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Abstract

Essays in International Finance

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This dissertation studies topics of international finance, such as constructing of financial stress indices, exploring the relation between financial stress and economic activity, and employing a novel approach, which is called Receiver Operating Curve (ROC), to assess the performance of early warning indicators in terms of capturing crisis and non-crisis periods. Each chapter of the dissertation investigates one of these three topics.

The first chapter focuses at creating three stress indices for Turkey by using the equal variance weighting method and principal component method, and portfolio theory method, namely, composite indicator of systemic stress which are the most widely used ones in the financial stress literature. After building the stress indices, by using the logit model, I calculate the effects of the indicators on the probability of a crisis occurring for financial institutions case. I find that while the CISS method captures systemic events better than the other two methods, the PCA method and EVW method appear to be able to capture non-systemic events.

The second chapter empirically examines how economic activity reacts

to the financial stress shocks depending on the stress regime in Turkey. By using quarterly data spans from 2002:Q1 - 2018:Q2, the effect of financial stress is examined using two threshold vector autoregression model (TVAR) for consumption, investment, real GDP, and unemployment by using financial stress index, credit growth, and domestic inflation rate as endogenous variables. The main result of this chapter is that financial stress is found to affect economic growth when the stress level is already high.

The third and last chapter studies to evaluate the performance of the EWIs in terms of capturing banking crises by using ROC analysis. We evaluate the EWIs both stand-alone and jointly to compare performance in both situations.

This thesis is dedicated to my parents, who taught me to perform all of life's tasks, regardless of their size, to the best of my ability and without any complaints. They are the people who I will always desire to be.

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Chapter 1

Assessing and Predicting Stress Events: The Case of Turkey

1.1 Introduction

It is seen that financial stability has become more on the agenda of decision-makers and academicians especially after experiencing the negative effects of the global financial crisis on the real and financial side of the economy. Therefore, in order to identify and monitor financial risks, measurement of financial stress, and the development of stress indices has become an important field of study. Although it has been observed that the measurement of financial stress have accelerated thanks to the new studies conducted after the global financial crisis, the financial stress indices calculated for the developing countries still need to be improved.

In this chapter, I ask whether there is a way to create a financial stress index to capture the historical stress periods and reflect correct stress levels related to the stress event. In the preliminary work, I create three stress indices by using the equal variance weighting method and principal component method, and portfolio theory method, namely, composite indicator of systemic stress which are the most widely used ones in the financial stress literature. After building the stress indices, by using the logit model, I calculate the effects of the indicators on the probability of a crisis occurring for financial institutions case. I also compare these methods in terms of capturing systemic events that are related to different sectors, particularly financial and real sectors. In the literature, several papers focus on constructing stress indices for only financial markets by using specific methods. The main contribution of this chapter relative to existing papers is that I construct indices for financial institutions and the real sector by using all the methods that are used in the literature, specifically for Turkey, and I compare the methods in terms of how well they capture systemic and non-systemic events. I can summarize the benefit of constructing indices for financial institutions and the real sector. The interaction between the financial sector and the real sector is so intense that the rise in vulnerability in each of sector has a significant impact on others. The real sector obtains the required funds to continue its operations from the financial institutions. If the credit conditions are tight and the profitability in the financial system is low, then the real sector and the households cannot obtain the required funds to make investments and consumption. There is also a feedback effect on financial institutions in terms of increasing the non-performing loan ratio. The second contribution of the chapter is to try to calculate the impacts of the indicators on the probability of systemic events occurring. The chapter proceeds as follows. Section 2 summarizes the prominent studies in the literature on the creating of systemic risk indices and the prediction of crises. Section 3 describes the data sources. Section 4 introduces the methodology which is used to construct the indices by using these three methods. Section 5 presents an empirical analysis. Section 6 provides results for applying discrete choice models to the financial markets stress index. Section 7 compares these three methods in terms of capturing systemic and non-systemic events. Section 8 discusses to create a unified index by employing all the variables used to develop the earlier three indices. Section 9 concludes.

