0.630
DSR – Private non-financial sector
AUC: 0.584
GDP by Expenditure
AUC: 0.620
Share Prices
AUC: 0.650
Interbank Rate
AUC: 0.627
Current Account Balance of GDP
AUC: 0.528
Total Reserves
AUC: 0.613
M3
AUC: 0.641
Sensitivity
Specificity

		Horizon																			
Variable	Type	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Credit to NFS from All sectors - Percentage of GDP	AUC	0.42	0.55	0.70	0.49	0.55	0.61	0.60	0.49	0.61	0.46	0.55	0.65	0.58	0.72	0.57	0.67	0.44	0.49	0.60	0.68
	High	0.60	0.83	0.80	0.77	0.87	0.80	0.83	0.68	0.79	0.72	0.79	0.81	0.88	0.90	0.79	0.91	0.62	0.77	0.91	0.82
	Low	0.21	0.26	0.58	0.21	0.22	0.42	0.36	0.27	0.43	0.19	0.30	0.47	0.29	0.53	0.32	0.35	0.25	0.20	0.29	0.53
Credit to NFS from All sectors - US dollar	AUC	0.72	0.72	0.85	0.76	0.82	0.60	0.65	0.76	0.65	0.48	0.58	0.55	0.58	0.57	0.62	0.54	0.43	0.60	0.58	0.72
	High	0.89	0.93	0.92	0.92	0.92	0.83	0.86	0.91	0.84	0.73	0.78	0.79	0.82	0.78	0.76	0.80	0.67	0.82	0.84	0.86
	Low	0.50	0.50	0.78	0.54	0.73	0.30	0.37	0.57	0.40	0.24	0.38	0.26	0.33	0.32	0.46	0.24	0.19	0.36	0.30	0.51
Credit to NFS from All sectors - Domestic currency	AUC	0.47	0.58	0.72	0.40	0.48	0.56	0.48	0.55	0.56	0.55	0.58	0.66	0.64	0.61	0.59	0.63	0.61	0.53	0.50	0.64
	High	0.67	0.76	0.82	0.64	0.72	0.78	0.65	0.75	0.79	0.72	0.78	0.76	0.82	0.88	0.84	0.88	0.69	0.78	0.80	0.79
	Low	0.24	0.41	0.61	0.15	0.22	0.34	0.25	0.33	0.32	0.38	0.31	0.54	0.47	0.34	0.36	0.31	0.53	0.28	0.20	0.48
Credit to government from All sectors - Percentage of GDP	AUC	0.65	0.60	0.60	0.63	0.60	0.69	0.58	0.57	0.54	0.67	0.48	0.63	0.45	0.75	0.48	0.60	0.45	0.59	0.54	0.78
	High	0.82	0.79	0.73	0.86	0.87	0.87	0.77	0.69	0.66	0.92	0.60	0.70	0.67	0.95	0.67	0.82	0.62	0.87	0.75	0.94
	Low	0.48	0.40	0.48	0.38	0.29	0.47	0.35	0.46	0.40	0.33	0.34	0.56	0.20	0.52	0.29	0.41	0.25	0.27	0.33	0.58
Credit to government - US dollar	AUC	0.65	0.65	0.83	0.83	0.81	0.49	0.68	0.60	0.72	0.42	0.53	0.57	0.53	0.55	0.52	0.50	0.59	0.62	0.61	0.71
	High	0.85	0.90	0.91	0.95	0.93	0.70	0.84	0.90	0.91	0.66	0.72	0.82	0.83	0.78	0.81	0.78	0.84	0.87	0.86	0.84
	Low	0.46	0.38	0.76	0.69	0.68	0.24	0.45	0.27	0.43	0.17	0.33	0.27	0.22	0.31	0.21	0.21	0.33	0.36	0.32	0.53
Credit to government - Domestic currency	AUC	0.60	0.55	0.59	0.61	0.55	0.67	0.43	0.48	0.68	0.64	0.41	0.66	0.59	0.64	0.52	0.51	0.55	0.63	0.48	0.65
	High	0.82	0.83	0.75	0.82	0.82	0.85	0.60	0.75	0.84	0.84	0.64	0.75	0.79	0.79	0.83	0.77	0.76	0.85	0.67	0.78
	Low	0.38	0.26	0.39	0.31	0.27	0.42	0.22	0.19	0.51	0.41	0.17	0.57	0.29	0.50	0.19	0.23	0.35	0.37	0.26	0.47
