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

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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. Several practical features of this challenge are translated into statistical evaluation criteria, including difficulties measuring the costs and advantages of various policy interventions, as well as requirements for the timeliness and stability of EWIs. We analyze the balance panel of possible EWIs for six countries that have experienced currency crisis and banking crisis in recent times. Using possible early warning indicators, we evaluate the suitability of these EWIs in view of their predictive power and stability of signals. The paper observes that credit disbursements to non-financial sectors and central government provides stable signal about systemic risks. Further debt service ratio, inter bank rates and total reserves are also found to be useful in predicting these crisis. Lastly, the paper observes that linear combination of these indicators improves the predictive power of EWIs further.

Keywords:EWIs, ROC, area under the curve, shrinkage
JEL Classification: C40, G01, G21

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1 Introduction

Early warning indicators (EWIs) are a critical component of time-varying macroprudential measures. A typical example is counter-cyclical capital buffers that can assist mitigate the significant losses associated with systemic risks from banking sector. However the choice of EWIs are always challenging. EWIs should have predictive power to highlight any systemic risk well in advance to facilitate policy reaction time. Further, EWIs must meet a number of additional conditions beyond the statistical predicting power. Signals, for example, must be stable and robust to reduce any policy cost. Another major challenge in this regard, is the interpretability of the EWIs and translate that into effective policy actions. With this background, the paper provides a holistic assessment of the signal strength of EWIs of systemic risks in predicting crisis for six countries using Receiver Operating Characteristics (ROC). The stability of signal strength is evaluated using area under the curve (AUC) of each indicators over different horizons prior to the crisis period. The paper, further, looks at the signals of individual EWIs and the time profile of the signal strength. Lastly, the paper combines the EWIs using linear combinations to validate the improvement of signaling due to combinations.

In economics, the standard procedure is to look into the marginal effect of a covariate on the likelihood of observing an outcome. However unlike any forecasting framework, the prediction of systemic risks should be fine in advance to take corrective actions. At the same time, any preventive policy action if taken well in advance, entails an opportunity cost. For EWIs, having the right time is critical. Macroprudential policies, on the one hand, take time to become effective (Basel Committee, 2010). Signals that arrive at an early stage, on the other hand, can be problematic because policy measures generate costs for society. Following the trade off between too long and too short horizons, we adopt an emerging consensus according to which a systemic risk should be signaled at least about 1.5 years but no more than 5 years prior to its materialization to allow policymakers time to implement counter-cyclical measures (Behn et al., 2013; Drehmann and Juselius, 2014). The choice of possible EWIs are driven by the importance of credit channel and influence of external sector in fuelling crisis. The predictive value of the EWIs are then be tested using standard inferential approaches. The loss functions associated with this predictive evaluation may differ, but unbiased estimates of the true model can be obtained if the model specification is a valid representation of the data generation process. Various loss functions, on the other hand, result in different models and parameter estimates, and hence possibly different conclusions about the functionality of a certain economic indicator when the statistical model is simply an approximation. We can decouple the decision problem from the loss function using the approaches we employ here; we don't need to build specific models. It's not that the loss function is unimportant; determining the best categorization for a given utility function over outcomes is critical.

Because calculating the costs and benefits of macroprudential policies is complex, the best alternative is to analyze EWIs using a variety of utility functions. Because the best decision under a given utility function entails a specific trade-off between Type I and Type II mistakes, one approach to do so is to evaluate the whole mapping between such trade-offs that a given EWI yields. The receiver operating characteristic (ROC) curve represents this mapping. The ROC curve has a lengthy history in other sciences, dating back to World War II, but its applications in economics are more limited. Cohen et al. (2009), Gorr and Schneider (2011), Berge and Jorda (2011), Jorda et al. (2011), Drehmann and Juselius (2014), Geršl and Jašová (2018) and Chen and Svirydzenka (2021) are recent exceptions. The ROC curve offers a number of helpful characteristics. The area under the curve (AUC) is a simple and easy-to-understand summary assessment of a binary signal's signaling quality. AUCs are also simply calculated. For comparing the AUCs of two signals, there exist parametric and non-parametric estimators, as well as confidence bands and Wald statistics. In this research, we employ AUC as the key metric for evaluating and comparing EWI classification performance, as well as to incorporate macroprudential policy considerations into the evaluation process. Beyond the prediction performance, the signal's steadiness is often ignored while selecting EWIs. For one thing, policymakers prefer to make decisions based on trends rather than reacting quickly to changes in signaling factors (Bernanke, 2004). EWIs that send out consistent and stable signals reduce uncertainty about trends, allowing for more clear policy responses. Lastly, less visible condition is that EWI signals be simple to understand, as any projections, including EWIs, that do not "make sense" are likely to be rejected by policymakers. Following Drehmann & Juselius(2013), we adopt three criteria for optimal EWIs of banking crises, including timing, stability, and interpretability.

This article's main contribution is that it is the first to assess the performance of EWIs via ROC analysis in terms of capturing financial crises for six countries (Brazil, Russia, Hungary, Turkey, South Africa, and Italy). These countries have experienced currency or banking crises in the recent times. We rely on two types of variables which caters to credit channel and external influences. The effectiveness of credit channel is evaluated through credit disbursement to different sectors. Apart from the credit data, we also use credit to GDP ratio and debt service ratio as additional indicators for assessing countries indebtedness. We use inter-bank rates and M3 as proxy of liquidity conditions. Lastly, we also consider current account balance as per cent of GDP, total reserves as control for external sector imbalances. Using these set of indicators, the paper finds that the credit disbursement to private non-financial sector and to the central government exhibit stable signal. The signal effects of the credit variables are visible in absolute terms as well as scaled by GDP. Further, the credit disbursement to private non-financial sectors by the banks appears to bear strong signals about systemic risks. Apart from these, the debt service ratio appears to have strong signal effect which remains stable over prediction horizon. Lastly, the total reserves is another promising indicator which provides strong signals as we approach to the crisis. Lastly, the paper observes that linear combination of these EWIs strengthens signal strength even further.

The rest of the paper is structured as follows - **section 2** reviews the most important studies in the field of Economics that have used ROC analysis. The data sources are described in **Section 3**. The methodology is introduced in **Section 4**, and the empirical results are presented in **Section 5**. The paper concludes by highlighting key findings in **Section 6**.

2 Literature Review

To begin with, Berge and Jorda (2011) created aggregate indices to assess economic activity. The ROC curve was then used to categorize economic activity into recessions and expansions. Gorr and Schneider (2011) applied ROC analysis to micro-level, monthly time data from the M3-Competition and its univariate forecast algorithms. They attempted to determine whether complicated univariate forecast algorithms perform better than basic ones in terms of ROC metrics. They found that sophisticated univariate approaches (including Flores-Pearce 2, ForecastPRO, Automat ANN, Theta, and SmartFCS) perform well for this objective when using the Cohen et al. (2009) analyzed the receiver operating characteristic (ROC) framework, which is well-known in the diagnostic decision-making literature, as an alternative to average lag length analysis for time series monitoring methods. They applied ROC curves approach using time series data on crime at the patrol district level in two cities.partial area under the ROC curve (PAUC) criterion as a forecast accuracy measure and paired-comparison testing using bootstrapping. The performance of early warning signs was evaluated using the ROC (Receiver Operating Characteristics) curve in a study undertaken by BIS economists Mathias Drehmann and Mikail Juselius (2014). The area under this curve (AUC) was used in the study to assess and compare the success of indicators in the classification of crises. For two indicators at a particular time before the crisis, they regarded the performance of the indicator with a bigger area under the ROC curve to be superior. They also took into account the signal's timeliness and steadiness as additional criterion. This is because macroprudential policies must be implemented over a period of time before they can be effective. As a result, they proposed the condition that the indications must arrive 1.5 to 5 years before to the crisis. They also took signal continuity into account while determining signal quality. They suggested that policymakers make judgments based on trends rather than abrupt shifts, therefore they assessed whether an indicator's signal quality deteriorates as the estimation time decreases. In other words, they presumed that this early warning indication is steady if the area under the curve increases as the crisis approaches. In addition, they asserted that indicators should be robust across samples and simple to interpret. They examined the performance of ten distinct early warning indicators in a study covering 26 nations from 1980 to 2012. They added the history of the country's financial crisis and the debt service ratio as two new indicators to these ten early warning indicators, in addition to the indicators in the literature (real credit growth, credit / GDP gap, growth rates of real estate prices, stock prices, and non-core liability ratio). In terms of the criteria given above, they concluded that the credit/ GDP gap and debt service ratio are the best performing indicators. Geršl and Jašová (2018) explored the role of credit-based variables as early warning indicators (EWIs) of banking crises in the context of emerging economies. They examined episodes of banking crises in 36 emerging economies from 1987 to 2015. To assess signal quality, they employed the ROC curve and compute AUC. Their findings show that nominal credit growth and the change in the credit-to-GDP ratio have the strongest signaling properties and outperform the credit-to-GDP gap in almost all policy-relevant horizon specifications. These findings contrast sharply with those obtained for advanced economies, where the credit-to-GDP gap is the single best performing EWI. These results underscore the importance of caution when adopting statistical techniques calibrated for advanced markets to emerging economies. Chen and Svirydzenka (2021) aimed to answer whether the upturns and downturns in financial variables serve as early warning indicators of banking crises. By employing signal extraction, ROC analysis, and discrete choice models and using data from 59 advanced and emerging countries, they demonstrated that while equity prices and the output gap are the best leading indicators in advanced markets; equity, property, and credit gap indicators provide valuable early warnings in emerging markets.

Three research come into prominence when we look at the studies done particularly for Turkey. Orhangazi (2014) investigated the link between capital inflows and periods of rapid credit expansion using a logit model. He created 12 logit models and used the ROC curve to evaluate their prediction potential. Cicek and Demirgil (2021) undertook a study with the goal of determining the causes of poverty in Turkey and determining the importance of these causes in explaining poverty. Logit models were created in the study by taking into consideration demographic and socioeconomic variables, as well as household features. They built ROC curves for each of these models and used the areas under the curve to select the optimal model. Financial sentiment analysis (FSA) and time series analysis (TSA) were used by Yasar and Kilimci (2020) to create a forecasting model for the US Dollar/Turkish Lira exchange rate. Word embedding methods Word2vec, GloVe, fastText, and deep learning models such as CNN, RNN, and LSTM were used to conduct FSA. Simple exponential smoothing, Holt–Winters, Holt's linear, and ARIMA models were used for TSA. They aimed to create models that can analyze sentiments with improved accuracy and performance by giving word vector spaces obtained from word embedding models as input to deep learning models on datasets collected from Twitter. Then, they labeled these sentiments as positive/negative. To accomplish so, they showed ROC curves of the combined categorization model for both Turkish and English Twitter documents. They argued that the combination of LSTM and GloVe provides the best categorization results for both types of Twitter documents.

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), and Jorda et al. (2011), 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 and Abramov, 2019). 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, 2020). 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 and 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 (Gwala, 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 3.1 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 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 Babecky 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 2.

Table 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 Standalone Indicators

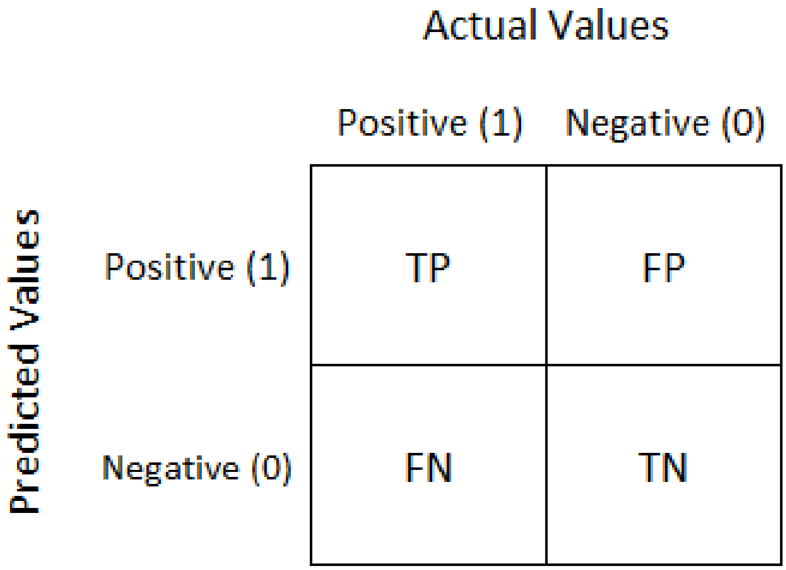
In this section, we discuss the receiver operating curve in general and how we may use it to compare the performance of the indicators in their standalone versions.

During World War II, the first ROC curve was utilized to analyze "radar signals." In order to detect enemy aircraft more accurately utilizing radar signals, the research related with ROC curves has begun. In the 1960s, ROC curves were first employed in medicine. In biostatistics and psychology, ROC curves are commonly employed in the evaluation of diagnostic tests. ROC curves are particularly useful when the outcome variable has two possible outcomes (depression present-absent, remission present-absent, recurrence present-absent, and so on), but the variable to be used in decision-making is continuous (such as cortisol, glycemia level).

In order to understand the ROC curves, it is necessary to know what the following expressions mean.