1.2 Literature Review

When I examine the studies on this subject, I identify two strands of literature. The first strand of literature aims to develop different stress indices by utilizing different methods and indicators. The second strand of literature tries to estimate systemic events by using discrete selection models. For the first strand of literature, Illing and Liu (2006) - Canada Financial Stress Index, Hakkio and Keeton (2009), Cardarelli et al. (2009), Oet et al. (2011), and Hollo et al. (2012) works are prominent in global context. I present these works in Table 1.1 by providing information about the variables which they use, the method of construction and the country in subject. I specifically utilize the method which is proposed in Hollo et al. (2012) paper, therefore I provide more detailed information about it in this section. Hollo et. al (2012) developed CISS (a composite indicator of systemic stress) which takes into account the interactions of sub-financial markets with each other. In this study, they stated that sub-markets are in constant interaction with each other and financial stress is actually higher than calculated depending on the correlation between them. CISS takes into account both the time-varying correlations between sub-financial markets and the relationships of financial markets with the real economy. In other words, the CISS approach reflects the "horizontal" dimension of stress by considering the interaction between sub-financial markets and reflects the "vertical" dimension of financial stress by including the interaction of stress with the real economy.

Table 1.1: The Prominent Stress Indices Developed For Other Countries

Index	**Variables**	**Method of Construction Index**	**Country**
Illing and Liu (2006)	11 daily market variables coming from banking sector, foreign exchange market, debt markets, equity markets	Explore different methods - Equal variance method, credit weights, principal component analysis	Canada
Hakkio and Keeton (2009)	11 daily market variables	Principal component analysis	USA - Kansas City
Cardarelli et. al (2009)	7 daily market variables coming from banking sector, securities markets, foreign exchange markets	Equal variance weighting method	17 developed countries
Oet et al. (2011)	11 daily market variables coming from banking sector, foreign exchange market, debt markets, equity markets	Implementing various methods - Dynamic weighting method, Principal component method, Equal variance weighting method	USA - Cleveland
Hollo et al. (2012)	15 daily market variables coming from equity, bond, money, foreign exchange, and hedging market	Portfolio theory (CISS)	Euro Area

When I review the studies done specifically for Turkey, three studies come into prominence. These studies consist of Cevik et al. (2013), Ekinci (2013) and Gunes (2016) papers. I present these works in Table 1.2 by providing same detailed information.

Table 1.2: The Prominent Stress Indices Developed For Turkey

Index	**Variables**	**Method of Construction Index**	**Country**
Ekinci (2013)	4 daily market variables consisting of banking sector, public sector, equity markets, stock exchange market	Equal variance weighting method	Turkey
Cevik et al. (2013)	9 monthly raw indicators related to banking sector risk, stock market risk, foreign exchange risk, foreign debt, country risk, foreign trade financing risk, credit risk, money market return/interest difference, and stock market return/interest difference	Principal component analysis	Turkey
Gunes (2016)	5 daily market variables consisting of money, debt, stock and foreign exchange market, banking sector	Explore different methods - Equal variance method, principal component analysis, portfolio theory	Turkey

For the second strand of literature, the papers of Lo Duca and Peltonen (2013) and Nelson and Perli (2007) come into prominence. Lo Duca and Peltonen (2013) first defined systemic events. For the determination of systemic events, they created a composite index for each country and marked the events exceeding the nineteenth percentile of this index value (which corresponds to the period of economic slowdown) as systemic events. They estimated systemic events by using discrete selection models that include local variables, global variables, and the interaction of these variables. Nelson and Perli (2007) used twelve financial indicators which are 2-year liquidity premium, 10-year liquidity premium, BBB risk spreads, AA risk spreads, high-yield risk spreads, 3-month Eurodollar confidence interval 1-year ahead, long bond implied volatility, eurodollar implied volatility, 10-year Treasury implied volatility, SP100 implied volatility (VXO), federal funds target – 2-year Treasury, (12-month ahead earnings/SP500)/ - (10-year Treasury). The information contained in the twelve individual variables was reduced to three summary statistics that capture their level, their rate of change, and their correlation. The three summary statistics combined into a single measure of financial fragility and used to model the probability of systemic events occurring at any given time by using the logit model. I present the information about stress indices in Table 1.3.