Credit to Private NFS - Percentage of GDP	AUC	0.57	0.46	0.69	0.68	0.58	0.55	0.39	0.52	0.70	0.63	0.59	0.60	0.47	0.59	0.53	0.55	0.54	0.63	0.44	0.65
	High	0.79	0.75	0.82	0.85	0.89	0.77	0.58	0.79	0.90	0.79	0.84	0.79	0.76	0.76	0.83	0.87	0.72	0.83	0.74	0.82
	Low	0.28	0.19	0.55	0.53	0.24	0.32	0.18	0.24	0.43	0.46	0.30	0.37	0.19	0.35	0.22	0.22	0.34	0.42	0.13	0.45
Credit to Private NFS - US dollar	AUC	0.73	0.75	0.82	0.69	0.81	0.62	0.63	0.76	0.62	0.53	0.59	0.53	0.60	0.49	0.62	0.50	0.43	0.54	0.57	0.65
	High	0.90	0.94	0.88	0.90	0.91	0.84	0.83	0.90	0.78	0.76	0.80	0.75	0.83	0.67	0.77	0.73	0.63	0.74	0.83	0.82
	Low	0.52	0.52	0.75	0.42	0.72	0.32	0.36	0.60	0.43	0.28	0.38	0.28	0.33	0.28	0.47	0.24	0.20	0.33	0.32	0.45
Credit to Private NFS - Domestic currency	AUC	0.56	0.68	0.65	0.72	0.63	0.57	0.58	0.45	0.62	0.65	0.55	0.58	0.48	0.58	0.55	0.50	0.49	0.42	0.50	0.54
	High	0.76	0.81	0.82	0.85	0.80	0.75	0.76	0.65	0.81	0.80	0.74	0.71	0.66	0.77	0.80	0.75	0.66	0.56	0.79	0.70
	Low	0.31	0.54	0.46	0.60	0.40	0.38	0.41	0.24	0.36	0.47	0.31	0.44	0.23	0.34	0.32	0.25	0.31	0.25	0.20	0.34

		Horizon																			
Variable	Type	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Credit to Private NFS from Banks - Percentage of GDP	AUC	0.63	0.59	0.60	0.69	0.66	0.62	0.60	0.56	0.72	0.82	0.60	0.53	0.53	0.69	0.58	0.61	0.49	0.69	0.58	0.70
	High	0.88	0.79	0.83	0.90	0.88	0.83	0.79	0.83	0.92	0.90	0.79	0.72	0.80	0.90	0.89	0.95	0.73	0.92	0.91	0.94
	Low	0.30	0.35	0.36	0.43	0.36	0.40	0.39	0.28	0.42	0.72	0.35	0.31	0.27	0.35	0.27	0.26	0.24	0.44	0.26	0.38
Credit to Private NFS from Banks - US dollar	AUC	0.74	0.73	0.84	0.69	0.79	0.65	0.64	0.76	0.60	0.58	0.46	0.51	0.58	0.48	0.65	0.54	0.58	0.52	0.59	0.61
	High	0.91	0.94	0.89	0.88	0.91	0.87	0.85	0.90	0.76	0.81	0.69	0.75	0.80	0.67	0.77	0.77	0.80	0.72	0.85	0.80
	Low	0.50	0.47	0.78	0.48	0.67	0.34	0.36	0.61	0.41	0.33	0.23	0.25	0.34	0.26	0.53	0.26	0.38	0.31	0.33	0.41
Credit to Private NFS from Banks - Domestic currency	AUC	0.62	0.73	0.55	0.72	0.67	0.66	0.62	0.63	0.62	0.74	0.57	0.52	0.62	0.63	0.64	0.54	0.52	0.66	0.48	0.59
	High	0.80	0.81	0.75	0.86	0.83	0.78	0.79	0.81	0.82	0.89	0.75	0.70	0.81	0.83	0.87	0.80	0.74	0.80	0.75	0.77
	Low	0.42	0.65	0.34	0.56	0.51	0.53	0.42	0.44	0.37	0.54	0.37	0.36	0.42	0.34	0.41	0.27	0.30	0.53	0.22	0.36
Credit-to-GDP ratios	AUC	0.57	0.46	0.69	0.68	0.58	0.55	0.39	0.52	0.70	0.63	0.59	0.60	0.47	0.59	0.53	0.55	0.54	0.63	0.44	0.65
	High	0.79	0.75	0.82	0.85	0.89	0.77	0.58	0.79	0.90	0.79	0.85	0.79	0.76	0.76	0.83	0.87	0.72	0.83	0.75	0.82
	Low	0.27	0.18	0.55	0.53	0.24	0.31	0.18	0.23	0.43	0.46	0.30	0.37	0.19	0.35	0.22	0.22	0.33	0.42	0.13	0.45