- Confusion Matrix is to show the current situation in the data set and the number of correct and incorrect predictions of our classification model. It is presented in Figure 1.
- True Positive (TP) : The model correctly predicted the positive class as a positive class.
- False Positive (FP) : The model predicted the negative class as a positive class.
- False Negative (FN) : The model predicted the positive class as a negative class.
- True Negative (TN) : The model correctly predicted the negative class as a negative class.

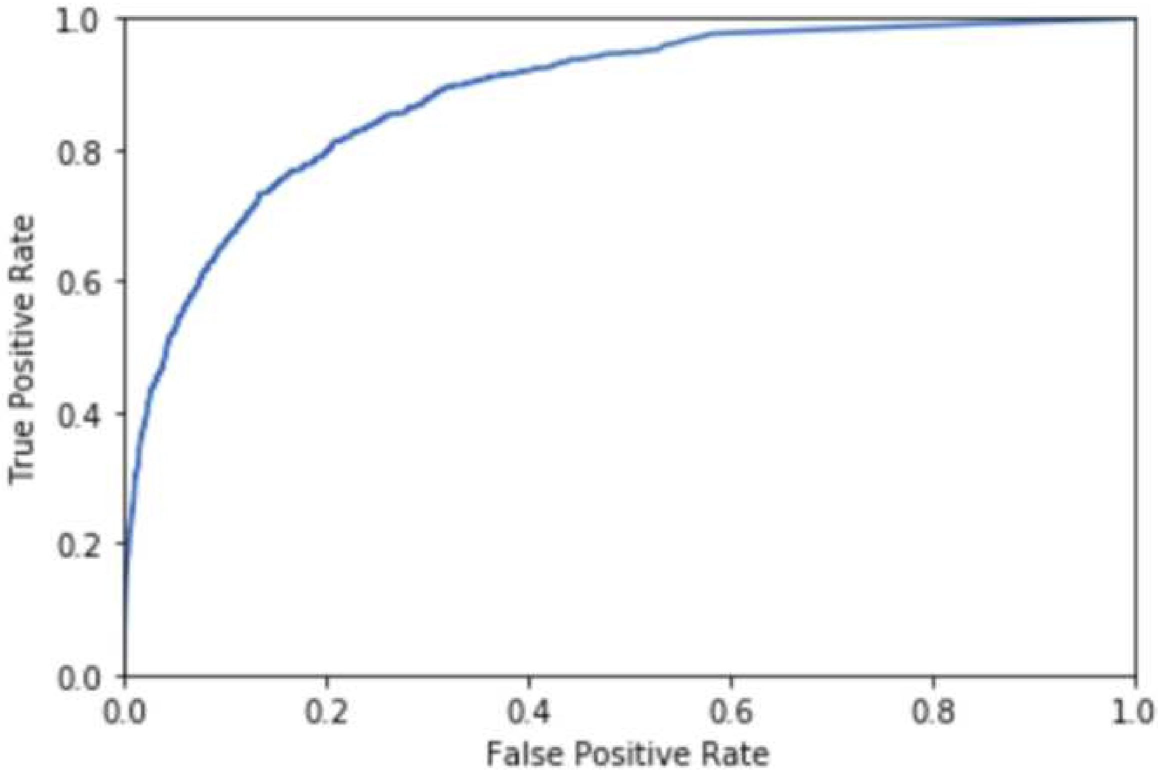
Figure 1: Confusion Matrix



ROC curves display all possible cut points for this continuous variable and provide estimations of the frequency of various outcomes - true positive (TP), true negative (TN), false positive (FP), and false negative (FN) for each cut-off point.

FPR (False Positive Ratio) is plotted on the x-axis, whereas TPR (True Positive Ratio) is plotted on the y-axis in ROC curves. An example of ROC curve is depicted in Figure 2. Different threshold values are used to produce TPR and FPR values, which are sensitivity and 1-specificity values, respectively. The ROC curve is made up of TPR and FPR pairings. It is possible to determine whether a test is useless or valuable based on its diagnostic success as determined by ROC analysis.

Figure 2: ROC curve



The true-positive rate informs us what percentage of predicted cases are present while the actual case is present. The false-positive rate is the percentage of cases that are mistakenly predicted as present but are not present. The mathematical expression for these two concepts are as follows.

$$\text{True Positive Rate} = \text{Sensitiviy} = \text{True Positives}/(\text{True Positives} + \text{False Negatives})$$

$$\text{False Positive Rate} = 1 \text{ -Specificity} = \text{False Positives}/(\text{False Positives}+\text{True Negatives})$$

When establishing the cut point, accepting a high or low value will result in different outcomes. When a low cut-off point is utilized in a test to distinguish between a crisis and a non-crisis condition;

- There will be a record of all of the crisis moments.

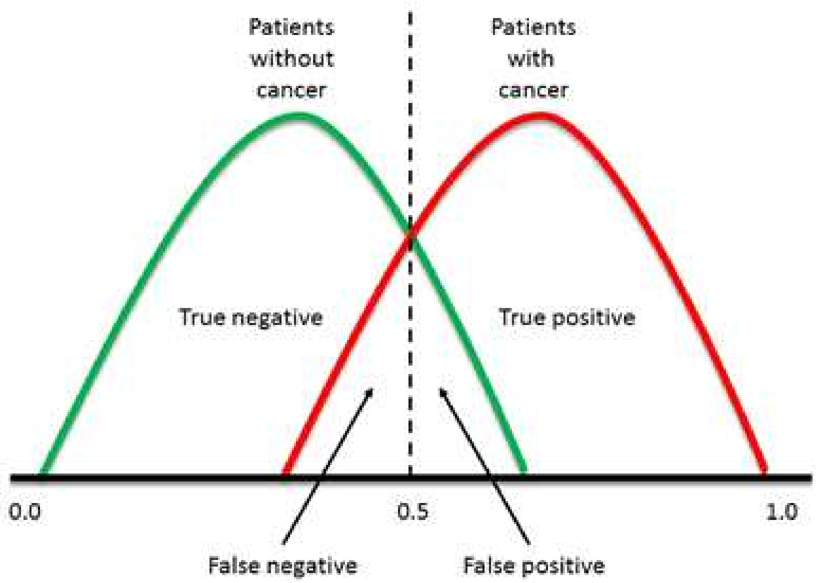
- Some of the no crisis periods will be diagnosed as crisis (false positive).
- The sensitivity of the screening test will improve, resulting in a higher true positive rate.
- On the other side, the screening test's sensitivity will fall, increasing the rate of false positives.

On the other hand, when a high cut-off point is utilized for a screening test;

- All of the times when there were no crisis will be discovered.
- Some of the crisis will be classified as no crisis (false negative).
- The sensitivity of the screening test will be reduced, lowering the true positive rate.
- On the other side, the specificity of the screening test will improve, lowering the percentage of false positives.

By providing Figure 3, we aim to explain the intuition behind the ROC curve graphically. The proportion of true positives to false positives is represented by the ROC curve. By putting these two measurements on the X and Y axes, we attempt to determine the area under the line (AUC-Area Under Curve). The greater the area below the line, the higher the model's success rate. The model‘s discriminatory power between two classes is high when AUC is big and TN and TP distributions do not intersect.

Figure 3: Intuition Behind the ROC Curve

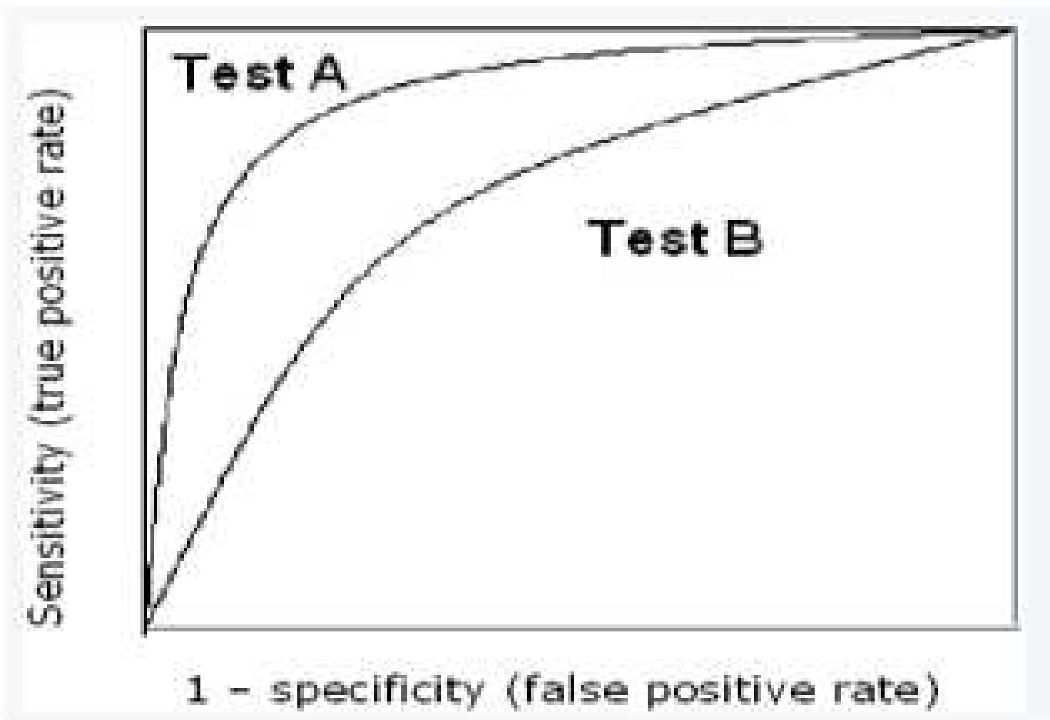


We can distinguish two extreme outcomes based on the ROC curve's discrimination power:

- Useless Test: If a diagnostic test can't tell the difference between crisis and no crisis situations, it's a waste of time and has the same chance as tossing a coin. The worthless test's ROC curve is on the diagonal line. It includes the point with a sensitivity of 50% and a specificity of 50%. The useless test has an area under the ROC curve of 0.5.
- Perfect Test: A diagnostic test is considered perfect if it can totally discriminate between crisis and no crisis situations. TPR (c) = 1, FPR (c) = 0 is the situation in this case. The majority of tests have a performance that falls between between useless and perfect.The discrimination power of the tests grows as they reach the upper left corner of the ROC curve ((0,1) point), where the test hits the perfect discrimination. AUC can take the "1" as the highest value.

In Figure 4, we depict the discrimination power of diagnostic tests by using AUC metrics. The figure shows that test A is superior to test B since the true positive rate is higher and the false positive rate is lower than test B at all cut-offs. Test A's area under the curve is bigger than Test B's area under the curve.

Figure 4: Discrimination Power of ROC Curve - Area Under the Curve



After introducing the method which we employ in this paper, we explain how to implement it in terms of evaluating the performance of EWIs in predicting crises.

The usage of macroprudential regulations has exploded since the financial crisis of 2008. While the instruments and regulations used to implement macroprudential policies differ, the main goal is to reduce systemic risk, which is defined as the possibility of widespread interruptions in the provision of financial services that have severe negative consequences for the real economy. Addressing the financial system's procyclicality, for example, by dictating the accumulation of buffers in "good times" so that they can be pulled down in "poor times," is a critical component of the macroprudential strategy. Countercyclical capital buffers and dynamic provisioning are two tools that have already been employed in this area. One of the most difficult tasks facing policymakers is identifying distinct states in real time, with a focus on recognizing unsustainable booms that could lead to a financial disaster.

To make matters concrete and illustrate how the policymaker's utility affects the choosing of an ideal EWI, assume a relatively simple economy that can be in three states: normal, boom ("good times"), and crisis ("bad times"). While policymakers are aware of when a crisis exists, the true status during normal and boom times (B=0 and B=1, respectively) is not readily visible. Policymakers in these states have the option of implementing a policy (P=1) or not (P=0).

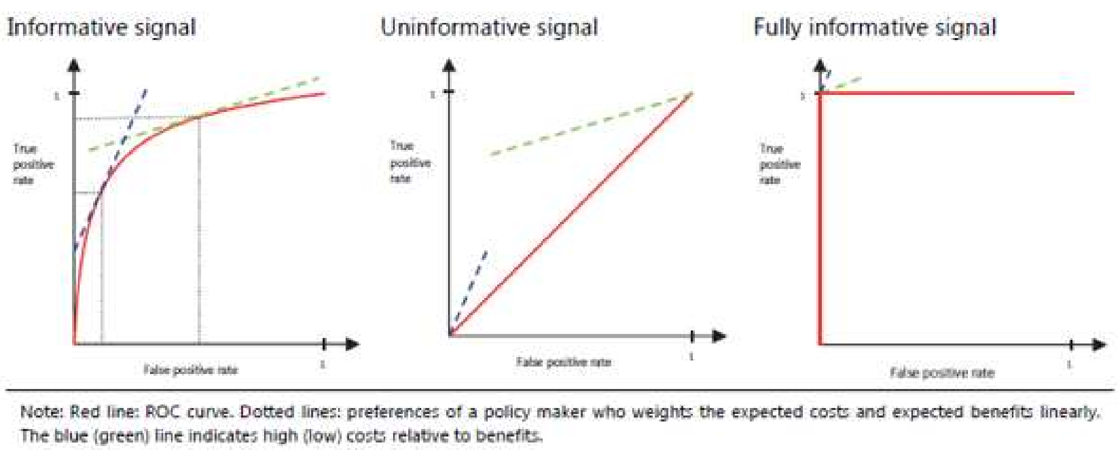
Although putting a policy in place is costly, it offers the advantage of avoiding economic losses in the event of a crisis. We denote the utilities of choosing policy P in state B by U_{PB} and define the natural assumptions as follows:

$$U_{11} > U_{01} \text{ and } U_{00} > U_{10}.$$

Furthermore, imagine the policymaker notices a real-valued signal S that contains incomplete information about the current condition. The signal can be anything from a statistical model's probability forecast regarding B to an observable economic variable. For the sake of simplicity, we assume that the greater the value of S, the more probable the economy is growing; nevertheless, any variable that falls in a boom will have this attribute when multiplied by -1. The policymaker's choice problem is to set a threshold, S, above which the probability of being in the boom state is high enough to make the cost-benefit trade-off of corrective policy interventions optimal. S becomes a binary EWI for the crisis state when such a threshold is set.