Table 1.3: Predicting Systemic Events By Using Logit Models

Index	**Variables**	**Method of Construction Index**	**Country**
Nelson and Perli (2007)	12 daily market variables coming from banking sector, money, foreign exchange, and equity markets	Equal Variance Weighting Method	USA
Lo Duca and Peltonen (2013)	11 daily market variables coming from banking sector, money, foreign exchange, and equity markets	Equal Variance Weighting Method	28 emerging and advanced economies

1.3 Data

I built "the financial institutions", "financial markets" and "real economy" stress indices in this study. While I obtain data for financial institutions part from Central Bank of Turkey (CBRT) and Banking Regulation and Supervision Agency (BRSA), I get data for financial markets and real economy part from Bloomberg Terminal, Central Bank of Turkey (CBRT), Capital Markets Board (CMB), Ministry of Development(MD), and Ministry of Finance and Treasury (MFT). While the frequency of the data for financial markets is daily, the frequency of the data for financial institutions and the real economy is monthly. The data for financial institutions only covers the Turkish banking sector, which consists of 51 banks. While the time frame of the financial markets data is from 3/7/2011 to 8/13/2018, it is from 06/2005 to 04/2018 for the real sector and financial institutions case. Because of having daily data for the financial markets, the data availability raises an issue. For the financial institutions data, I start from 06/2005 because of the fact that the data for participation banks are available after 06/2005. Under the blocks which are seen in Tables 1.4 to 1.6, I select some sub-indicators associated with that blocks. For example, one of the indicators which I determine for the block of financial institutions is profitability, which has the return on assets, return on equity, and net interest margin as sub-indicators. I present the sub-indicators for these indicators in Tables 4 to 6. While determining the indicator for the financial institutions block, I make use of Financial Soundness Indicators (core and encouraged FSIs which are published by IMF. For the financial markets block, I benefit from Oet et al. (2011)'s paper which creates the Cleveland Financial Stress Index using daily published stress indicators of four financial markets. For the real economy block, I select the indicators depending on the main macroeconomic indicators reflecting the situation on the real side of the economy.

Table 1.4: Indicators and Sub-Indicators for Financial Institutions

Blocks	Indicators
Profitability	Return on Assets
	Return on Equity
	Net Interest Margin
Capital	Capital Adequacy Ratio
	Leverage Ratio
	Z-Score
Funding	Wholesale Funding
	Credit-Deposit Ratio
	FX Liabilites/Total Liabilities
Loan Losses	Non-performing Loan Ratio
	Change in Non-performing Loan / Change in Loan
	Non-performing Loan to Equity
	Provisions to Average Loans
Interconnectedness	(Receivables from financial inst. + payables to financial inst.)/Total Assets

In here, I try to give some detailed information about how I calculated some of the ratios which are not known widely in financial institutions case. **Leverage ratio** is calculated by $1 - \frac{\text{Total Equity}}{\text{Total Assets}}$. **Wholesale funding** is obtained by dividing the sum of Payables to Money Market, Payables to Securities Market, Payables to Banks, and Funds from Repo Transactions to total liabilities. In the case of loans not paid back after 90 days from their maturity date, the banks have to set aside provisions for these loans. This is called as **special provisions**. **Z-score** compares the buffer of a country's banking system (capitalization and returns) with the volatility of those returns. It is estimated as $\frac{\text{ROA}+(\text{equity/assets})}{\text{sd(ROA)}}$ where sd(ROA) is the standard deviation of ROA.