DSR - Private non-financial sector	AUC	0.40	0.50	0.81	0.54	0.53	0.54	0.54	0.55	0.41	0.62	0.62	0.51	0.48	0.63	0.58	0.58	0.58	0.51	0.59	0.56
	High	0.59	0.78	0.93	0.74	0.76	0.65	0.78	0.78	0.63	0.87	0.73	0.74	0.75	0.87	0.85	0.85	0.80	0.68	0.86	0.67
	Low	0.20	0.22	0.67	0.37	0.27	0.43	0.30	0.28	0.18	0.37	0.49	0.29	0.23	0.33	0.28	0.29	0.39	0.34	0.33	0.45
GDP by Expenditure	AUC	0.48	0.53	0.62	0.57	0.47	0.50	0.51	0.68	0.61	0.65	0.58	0.76	0.70	0.77	0.56	0.75	0.46	0.61	0.46	0.73
	High	0.69	0.72	0.81	0.74	0.70	0.70	0.75	0.82	0.83	0.79	0.75	0.86	0.81	0.94	0.82	0.88	0.67	0.83	0.74	0.90
	Low	0.28	0.33	0.47	0.42	0.24	0.28	0.26	0.54	0.39	0.50	0.45	0.67	0.55	0.57	0.28	0.58	0.23	0.32	0.20	0.55
Share Prices	AUC	0.61	0.48	0.81	0.77	0.60	0.58	0.64	0.54	0.63	0.63	0.68	0.64	0.64	0.45	0.55	0.49	0.77	0.62	0.64	0.62
	High	0.80	0.74	0.90	0.91	0.81	0.74	0.87	0.73	0.83	0.81	0.89	0.76	0.85	0.71	0.79	0.81	0.92	0.84	0.90	0.74
	Low	0.45	0.22	0.73	0.63	0.31	0.42	0.33	0.35	0.33	0.43	0.36	0.51	0.39	0.19	0.28	0.18	0.56	0.41	0.32	0.51
Interbank Rate	AUC	0.57	0.70	0.46	0.58	0.52	0.56	0.66	0.43	0.50	0.53	0.73	0.53	0.75	0.37	0.65	0.57	0.56	0.59	0.72	0.58
	High	0.80	0.88	0.63	0.78	0.64	0.73	0.87	0.65	0.74	0.63	0.81	0.66	0.88	0.56	0.88	0.88	0.78	0.80	0.89	0.71
	Low	0.36	0.51	0.27	0.39	0.38	0.36	0.44	0.20	0.26	0.44	0.63	0.41	0.56	0.17	0.33	0.25	0.32	0.39	0.53	0.42

		Horizon																			
Variable	Type	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Current Account Balance of GDP	AUC	0.75	0.60	0.79	0.64	0.64	0.60	0.53	0.70	0.52	0.61	0.54	0.58	0.59	0.58	0.82	0.54	0.57	0.49	0.66	0.62
	High	0.91	0.83	0.89	0.85	0.78	0.72	0.75	0.83	0.65	0.80	0.74	0.76	0.82	0.82	0.90	0.78	0.74	0.65	0.91	0.76
	Low	0.50	0.33	0.66	0.42	0.48	0.44	0.30	0.58	0.40	0.40	0.33	0.38	0.37	0.33	0.74	0.29	0.43	0.30	0.41	0.43
Total Reserves	AUC	0.46	0.61	0.65	0.44	0.74	0.53	0.47	0.59	0.48	0.64	0.42	0.42	0.55	0.46	0.64	0.54	0.52	0.56	0.77	0.67
	High	0.69	0.78	0.84	0.64	0.92	0.76	0.68	0.80	0.72	0.92	0.66	0.63	0.80	0.65	0.91	0.75	0.70	0.78	0.90	0.77
	Low	0.24	0.40	0.44	0.23	0.48	0.27	0.24	0.38	0.24	0.33	0.18	0.20	0.29	0.25	0.36	0.26	0.32	0.28	0.65	0.57
M3	AUC	0.59	0.54	0.49	0.72	0.53	0.61	0.44	0.71	0.65	0.61	0.60	0.61	0.52	0.55	0.66	0.47	0.56	0.74	0.71	0.79
	High	0.75	0.74	0.73	0.87	0.74	0.80	0.67	0.90	0.88	0.81	0.81	0.85	0.78	0.78	0.86	0.76	0.80	0.91	0.89	0.94
	Low	0.40	0.32	0.23	0.57	0.27	0.39	0.20	0.48	0.43	0.36	0.33	0.37	0.27	0.29	0.41	0.18	0.31	0.52	0.46	0.60

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