In an ideal circumstance, the chosen S threshold would reliably signal the status. In actuality, though, some noise will be associated with the signal. This indicates that the rate of true positives, $TPRS(\theta) = P(S > \theta \mid B = 1)$, and the rate of false positives, $FPRS(\theta) = P(S > \theta \mid B = 0)$, have a trade-off. TPR will be close to one for very low threshold values, for example, but the same will be true for FPR. When the threshold is set too high, the result is the polar opposite. The trade-offs between the TPR and FPR rates will shift near to the upper left limit of a unit square if S is very informative, and along a 45° line if it is uninformative, for intermediate values of the threshold. The receiver operating characteristic (ROC) is the mapping from FPR to TPR for all feasible thresholds, and it is defined as $TPR = ROC(FPR)$. The red lines in Figure 5 illustrate the trade-offs of three hypothetical variables.

Figure 5: Assessing Signal Quality



(Source: Drehmann & Juselius (2013))

How should policymakers determine the threshold level in the face of a trade-off between true and false positives? Baker and Kramer (2007), Cohen et al. (2009) proved that the policymaker should set the threshold so that the ROC curve's slope equals the predicted marginal rate of substitution between the net utility of accurate expansion and recession prediction.

$$\frac{dROC}{dFPR} = \frac{\left(U_{00} - U_{10}\right)\left(1 - \pi\right)}{\left(U_{11} - U_{01}\right)\pi}$$

where π is the unconditional probability of a crisis. For example, if the cost of adopting a policy action outweighs the predicted benefits, the policymaker will be wary of a high FPR. The steep blue line in Figure 5 exemplifies this. If the cost of a crisis is relatively high, as illustrated by the flat green line in the graph, the converse is true. The best threshold is the one that corresponds to the tangent points in Figure 5 between the red and green or blue curves.

Unfortunately, determining the predicted costs and benefits of macroprudential regulation, as well as the best trade-off between the TPR and FPR of different signals, is difficult. As a result, the question is how to assess the quality of various signals in the lack of information on the costs and benefits of policy measures. Examining the complete ROC curve, which effectively amounts to evaluating the signal throughout the entire range of conceivable utility functions, is one possible method. The area under the ROC curve can be read as the chance that the distribution of S during the boom is stochastically greater than during normal times, which is a useful attribute. This fact implies that the area under the curve (AUC) is a useful and easy-to-understand summary measure of S's signaling quality. The AUC of signal S is calculated as follows:

$$AUC(S) = \int_0^1 ROC(FPR(S))dFPR(S)$$

AUC rises with the indicator's predictive power across all feasible thresholds and is between 0 and 1. For uninformative indications, it takes the value 0.5. If S is informative and stochastically larger in booms than in normal times, AUC is greater than 0.5. In contrast, if S is informative and stochastically smaller in booms than in normal times, AUC is smaller than 0.5. We utilize the AUC to compare the relative performance of different EWIs in this work because of its valuable property and the lack of specific evidence regarding the costs and benefits of macroprudential regulation.

In this part, we also highlight two key features of an ideal EWI and officially describe the criteria for selecting one indication over another. Throughout the debate, we assume that the indicators rise in tandem with the likelihood of a crisis. In general, falling indicators can be accommodated by reversing their interpretation (i.e. multiplying by -1) or by adjusting the inequalities of the criteria.

For policymakers, the proper timing of an ideal EWI is critical, and it has two dimensions. First, EWIs must detect crises early enough to allow policy responses to be enacted in a timely manner. The amount of time required relies, among other things, on the lead-lag connection between modifying a macroprudential tool and the influence on the policy goal. In contrast to monetary policy, where it is generally accepted that interest rates take at least a year to affect inflation, the relationship between macroprudential measures and inflation is less well understood. It will, however, most certainly be at least as long. Under Basel III's countercyclical capital buffer framework, for example, banks have one year to comply with increasing capital requirements. Furthermore, data are published with lags, and policymakers often do not react to data changes immediately, preferring to examine trends for a period of time before making policy changes. As a result, EWIs should begin generating signals at least six quarters before a crisis occurs.

Second, because macroprudential interventions have costs, ideal EWIs should not flag crises too early. If adopted policies are implemented too soon, this can erode support for them. It's tough to know when something is "too early" for an optimal EWI. However, in order to be conservative, we conduct our empirical research over a five-year period.

We compute $AUC(S_{i,h})$ for all horizons h within a 5-year window before a crisis, i.e, h runs from -20 to -1 quarters, to evaluate the proper timing of an indicator S_i. When we compute $AUC(S_i, h)$, we do not consider the signals in all other quarters than h in the forecast window. For instance, at horizon -5, $TPR(S_i, -5)$ is only determined by signals issued 5 quarters before crises. On the other hand, $FPR(S_i, -5)$, depends on all signals issued outside the five year forecast window before crises.
Following Drehmann & Juselius (2013), we incorporate the stability and robustness of signal strength using three criteria

Criterion 1:

If $AUC(S_{i,h}) > 0.5$ for some horizon h [-20,-6] , an EWI S_i has the correct timing. If the direction of an indicator reverses across distinct time horizons, a special challenge linked to Criterion 1 can occur. In these circumstances, rather than multiplying S by -1 at the problematic horizons, we utilize $AUC(S_{i,h}) \neq 0.5$ in Criterion 1.

Signal stability is a significant additional requirement that has mostly been disregarded in the literature thus far. As previously stated, policymakers do not react instantly to data changes in practice, but rather make decisions based on trends.

Criterion 2:

An EWI S_i is stable if $AUC(S_{i,-6-j}) \leqslant AUC(S_{i,-6}) \leqslant AUC(S_{i,-6+k})$

Any informative signal that reverses direction during the policy relevant horizons is considered unstable by definition.

Criterion 3:

EWI S_i outperforms EWI S_j for horizon h if $AUC(S_{i,h}) > AUC(S_{j,h})$. To compare an increasing indicator, $S_{i,h}$, with a falling indicator, $S_{j,h}$ say, we would multiply the latter by -1 or substitute $AUC(S_{i,h})$ in Criterion 3 by 1–$AUC(S_{i,h})$.

Robustness and interpretability are two more obvious needs. The signaling quality of an EWI, for example, should be consistent among samples and not unduly sensitive to the precise crises date used. Of fact, while robustness assessments help us to identify common aspects in historical data, it is impossible to predict EWIs' future stability.

EWI signals should be simple to understand; in other words, an ideal EWI should not only meet the statistical criteria listed above, but also "make sense." Otherwise, an EWI will not be deployed since practitioners emphasize forecast interpretability over accuracy, and projections will be adjusted if they lack valid explanations. Furthermore, EWIs with strong conceptual foundations are better adapted to clear communication, which is an essential part of macroprudential policymaking.

4.2 Combining Indicators

Early warning indicators can be selected based o0n their signal strength and thereby can be used for predicting any elevation in the systemic risk. However the main drawback of 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 interpret-ability 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 a linear combinations i.e. $\sum_i \theta_i EWI_{it}$ as it has a natural interpretability due to linear additivity of the indicators. Su & Liu (1993) proposed an optimal linear combinations 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

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

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 The Behaviour of Indicator Variables Around Systemic Crises

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 3.8.1 and 3.8.2. The majority of 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 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 3.8.3. 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 6 - 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). While some indicators appear to hover above the median value have strong ability for predicting forthcoming crises in the graph, some of them Certain indicators, such as credit to non-financial sector and government as a percentage of GDP, DSR and credit-to-GDP gap show distinct tendencies to rise long before a crisis and collapse shortly before or immediately after it begins. These indicators appear to hover above the median value in normal times while approaching the crisis periods.

Figure 6: Indicator variables around crises

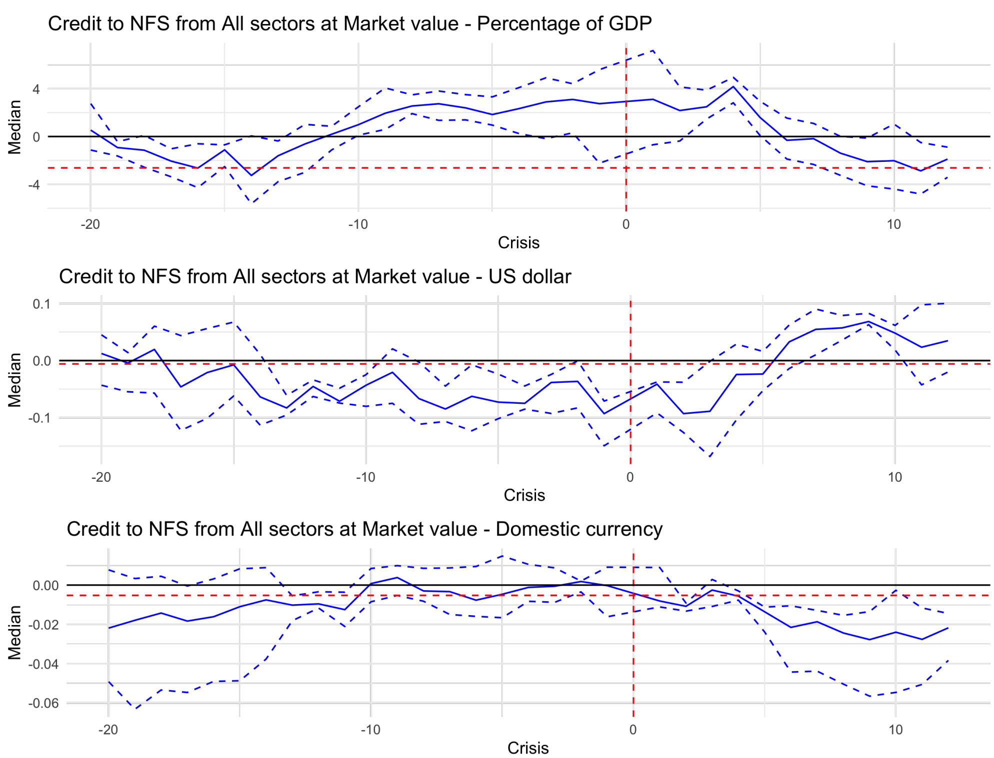
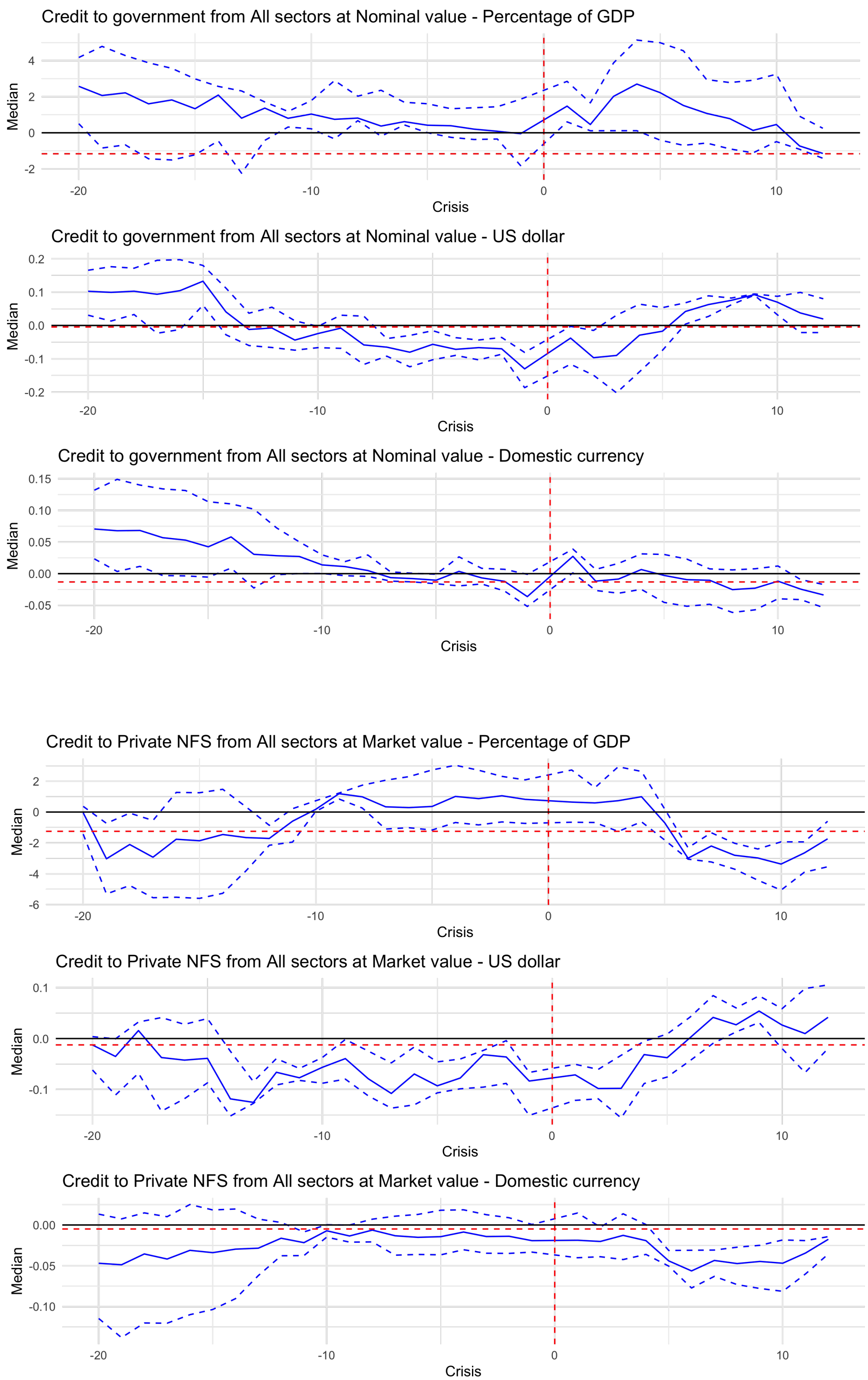
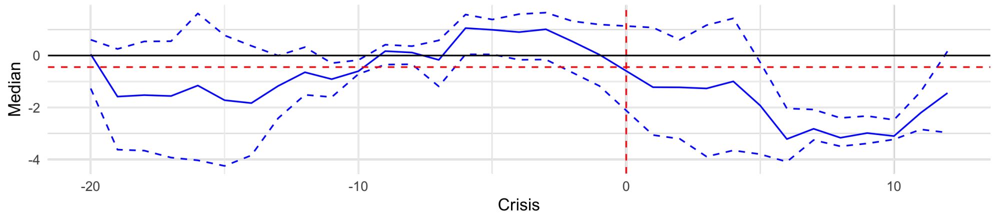