Table 1.5: Indicators and Sub-Indicators for Financial Markets

Blocks	Indicators
FX Market	Weighted TL Collapse
	Implied FX Volatility
	Realized FX Volatility
	USD/TL 25 Delta Risk Reversal
	USD/TL 3 Month Forward and Spot Rate Difference
Stock Market	Stock Index Return and Bond Return Correlation
	Stock Index Realized Volatility
	Price – Equity Ratio
	Weighted Equity Collapse
Funding Cost	Interbank Repo Rate
	Bank Bond Yield Difference
	Traded Volume of Benchmark Bond
	Public Debt Premium
Credit Risk Indicators	Yield Curve Slope Difference
	Realized Volatility of 2 Year Government Bond Return
	CDS

There are some indicators that are not known publicly. So, I also try to describe these indicators. The market‘s estimate of how much a currency pair will fluctuate over a certain period in the future is called **implied volatility**. What has already happened is known as historical or **realized volatility**, whereas what market participants think is going to happen is referred to as implied volatility. The former can be used to predict the latter, but the latter is a market input, determined by the people that are participating in the forex options market. **25-delta risk reversals** show the difference in volatility, and therefore price, between puts and calls on the most liquid out-of-the-money (OTM) options quoted on the OTC market. Positive values indicate calls being more expensive than puts (upside protection on the underlying forex spot is relatively more expensive), while negative values indicate puts are more expensive than calls (downside protection is relatively more expensive). Significant changes can indicate a change in market expectations for the future direction in the underlying forex spot rate. A positive risk reversal means the volatility of calls is greater than the volatility of similar puts, which implies more market participants are betting on a rise in the currency than on a drop, and vice versa if the risk reversal is negative. It is also beneficial to define the delta. **Delta** is the change in an option's value for a change in the price of the underlying product. **A spot rate**, or **spot price**, represents a contracted price for the purchase or sale of a commodity, security, or currency for immediate delivery and payment on the spot date, which is normally one or two business days after the trade date. **A forward rate** is a contracted price for a transaction that will be completed at an agreed-upon date in the future. **Trade-weighted effective exchange rate index** is compiled as a weighted average of exchange rates of home versus foreign currencies, with the weight for each foreign country equal to its share in trade. If the index rises, the purchasing power of that currency rises. **Trade-weighted exchange rate index collapse** shows the ratio of the exchange rate index at the respective observation date to the maximum value in the year. **The price-to-earnings ratio (P/E ratio)** is the ratio for valuing a company that measures its current share price relative to its per-share earnings. In short, the P/E shows what the market is willing to pay today for a stock based on its past or future earnings. A high P/E could mean that a stock's price is high relative to earnings and possibly overvalued. Companies that grow faster than average typically have higher P/Es, such as technology companies. A higher P/E ratio shows that investors are willing to pay a higher share price today because of growth expectations in the future. **The interbank lending market** is a market in which banks extend loans to one another for a specified term. Most interbank loans are for maturities of one week or less, the majority being overnight. Such loans are priced at the **interbank rate**. **Bank bond yield difference** shows the government and bank bond yield for a maturity of 3 years. **Yield curves** track the relationship between interest rates and the maturity of Treasury securities at a given time. The slope of the yield curve provides an important clue to the direction of future short-term interest rates; an upward sloping curve generally indicates that the financial markets expect higher future interest rates; a downward sloping curve indicates expectations of lower rates in the future. **Credit default swaps** are derivative contracts that enable investors to swap credit risk with another investor. The investor can use CDS to hedge an existing government bond position against losses. CDS shows us the relative riskiness of the country.

Table 1.6: Indicators and Sub-Indicators for Real Sector

Blocks	**Indicators**
Labor Market	Employment Ratio
	Labor Force Participation Ratio
	Seasonally Adjusted Unemployed Ratio
	Non-farming Employment Ratio
Production	Industrial Production Index
	Purchasing Managers' Index (PMI)
	Capacity Utilization Ratio
Consumption	Consumer Price Index
	Sales of White Appliances
Expectations	Consumer Confidence Index
	Real Sector Confidence Index

Employment ratio is calculated as dividing employed people to the total noninstitutionalized, civilian working-age population. **Labor force participation ratio** is measured as the sum of all workers who are employed or actively seeking employment (labor force) divided by the total noninstitutionalized, civilian working-age population. **Unemployment ratio** is calculated as dividing total unemployed people to the total labor force (employed+unemployed). **Consumer Confidence Index** measures how optimistic or pessimistic consumers are regarding their expected financial situation.**Real Sector Confidence Index** reflects how companies perceive the economy in the future and how they can change their production and investment according to these perceptions.

1.4 Methodology

In this study, I use the equal variance weighting method, principal component analysis, and portfolio theory method. First, I explain how I standardize the indicator values by using cumulative distributon functions. Then, I provide detailed information about the theoretical underpinnings of these three methods.

1.4.1 Standardization of Indicators

In each method, I standardize the values of sub-indicators between 0 and 1 by using cumulative distribution functions. While for the sub-indicators whose increase is regarded bad, I use $\frac{Rank(x)}{n}$, for the sub-indicators whose increase is regarded good, I use $1 - \frac{Rank(x)}{n}$ function.

For the financial institutions block, I use $\frac{Rank(x)}{n}$ for all indicators except capital adequacy ratio, return on assets, return on equity and net interest margin and z-score. For the financial markets block, I use $\frac{Rank(x)}{n}$ for all indicators except traded volume of benchmark bond. For the real sector block, I use 1 - $\frac{Rank(x)}{n}$ for all indicators except seasonally adjusted unemployment rate and consumer price index.

1.4.2 Equal Variance Weighting Method

Equal variance weighting method which is easy to apply and one of the most commonly used methods in the literature due to its understandability (Balakrishnan et al., 2011). In this method, first, raw stress indicators are converted into the standardized values by using cumulative distribution functions: In equal variance weighting method, it is accepted that all sub-indices have the same importance and therefore all sub-indices are given equal weight.

$$s_n = \frac{Rank(x)}{n} \quad \text{or} \quad s_n = 1 - \frac{Rank(x)}{n}$$

$$EVW = \frac{\sum_{i=1}^{n} s_n}{n}$$

I create “financial institutions ”,“financial markets ”and“ real economy ”blocks for the building up stress indices. In Table 1.7, I provide an example of selected indicators to show the risk accumulation in the related block.

Table 1.7: Blocks of Stress Indices and Used Indicators

Blocks	**Indicators**
Financial Institutions	Profitability
	Capital Adequacy
	Funding
	Credit Losses
	Connectedness
Financial Markets	FX Market
	Stock Market
	Funding Costs
	Credit Risk Indicators
Real Economy	Labor Market
	Production
	Consumption
	Expectations

In addition to this, I also determine indicators related to these blocks. For example, one of the indicators which I determine for the block of profitability is the return on assets, I follow the following steps to calculate the risk accumulation in each block using the identified indicators:

- The values of indicators are set between 0 and 1 by using cumulative distribution functions. While for the indicators whose increase is regarded bad, it is used $\frac{Rank(x)}{n}$, for the indicators whose increase is regarded good $1 - \frac{Rank(x)}{n}$ function is used, such as for capital adequacy ratio, it is used $1 - \frac{Rank(x)}{n}$, but for non-performing loans ratio, it is used $\frac{Rank(x)}{n}$.
- The block value, such as profitability, is calculated by taking the weighted average of the indicator values.
- The stress value for the financial institutions is calculated using the weighted average of all block values.

1.4.3 Principal Component Analysis Method

PCA explains patterns of correlations within a set of observed indicators. In other words, it identifies sets of highly correlated indicators and infers an underlying factor structure. There may be relationships between each factor and each item. While some of these relationships may be weak, others are more pronounced, suggesting that these items represent an underlying factor well. Before carrying out a PCA, I look for the requirements of using this method by answering the following questions:

- Is the sample size sufficiently large?

- Are the observations independent?
- Are the indicators sufficiently correlated?