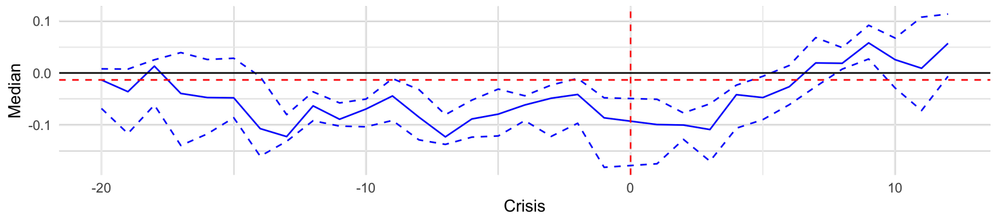
Figure 7: Indicator variables around crises



Credit to Private NFS from Banks, total at Market value - Percentage of GDP

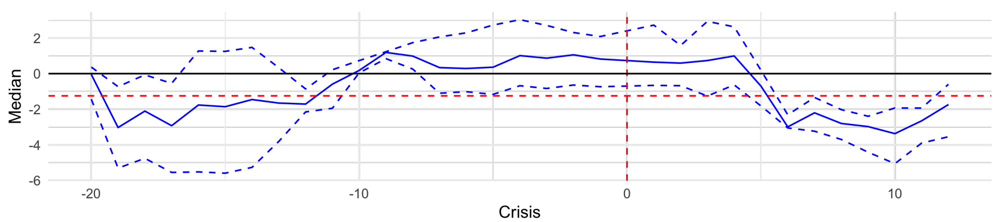


Credit to Private NFS from Banks, total at Market value - US dollar

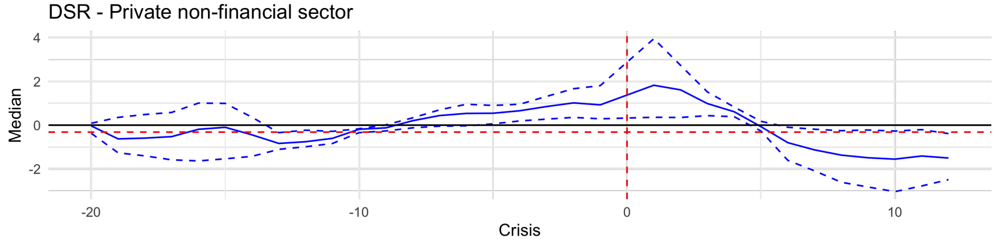


Credit to Private NFS from Banks, total at Market value - Domestic currency

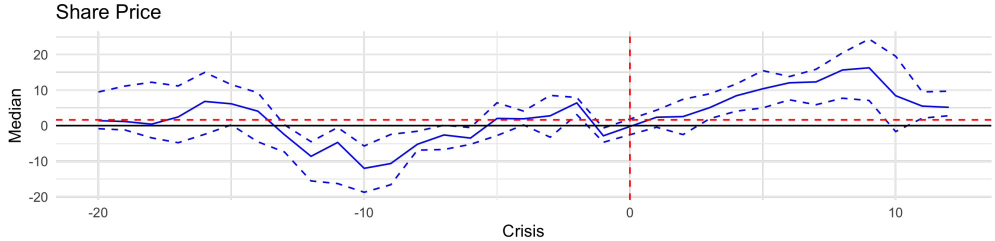
Credit-to-GDP ratios

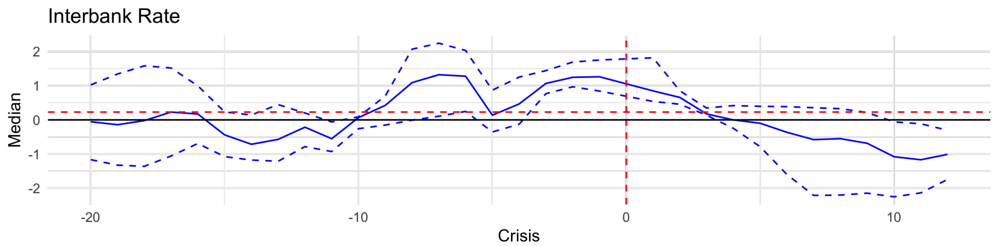


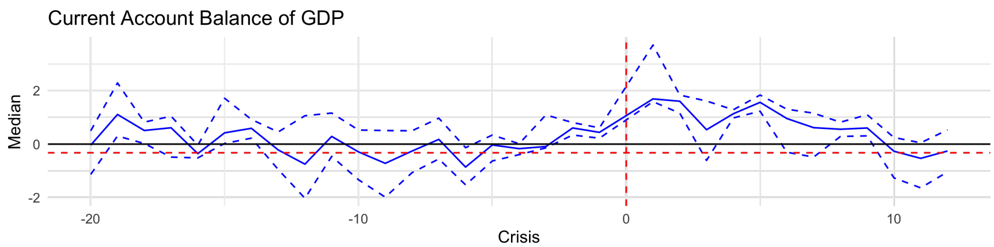
DSR - Private non-financial sector

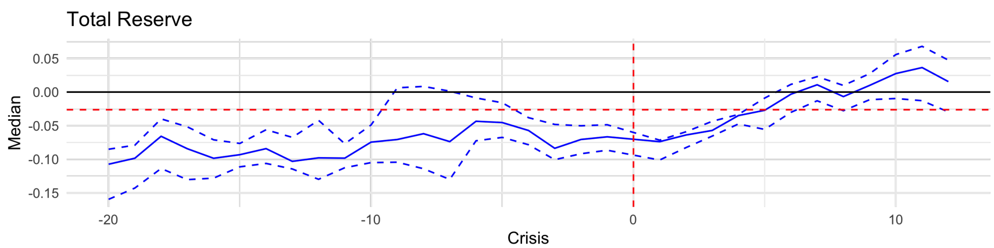


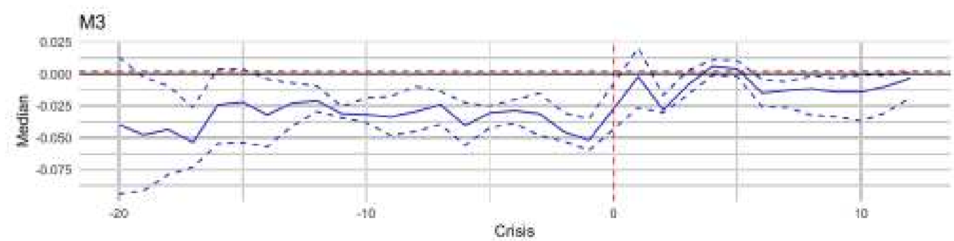
Share Price




Interbank Rate
Median
2
1
0
-1
-2
-20
-10
0
10
Crisis


Current Account Balance of GDP
Median
2
0
-2
-20
-10
0
10
Crisis


Total Reserve
Median
0.05
0.00
-0.05
-0.10
-0.15
-20
-10
0
10
Crisis


M3
Median
0.025
0.000
-0.025
-0.050
-0.075
-20
-10
0
10
Crisis

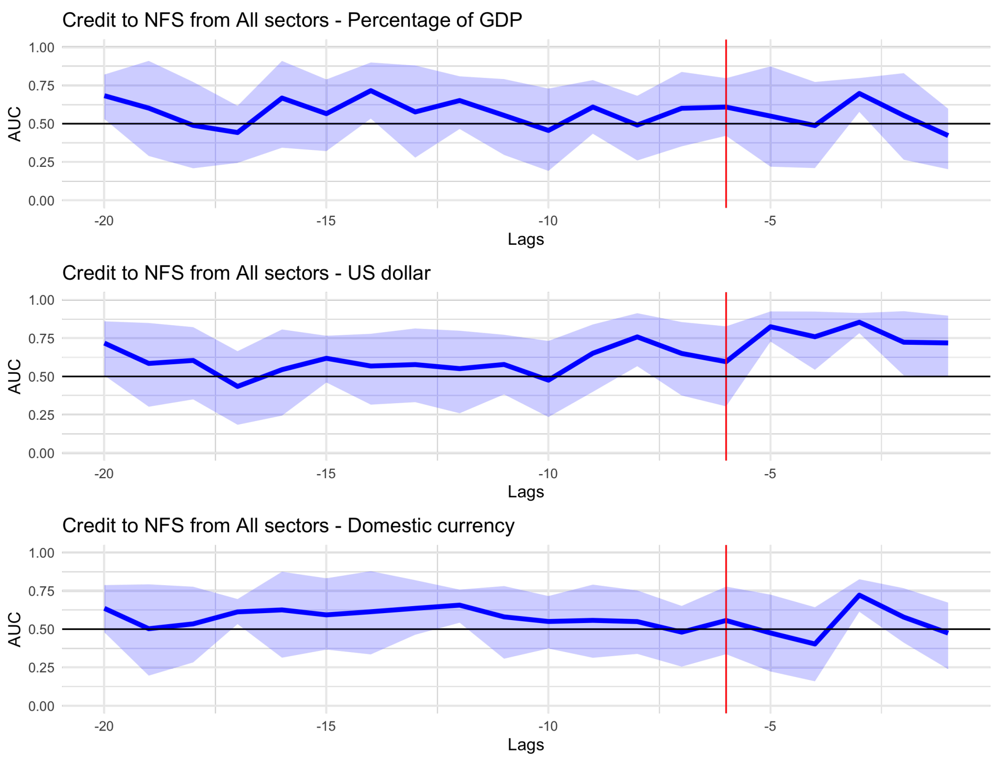
5.2 The Signalling Quality of Different Standalone EWIs

The findings of assessing whether proposed EWIs meet the three 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 Figure 8 - 14 (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 signal of indicators is assessed with respect to AUC threshold value of 0.5. Hence higher value of AUC above the black line, therefore, supports better strength in signal of the indicators. On the contrary, AUC value below the threshold signify lack of signal strength of the indicators ahead of the crisis horizon. Lastly, ROC curves estimates for horizon of 8 quarters before crisis are shown in Appendix.