For the first question, as a rule of thumb, the number of (valid) observations should be at least ten times the number of items used for analysis. This only provides a rough indication of the necessary sample size. MacCallum et al. (1999) suggest the following:

- When all communalities are above 0.60, small sample sizes of below 100 are adequate.
- With communalities around 0.50, sample sizes between 100 and 200 are sufficient.
- When communalities are consistently low, with many or all under 0.50, a sample size between 100 and 200 is adequate if the number of factors is small and each of these is measured with six or more indicators.
- When communalities are consistently low and the factors numbers are high or are measured with only a few indicators (i.e., 3 or less), 300 observations are recommended.

For the second question, I should ensure that the observations are independent. This means that the observations need to be completely unrelated. It is mostly related to the survey questions.

For the third question, there are two methods in order to identify whether the indicators are sufficiently correlated or not. The first thing that can be done is to examine the correlation matrix. If single correlations are very low, this does not necessarily mean that PCA is not a true technique to make an analysis. Only when all the correlations are around zero, then PCA is no longer useful. The second method which is used to determine whether the items correlate sufficiently is The Kaiser–Meyer–Olkin (KMO) statistic. The KMO statistic also called the measure of sampling adequacy (MSA). It indicates whether the other indicators in the dataset can explain the correlations between indicators. Kaiser (1974), who introduced the statistic, provides a set of threshold values for KMO and MSA which gives insight into the adequacy of correlations. If the KMO statistic is below 0.50, then it is unacceptable. In fact, the KMO statistic is simply the overall mean of all indicator-specific MSA values. Consequently, all the MSA values should also lie above the threshold level of 0.50. If this is not the case, they argue that these indicators should be removed from the analysis.

If our data satisfy all the conditions, then PCA analysis can ve used. PCA‘s objective is to reproduce a data structure with only a few factors. PCA provides this by creating a new set of factors as linear composites of the original indicators, which reproduces the original indicators' variance as best as possible. These linear composites are called principal components. More precisely, PCA computes eigenvectors. These eigenvectors which include the factor weights, which shows what percentage of the total variance each factor accounts for. For example, if the first factor‘s eigenvalue is 2.10, then it accounts for 42% $(2.1/5 = 42\%)$ of the overall variance. Extracting a second factor will allow us to explain another part of the remaining variance. But the eigenvalue of the second factor is lower than the first one. If the eigenvalue of the second factor is 2.1, then these two factors account for 68% $((2.1+1.3)/5 = 68\%)$ of the total variance.

The other two important concepts related to PCA analysis are commonality and uniqueness. Communality indicates how much variance of each indicator that can be captured by the factors, Uniqueness, which is 1-communality, shows what percentage of a indicator's variance that the factors do not capture. As a rule of thumb, the extracted factors should account for at least 50% of a indicator's variance. Thus, the uniqueness should be below 0.50.

The essential step in PCA analysis is to determine the number of factors that can be extracted from the data. An intuitive way to decide on the number of factors is to extract all the factors with an eigenvalue greater than 1. This is because of the fact that each of the factors with an eigenvalue greater than 1 accounts for more variance than a single indicator. Extracting all the factors with an eigenvalue greater than 1 is known as the Kaiser criterion or latent root criterion and is commonly used to determine the number of factors.

Another way to decide the number of factors to get is to plot each factor's eigenvalue (y-axis) against the factor with which it is associated (x-axis). This produces a scree plot, which typically has a distinct break in it, thereby showing the "correct" number of factors. This distinct break is called as the "elbow." It is generally recommended that all factors should be retained above this break, as they contribute most to the explanation of the variance in the dataset.

Factor loadings which are another significant concept in PCA analysis show us correlations between the factors and the indicators and can take values ranging from -1 to +1. A high factor loading indicates that a certain factor represents an indicator well. I evaluate it by looking at absolute values because the correlation between an indicator and a factor can also be negative. Using the highest absolute factor loadings, I assign each indicator to a certain factor.

1.4.4 Portfolio Theory Method - Composite Indicator of Systemic Stress

In addition to the principal component analysis method, the portfolio theory method, namely, the composite systemic stress index (CISS - Composite Index of Systemic Stress) which is developed by Hollo et al. (2012) also takes into account the interactions of sub-financial markets with each other. In this method, firstly, they standardize raw stress indicators by using cumulative distribution functions (CDF). The methodological originality of the index stems from the use of the portfolio method in the aggregation of sub-market indices. According to the portfolio method, not only the variances of the sub-indices but also the cross-correlations change over time with each other as shown in the following formula. Thus, the index has a structure that gives more weight to the financial stress that occurs in several sub-markets at the same time. CISS index is calculated as follows according to the portfolio theory:

$$CISS_t = (wos_t)\, C_t\, (wos_t)'$$

where $w_i = (w_1, w_2, w_3, w_4)$ indicates the weights of indicators for each sub-financial market, $s_t = (s_{1,t}, s_{2,t}, s_{3,t}, s_{4,t})$ indicates the values vector of indicators for each sub-financial market. $w_t os_t$ represents the Hadamar product of the weight vector and the values vector in the period t. C_t is the matrix of time-dependent cross-correlation coefficients $(\rho_{ij,t})$ between the indicators i and j.

Through the following formula group, they convert relative covariances $(\delta_{ij,t})$ and volatilities $(\delta^2_{i,t})$ to $\rho_{ij,t}$ in a recursive manner by using the exponential floating-weighted average method.

$$\delta_{ij,t} = \lambda\delta_{ij,t-1} + (1-\lambda)\bar{s}_{i,t}\bar{s}_{j,t}$$

$$\delta_{i,t}^2 = \lambda\delta_{i,t-1}^2 + (1-\lambda)\bar{s^2}_{i,t}$$

$$\rho_{ij,t} = \frac{\delta_{ij,t}}{\delta_{i,t}\delta_{j,t}}$$

In this formula group, they obtain $\bar{s}_{i,t}$ by subtracting the theoretical average of indicators from 0.5. They also assume that the flattening parameter (λ) in the exponential floating weighted average calculation does not change over time and remains constant at 0.93. With the addition of the correlation between the indicators in the calculation of the stress index, the method provides more weight to the stress that occurs in more than one indicator, it brings a systemic feature to the index.

In the calculation of the CISS value, they obtain the weights of indicators for each sub-market segment (w_i) with Principal Component Analysis based on their proportions of variance. They also calculate sub-indicator values($s_{i,t}$) by getting the weighted average of factor loadings.

1.4.5 Logit and Probit Model

The regression analysis, which is a parametric method, is the process of generating the most accurate estimation under certain assumptions. The least-squares method is used to select parameters that will minimize the sum of the squares of error terms in the estimation. In the early warning system, the dependent variable has a discrete value (with or without a crisis), while the estimated probability of a crisis is in the range of (0.1). However, with linear regression, estimates may be outside the range of (0.1). Therefore, a transformation is needed. The most commonly used methods for this purpose are the Logit and Probit models.

$$y_i^* = x_i'\beta + u$$

$$y_i = 1 \text{ if } y_i^* > 0$$

$$y_i = 0 \text{ if } y_i^* \leq 0$$

$$Pr(y = 1) = Pr(x'\beta + u > 0) = Pr(-u < x'\beta) = F(x'\beta)$$

F (.) Is the cumulative distribution function of u. The Logit and Probit models differ in the selection of the F (.) Function. I summarize the four commonly used functions in Table 1.8.

Table 1.8: Models used describing crisis risk

Model	$p = Pr(y = 1\|x)$	**Marginal effect** $\frac{\partial p}{dx_j}$
Logit	$\Lambda(x'\beta) = \frac{e^{x'\beta}}{(1 + e^{x'\beta})}$	$\Lambda(x'\beta)\{1 - \Lambda(x'\beta)\}\beta_j$
Probit	$\Phi(x'\beta) = \int_{-\infty}^{x'\beta} \emptyset(z)dz$	$\Phi(x'\beta)\beta_j$
Linear Probability	$F(x'\beta) = x'\beta$	β_j
Complementary Log-Log	C($x'\beta$) = 1 – exp{-exp($x'\beta$)}	exp{-exp($x'\beta$)}exp($x'\beta$) β_j

After forming the stress indices, by using the logit model, I aim to calculate the effects of the indicators on the probability of a stress event occurring for financial markets case.