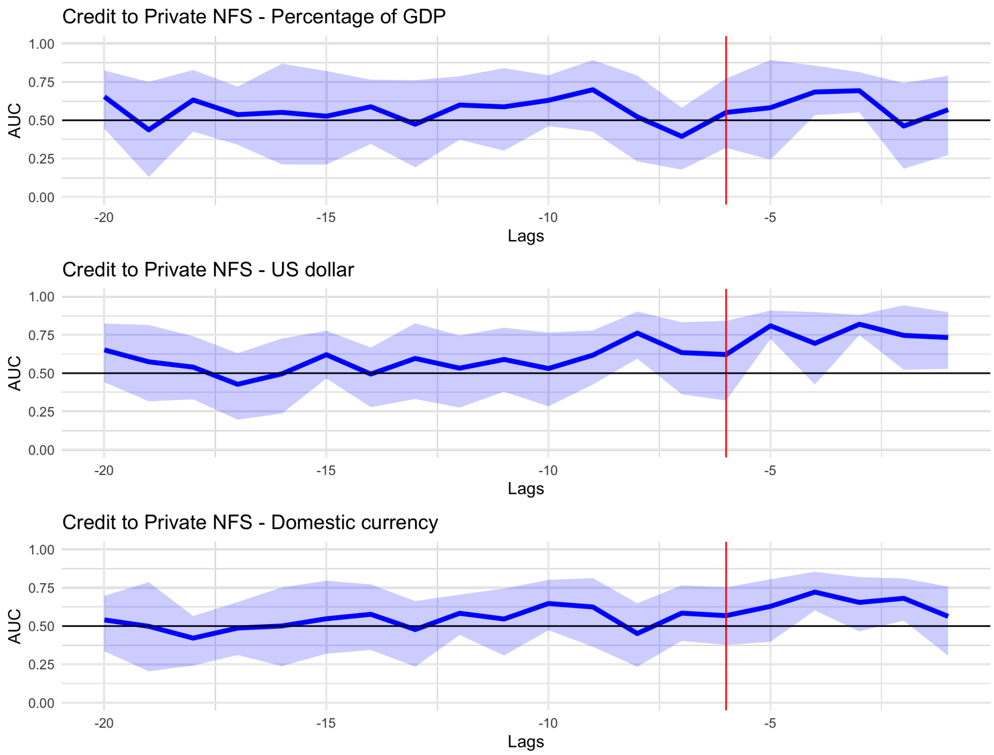
First, we evaluate the signal strength of credit variables. Following Figure 8, the credit to non-financial sectors showcase a consistent signal prior to 6 quarters of crisis as the AUC estimates of these variables stayed above the threshold value. Further, the strength of signal also remained steady up to 20 quarters before the crisis period with marginal slips around 10th and 17th 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 satisfy the robustness and stability criteria near the threshold of 6 quarters before crisis.

Figure 8: EWIs and policy requirements – AUCs over time



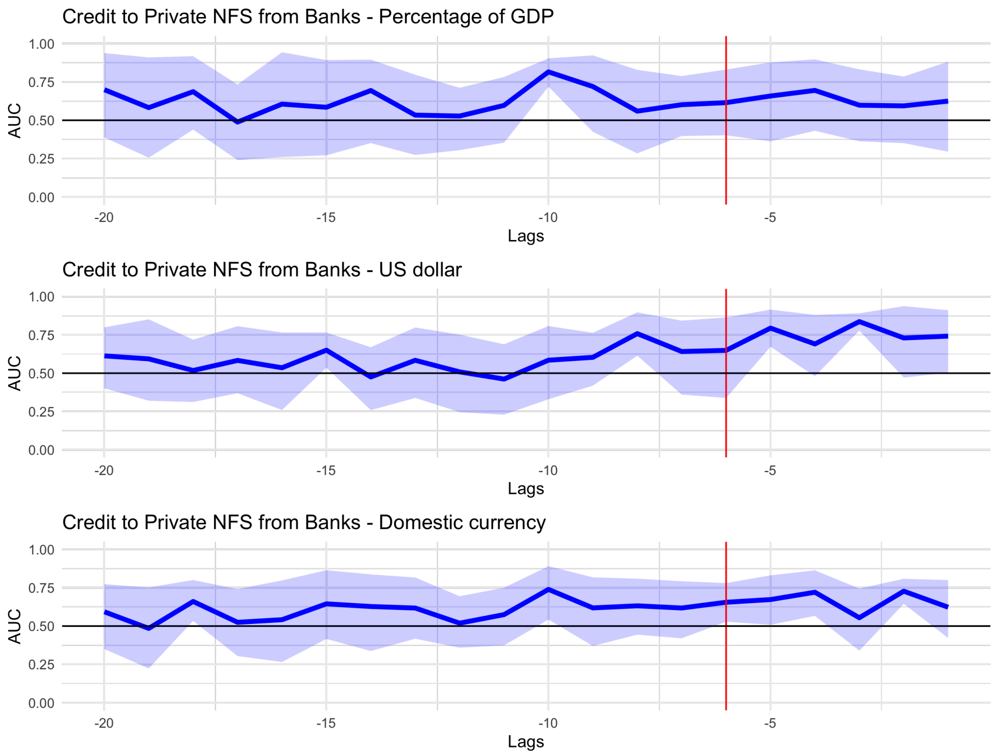
The signal strength of credit to private non-financial sector also demonstrated similar signal strength. The credit to private non-financial sector scaled by GDP and dollar denominated credit value to private non-financial sector showed better signal strength among other components. The stability of signal strength was, however, remained elevated for dollar denominated credit amount to this sector (following Fig. 9).

Figure 9: EWIs and policy requirements – AUCs over time



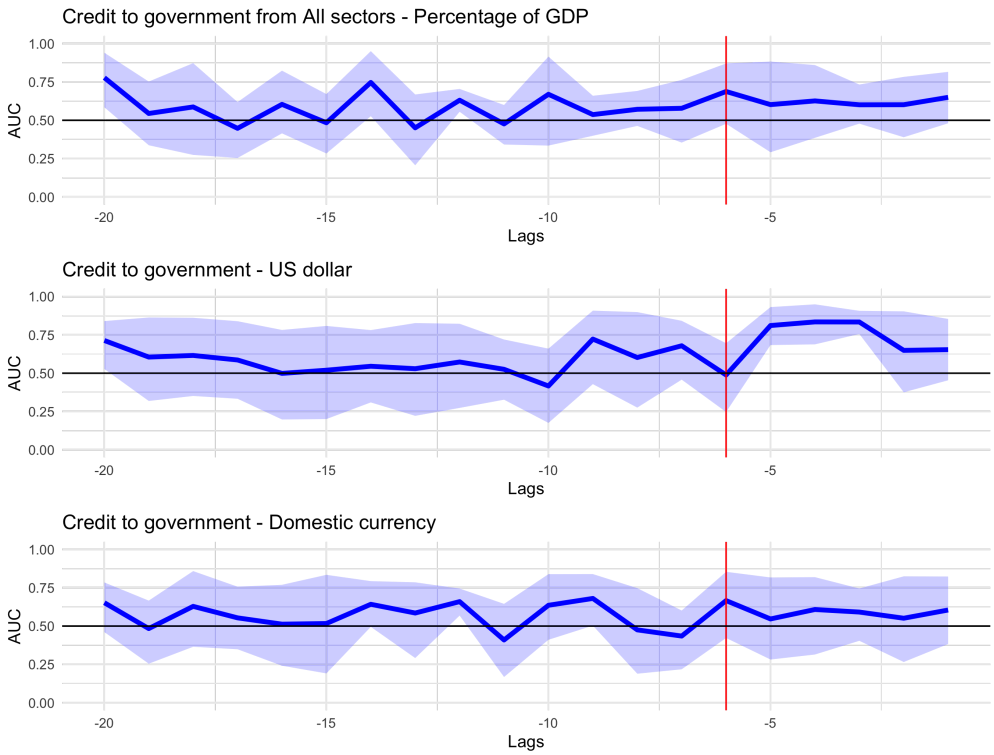
The credit disbursement to private non-financial sector from banks also showed strong signal prior to the crisis. The credit disbursed by the banks as percentage of nominal GDP exhibit better stability and robustness over the prediction horizons, prior to 6 quarters of the crisis. The absolute credit value also remained stable in 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 (refer to Figure 10).

Figure 10: EWIs and policy requirements – AUCs over time



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 Fig. 11).

Figure 11: 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 Fig 12). 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 13). Lastly, the total reserve appeared to be better indicator of systemic risk compared to money supply (refer to Figure 14).

Figure 12: EWIs and policy requirements – AUCs over time

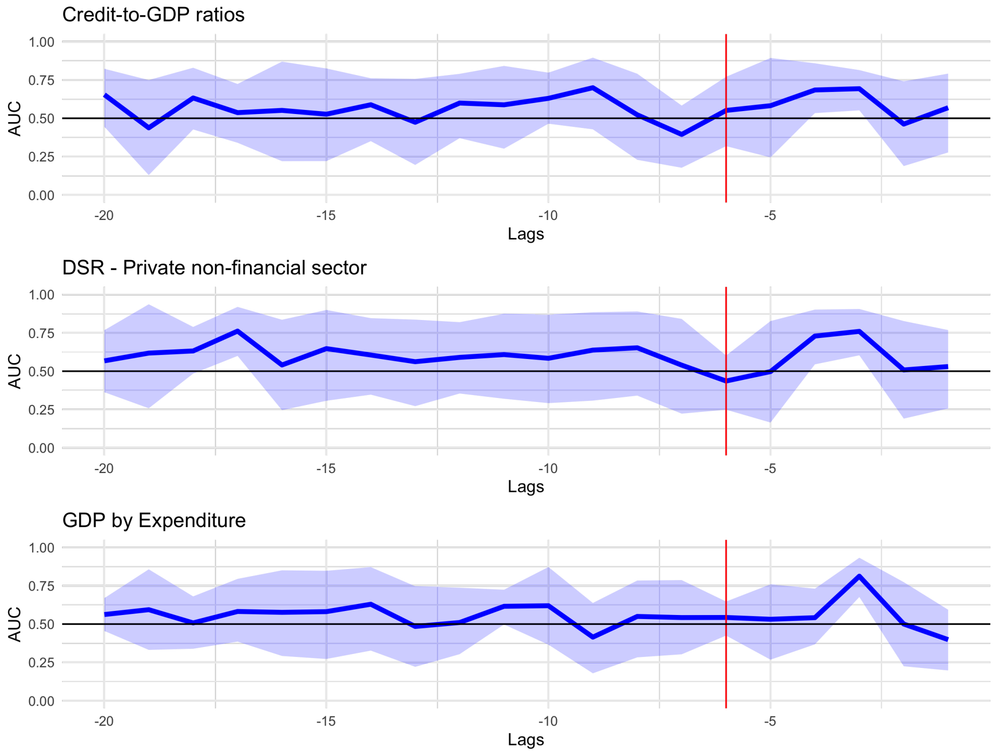
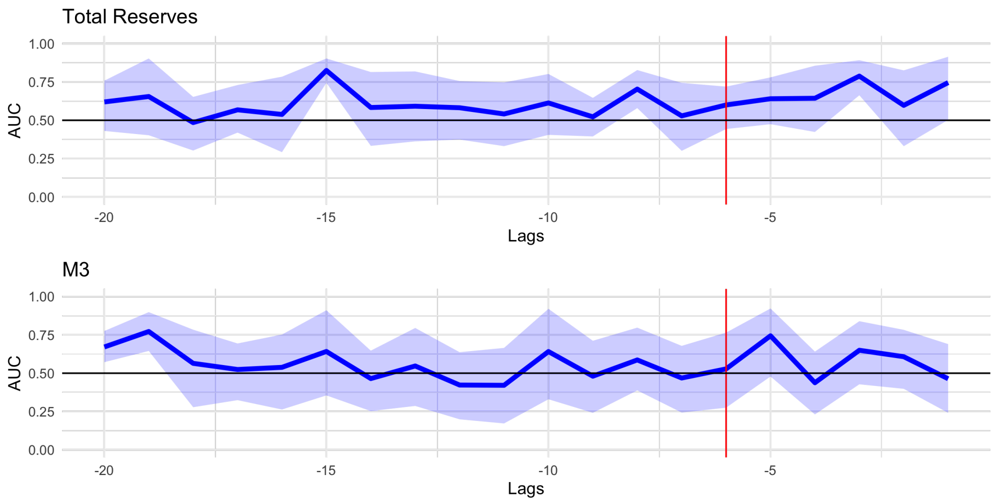


Figure 13: EWIs and policy requirements – AUCs over time

Figure 14: EWIs and policy requirements – AUCs over time



The signal strength appears to be varying over prediction horizon. These indicators provide a greater signal in predicting systemic risk and the significance of these indicators also signify various aspects of systemic risk faced by these countries. First, our analysis looks at balanced panel of countries starting from 2001 onward. Majority 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 channel strengthens the signal strength from credit indicators before the crisis. Second, the selected countries also experienced greater integration with 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 lead 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 more strong in signaling compared to their domestic currency counterparts. The variation of exchange rate may be pinned as 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 & Juselius (2013), we don't observe any single indicator dominating in signal strength over short and medium horizon prior to crisis. This happens due to the fact that 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 signalling vis-a-vis the medium term signalling, thereby cannot be established for any particular 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.

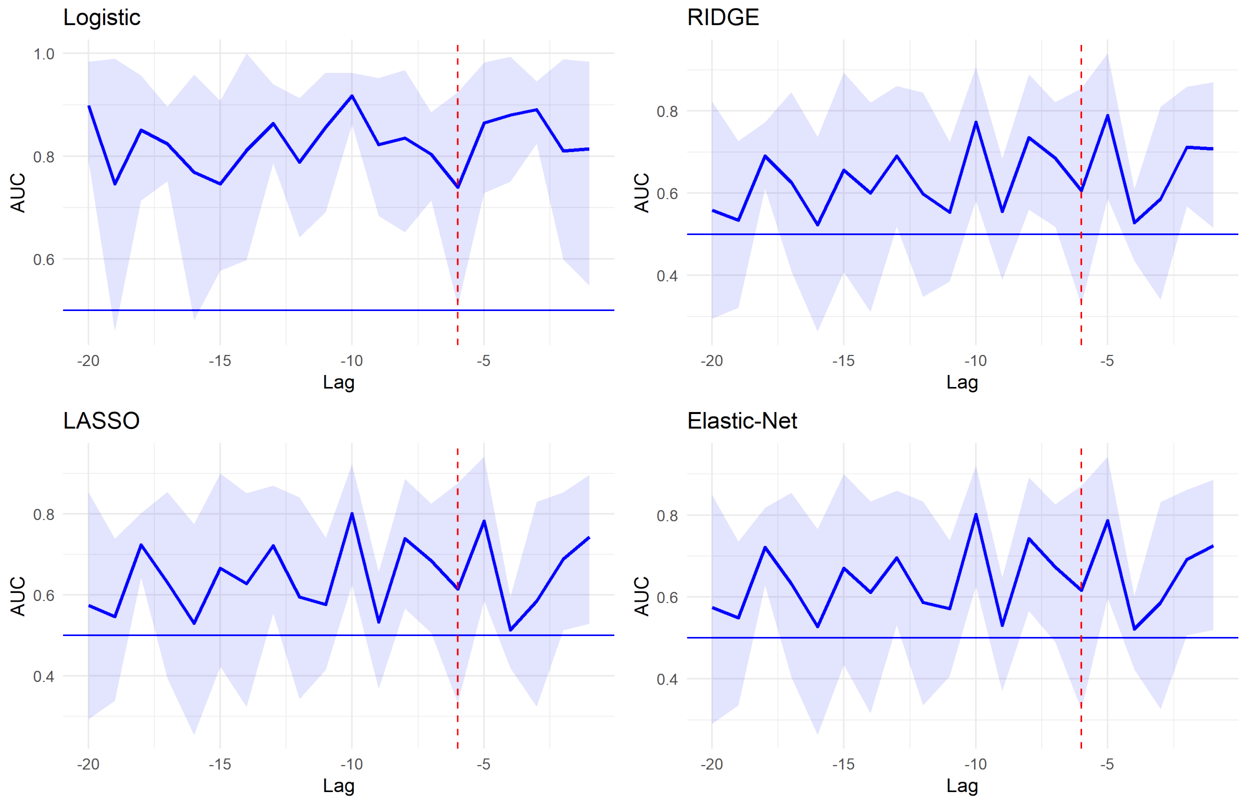
The lack of absolute supremacy of any particular indicator in terms of signal strength, rules out the possibility of single indicator based monitoring of systemic risk. Rather, it advocates for a combination of indicators to predict the systemic risk episodes. However, any combination of these indicators 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 non-financial sector (in dollar) (ii) credit to non-financial sector (per cent to GDP) (iii) credit to private non-financial sector (in dollar) (iv) credit to private non-financial sector as per cent of GDP (v) credit to non-financial sector from banks (per cent to GDP) (vi) credit to non-financial sector from banks (in dollar) (vii) credit to non-financial sector from banks (in local currency) (viii) credit to 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 strength the signal strength further. As indicated earlier, an ideal combination of these indicators can be thought of as a separating hyper-plane where linear combination of these indicators separate out the classes (*here, there are classes namely crisis and non-crisis*). We estimate the hyper-plane using logit and probit model with shrinkage. We use logistic regression with and without shrinkage to obtain linear combination of early warning indicators.

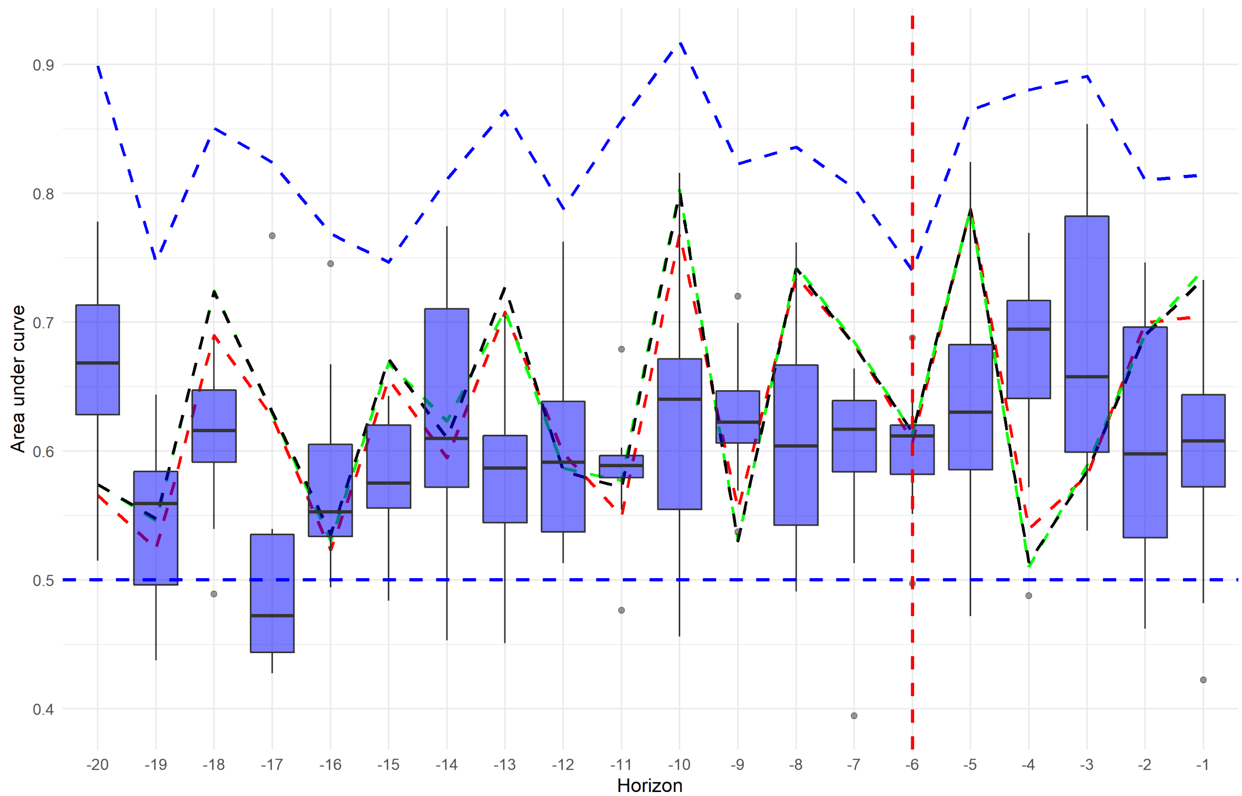
The combination of EWIs using logit model yields improvement of signal strength over all horizons. In particular, the signal of the EWI combinations remains at an elevated position compared to the threshold value of 0.5. However, the parameter space remains unrestricted in the logit regression due to 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 indicator 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 15).

Figure 15: Signal assessment of EWI combinations



Next, we compare the signal strength of individual EWIs with the combined indicators. The variation in signal strength of individual indicators are 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 16).

Figure 16: Comparison of signal strength



(*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

In this paper, the paper try to analyze the effectiveness of EWIs in capturing and predicting banking and currency crises in cross-country set up using receiver operating characteristics (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 cost. 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 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 be 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 optimum policy instrument.

The paper contributes to the empirical evaluation and assessment of early warning indicators for managing systemic risks in banking and external sector. The methodology adopted in this paper, evaluates on the signaling strength of the EWIs in predicting systemic risk events over short and medium horizons. The framework uses deviation of the indicators from their long term trend as a source of risk. In the process, it uses HP filter recursively on the time horizon to determine the trend component. The choice of smoothing parameter follows Drehmann & Juselius (2013). 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.

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7 Appendices

7.1 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 - Percentage 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 - Domestic 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

7.2 Unit root test

	Country	Variable	No-drift No-Trend	Drift-No Trend	Drift-Trend
1	Brazil	A	0.98	0.99	0.92
2	Brazil	B	0.89	0.61	0.62
3	Brazil	C	0.99	0.99	0.98
4	Brazil	D	0.87	0.92	0.97
5	Brazil	E	0.98	0.99	0.92
6	Brazil	F	0.90	0.59	0.48
7	Brazil	G	0.99	0.99	0.99
8	Brazil	H	0.99	0.98	0.38
9	Brazil	I	0.85	0.62	0.75
10	Brazil	K	0.99	0.99	0.62
11	Brazil	L	0.94	0.70	0.73
12	Brazil	M	0.74	0.57	0.91
13	Brazil	O	0.99	0.98	0.38
14	Brazil	P	0.36	0.08	0.30
15	Brazil	Q	0.93	0.26	0.98
16	Brazil	R	0.96	0.92	0.64
17	Brazil	S	0.16	0.31	0.05
18	Brazil	T	0.06	0.14	0.04
19	Brazil	U	0.71	0.52	0.98
20	Brazil	V	0.99	0.99	0.28

	Country	Variable	No-drift No-Trend	Drift-No Trend	Drift-Trend
1	Turkey	A	0.65	0.36	0.03
2	Turkey	B	0.92	0.31	0.94
3	Turkey	C	0.99	0.99	0.99
4	Turkey	D	0.01	0.01	0.12
5	Turkey	E	0.65	0.36	0.03
6	Turkey	F	0.69	0.02	0.27
7	Turkey	G	0.99	0.99	0.99
8	Turkey	H	0.97	0.84	0.12
9	Turkey	I	0.90	0.58	0.96
10	Turkey	K	0.99	0.99	0.99
11	Turkey	L	0.93	0.69	0.76
12	Turkey	M	0.84	0.60	0.96
13	Turkey	O	0.97	0.84	0.12
14	Turkey	P	0.44	0.25	0.04
15	Turkey	Q	0.99	0.93	0.55
16	Turkey	R	0.90	0.73	0.01
17	Turkey	S	0.01	0.01	0.01
18	Turkey	T	0.15	0.02	0.11
19	Turkey	U	0.77	0.29	0.93
20	Turkey	V	0.99	0.99	0.99

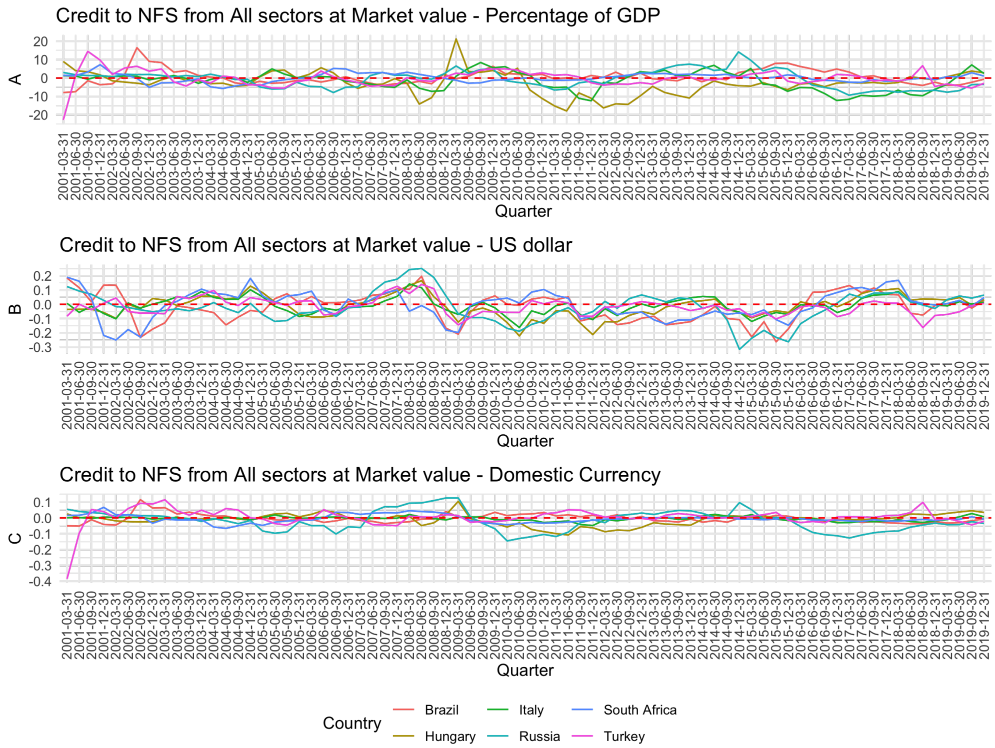
	Country	Variable	No-drift No-Trend	Drift-No Trend	Drift-Trend
1	South Africa	A	0.97	0.98	0.01
2	South Africa	B	0.95	0.45	0.47
3	South Africa	C	0.99	0.99	0.60
4	South Africa	D	0.93	0.99	0.44
5	South Africa	E	0.97	0.98	0.01
6	South Africa	F	0.98	0.91	0.35
7	South Africa	G	0.99	0.99	0.99
8	South Africa	H	0.72	0.39	0.74
9	South Africa	I	0.89	0.22	0.68
10	South Africa	K	0.98	0.98	0.06
11	South Africa	L	0.71	0.32	0.82
12	South Africa	M	0.85	0.17	0.67
13	South Africa	O	0.72	0.39	0.74
14	South Africa	P	0.52	0.08	0.28
15	South Africa	Q	0.98	0.01	0.91
16	South Africa	R	0.97	0.84	0.21
17	South Africa	S	0.16	0.15	0.10
18	South Africa	T	0.17	0.05	0.24
19	South Africa	U	0.98	0.50	0.94
20	South Africa	V	0.97	0.97	0.30

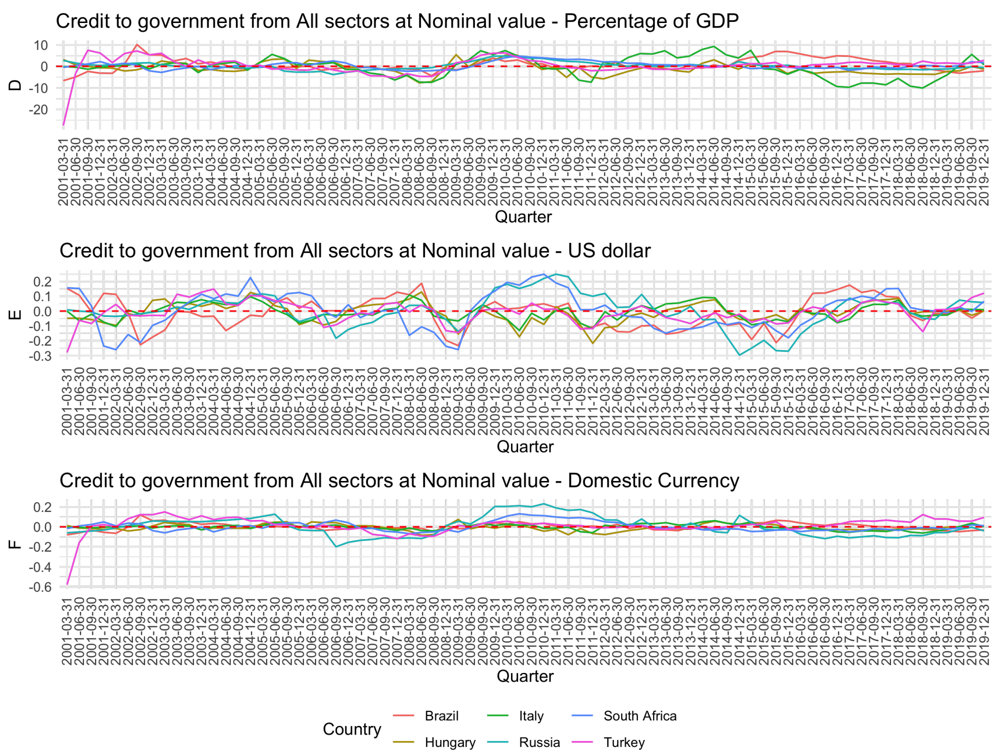
	Country	Variable	No-drift No-Trend	Drift-No Trend	Drift-Trend
1	Russia	A	0.85	0.84	0.37
2	Russia	B	0.85	0.66	0.29
3	Russia	C	0.98	0.99	0.53
4	Russia	D	0.01	0.01	0.01
5	Russia	E	0.85	0.84	0.37
6	Russia	F	0.76	0.67	0.45
7	Russia	G	0.99	0.99	0.67
8	Russia	H	0.94	0.60	0.49
9	Russia	I	0.83	0.64	0.35
10	Russia	K	0.96	0.98	0.47
11	Russia	L	0.95	0.38	0.78
12	Russia	M	0.77	0.58	0.51
13	Russia	O	0.94	0.60	0.49
14	Russia	P	0.60	0.42	0.29
15	Russia	Q	0.56	0.01	0.01
16	Russia	R	0.92	0.79	0.32
17	Russia	S	0.01	0.03	0.21
18	Russia	T	0.03	0.01	0.01
19	Russia	U	0.77	0.43	0.66
20	Russia	V	0.99	0.99	0.43

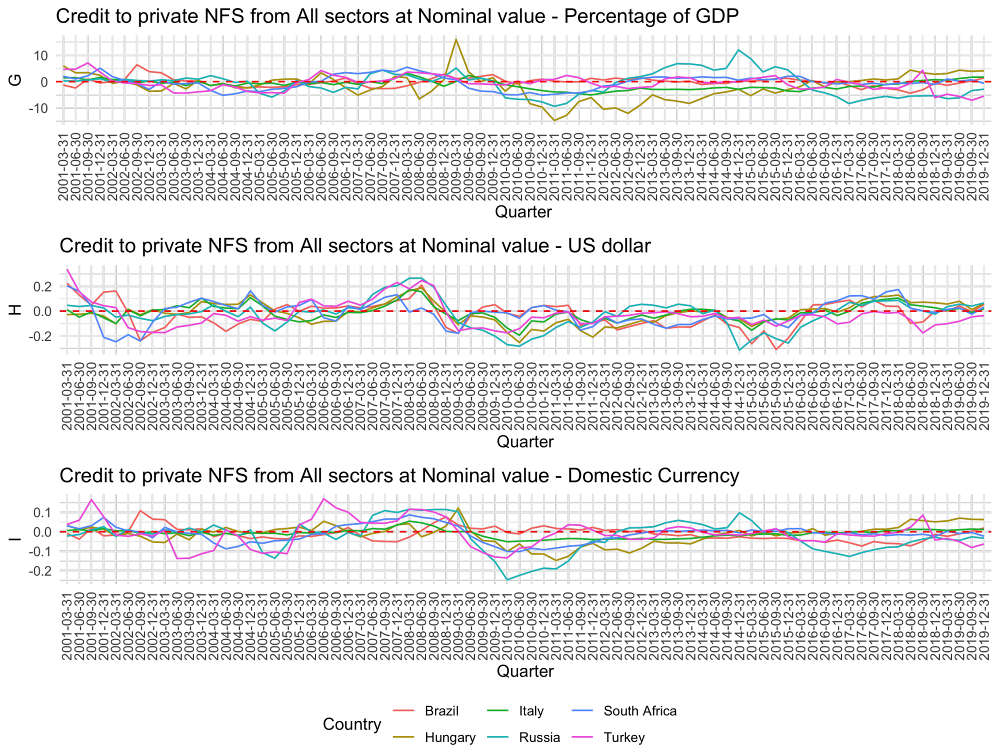
	Country	Variable	No-drift No-Trend	Drift-No Trend	Drift-Trend
1	Hungary	A	0.76	0.41	0.98
2	Hungary	B	0.81	0.11	0.73
3	Hungary	C	0.99	0.36	0.82
4	Hungary	D	0.76	0.42	0.96
5	Hungary	E	0.76	0.41	0.98
6	Hungary	F	0.89	0.08	0.54
7	Hungary	G	0.99	0.83	0.03
8	Hungary	H	0.70	0.50	0.96
9	Hungary	I	0.75	0.23	0.78
10	Hungary	K	0.99	0.31	0.88
11	Hungary	L	0.62	0.63	0.84
12	Hungary	M	0.67	0.31	0.69
13	Hungary	O	0.70	0.50	0.96
14	Hungary	P	0.41	0.79	0.90
15	Hungary	Q	0.98	0.95	0.88
16	Hungary	R	0.93	0.86	0.68
17	Hungary	S	0.05	0.50	0.01
18	Hungary	T	0.05	0.37	0.16
19	Hungary	U	0.64	0.47	0.92
20	Hungary	V	0.99	0.99	0.97

	Country	Variable	No-drift No-Trend	Drift-No Trend	Drift-Trend
1	Italy	A	0.95	0.50	0.91
2	Italy	B	0.87	0.08	0.61
3	Italy	C	0.99	0.15	0.94
4	Italy	D	0.91	0.81	0.55
5	Italy	E	0.95	0.50	0.91
6	Italy	F	0.91	0.16	0.25
7	Italy	G	0.99	0.92	0.44
8	Italy	H	0.80	0.02	0.99
9	Italy	I	0.76	0.14	0.77
10	Italy	K	0.86	0.01	0.95
11	Italy	L	0.61	0.29	0.99
12	Italy	M	0.71	0.18	0.89
13	Italy	O	0.80	0.02	0.99
14	Italy	P	0.56	0.52	0.87
15	Italy	Q	0.67	0.18	0.32
16	Italy	R	0.33	0.15	0.41
17	Italy	S	0.01	0.33	0.13
18	Italy	T	0.37	0.75	0.55
19	Italy	U	0.95	0.70	0.64
20	Italy	V	0.99	0.50	0.49

7.3 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
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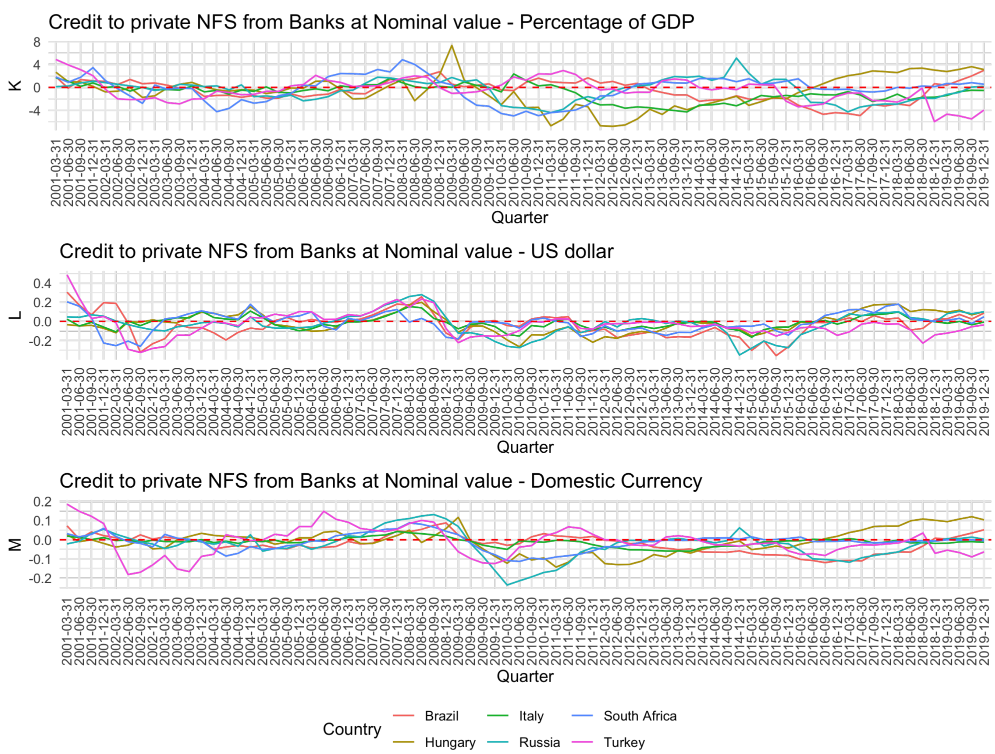
Hungary
Italy
Russia
South Africa
Turkey


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
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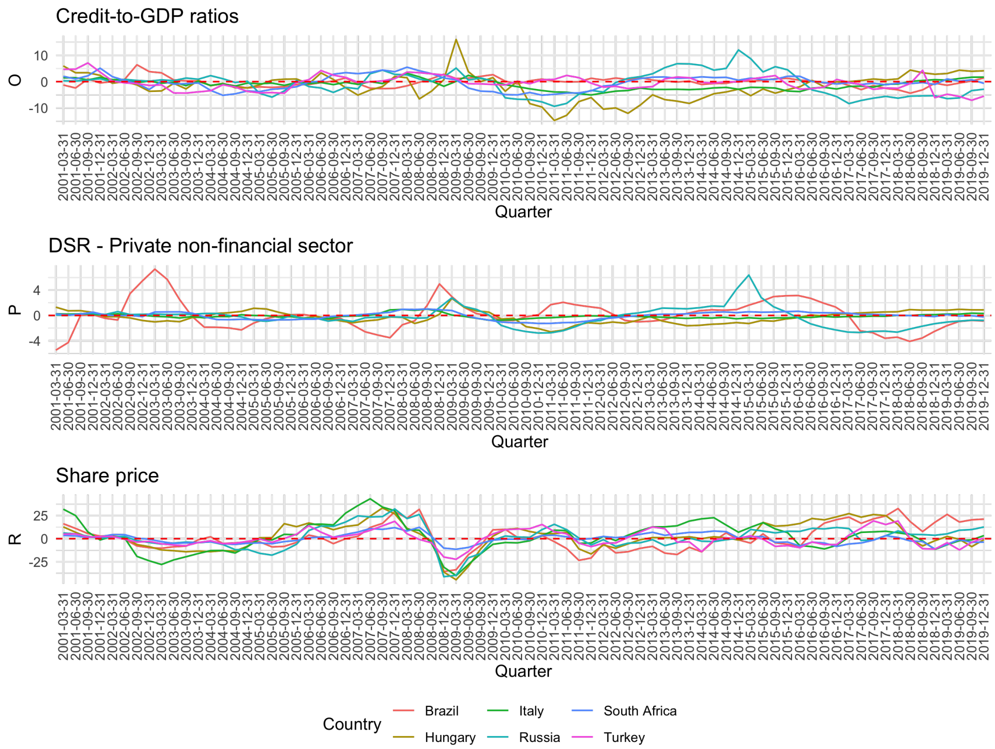
Country
Brazil
Hungary
Italy
Russia
South Africa
Turkey


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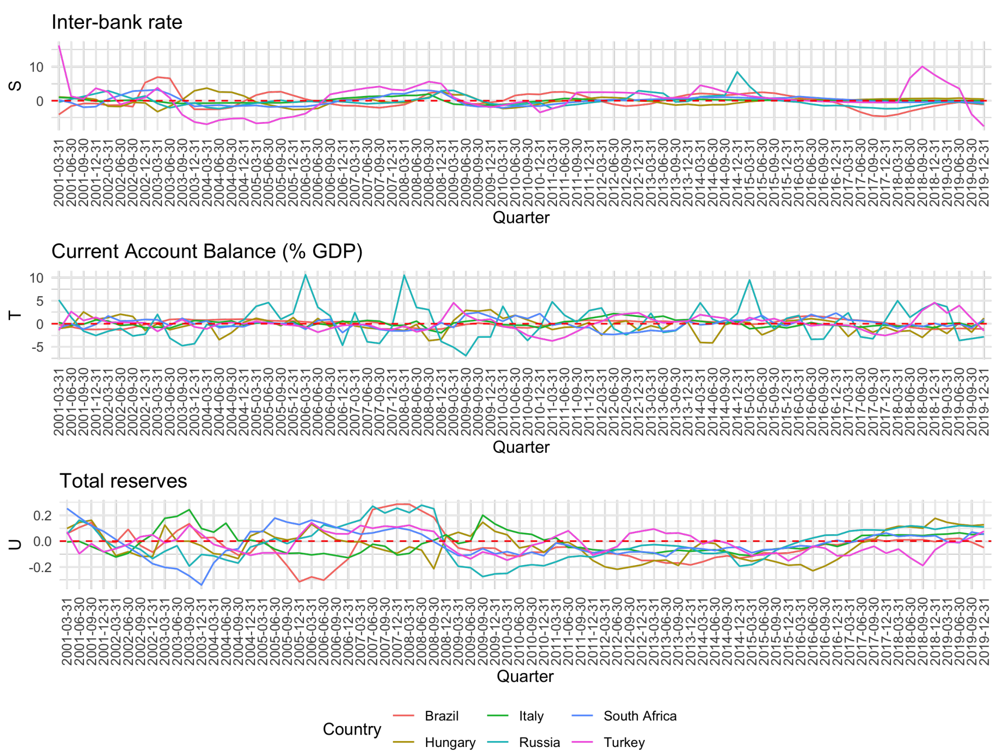
Italy
Russia
South Africa
Turkey


Inter-bank rate
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Current Account Balance (% GDP)
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Country
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Hungary
Italy
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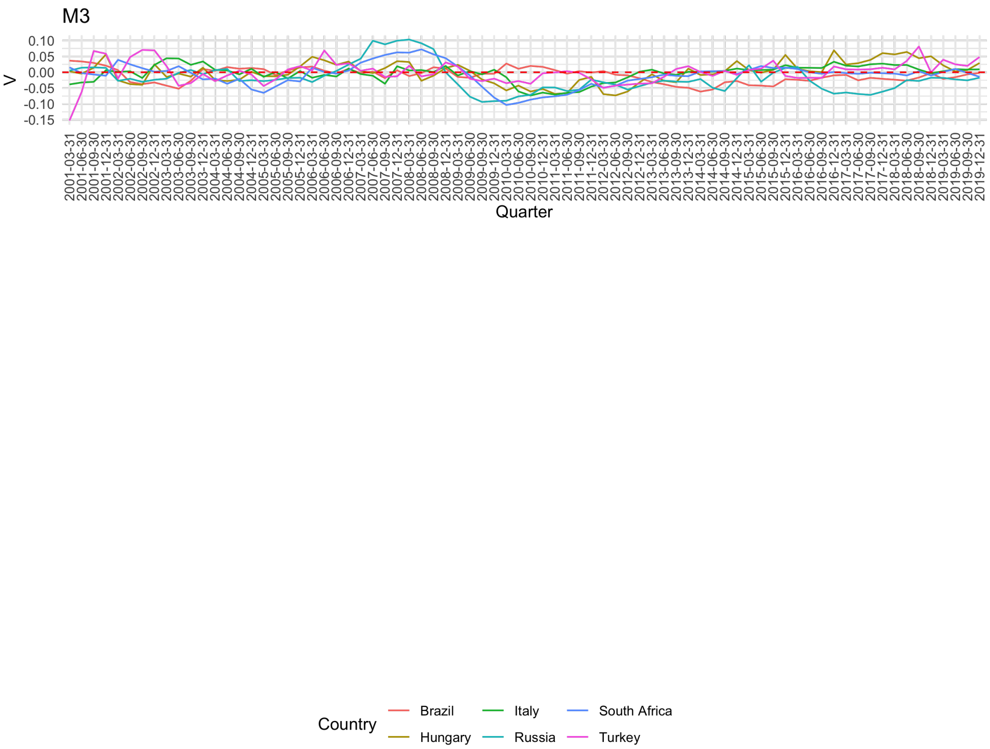
South Africa
Turkey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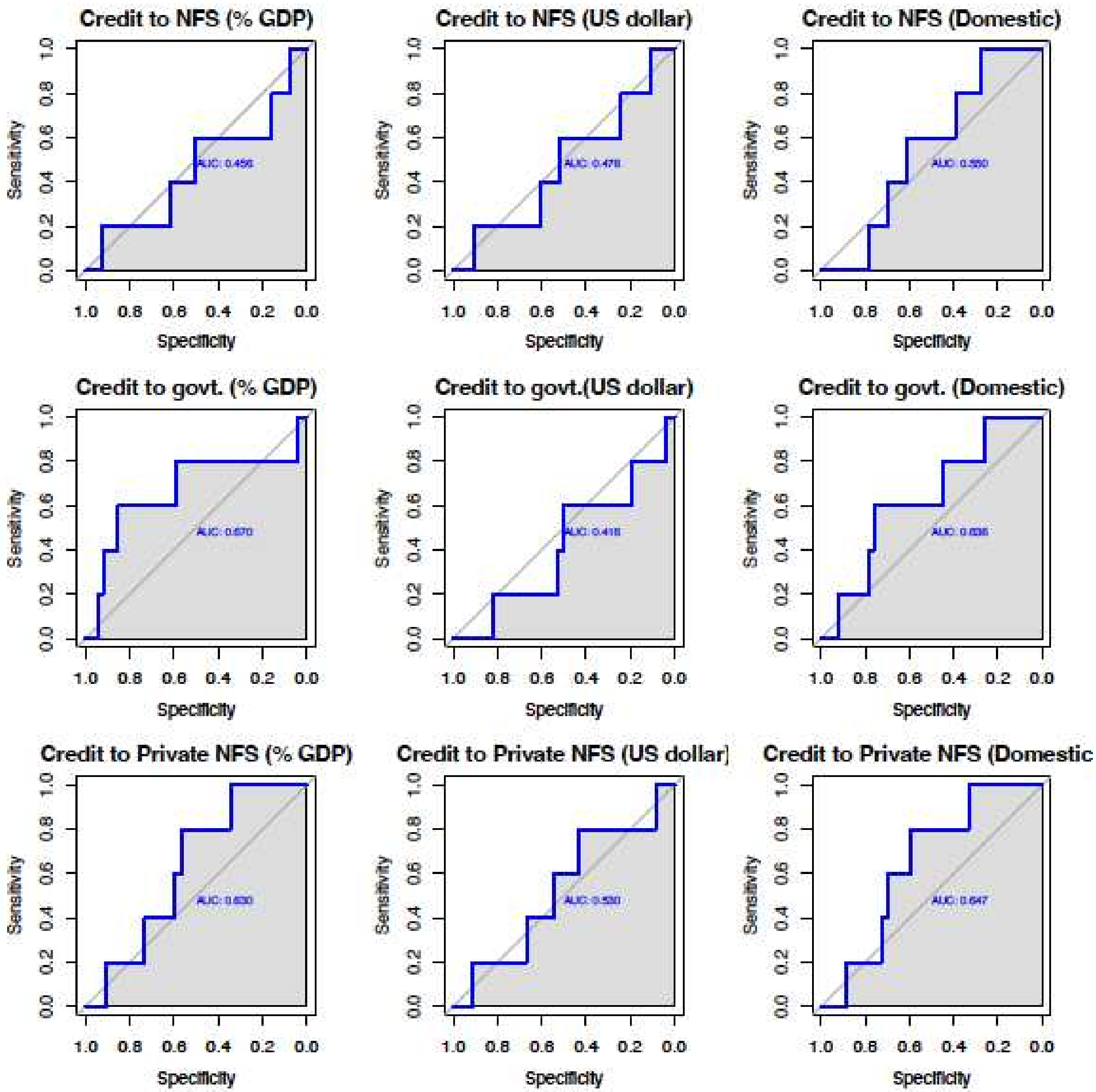
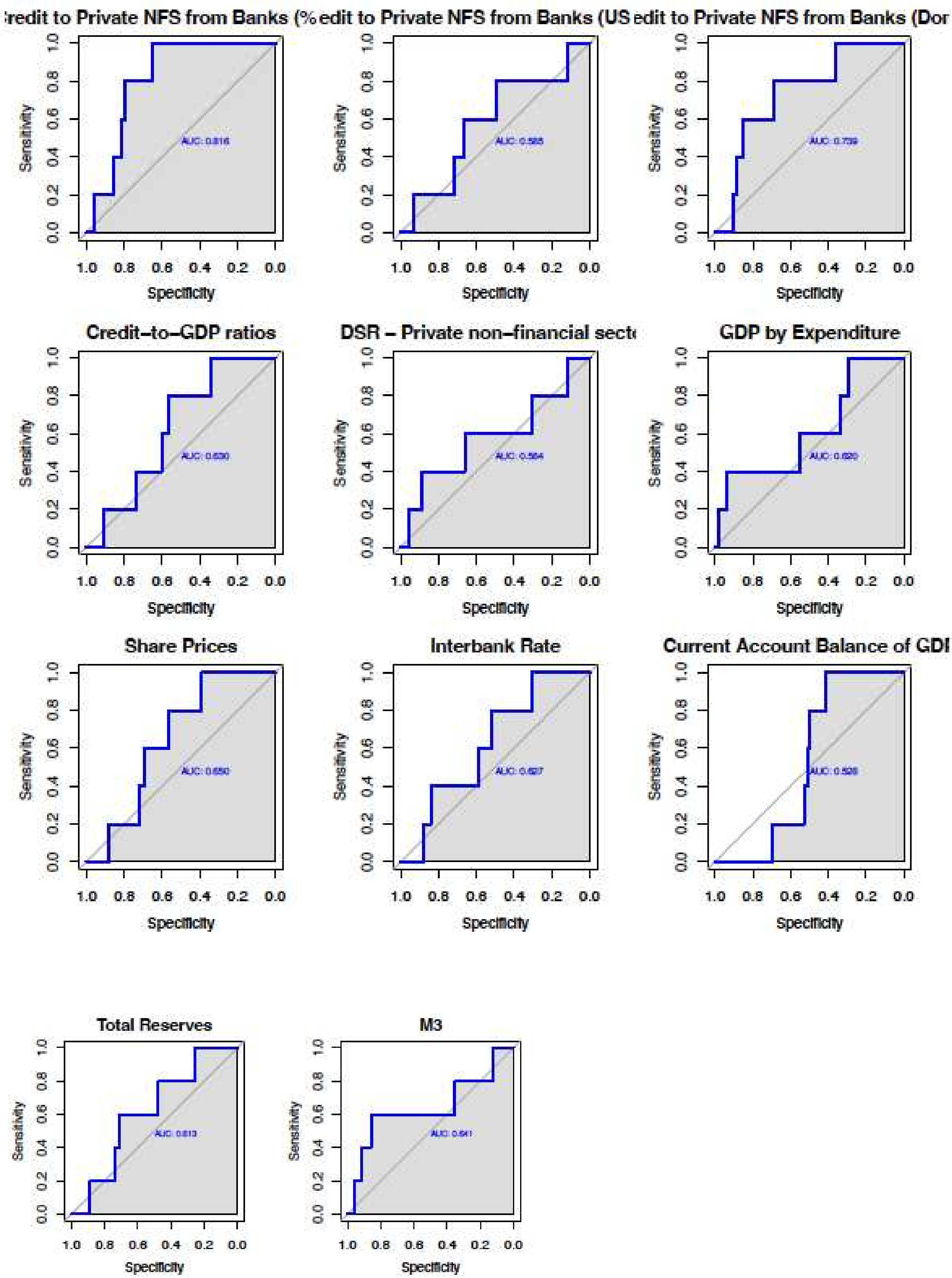
Turkey

7.4 ROC curves for horizon -8 and AUCs for different horizons




redit to Private NFS from Banks (%
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edit to Private NFS from Banks (Dor
Credit–to–GDP ratios
DSR – Private non–financial secto
GDP by Expenditure
Share Prices
Interbank Rate
Current Account Balance of GDI
Total Reserves
M3
Sensitivity
Specificity
1.0 0.8 0.6 0.4 0.2 0.0

Variable	Type	Horizon 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

Variable	Type	Horizon 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