1.5 Empirical Results

In this section, I obtain the stress indices by using these three methods and present the graphs of stress indices and some supplementary tables.

1.5.1 Equal Variance Weighting Method

After getting data for these three blocks, I calculate the stress indices according to the equal variance weighting methodology which I discuss in the "Methodology" section. I built up three indices which are for financial institutions, financial markets, and the real sector. I show these indices in Figures 1.1 to 1.3.

Figure 1.1: Stress Index for Financial Institutions with EVW Method

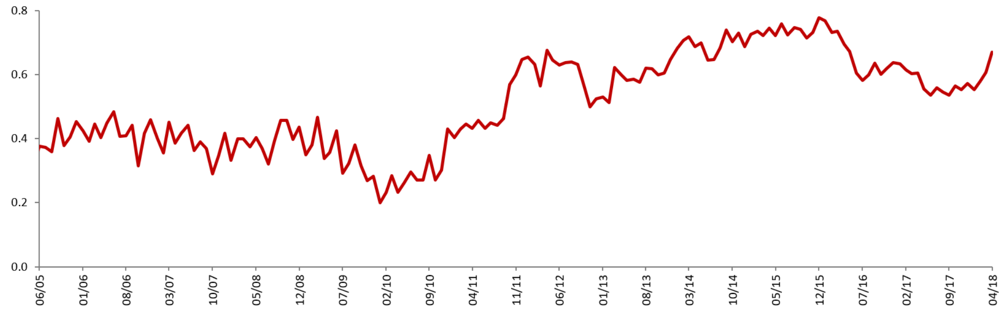
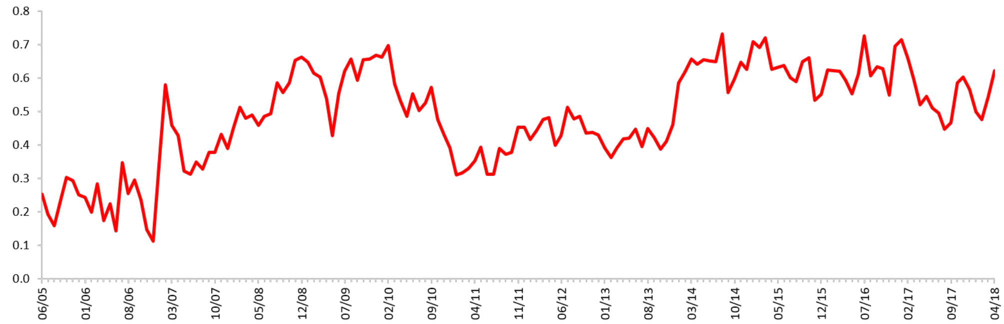


Figure 1.2: Stress Index for Financial Markets with EVW Method

Figure 1.3: Stress Index for Real Economy with EVW Method



1.5.2 Principal Component Analysis Method

For the financial institutions block, I present the results for KMO, PCA results (eigenvalues and proportion of variance) and factor loadings in Tables 1.9 to 1.11. I place supplementary graphs and tables such as correlation matrix, scree plot and PCA weights for the financial institutions stress index in Appendix. Since the KMO values of all indicators are greater than 0.5, I include all indicators to the analysis. By using the Kaiser criterion which provides suggestions to extract all the factors with an eigenvalue greater than 1, I extract three factors. The scree plot also supports the number of factors extracted. I obtain the weights of indicators for each of the sub-financial institution segments from PCA results based on their proportions of variance. After that, for each factor, I remove the loadings (correlation coefficient) values which are lower than 0.3. I assign each indicator to a certain factor based on its maximum absolute factor loading. Then I calculate the weights of the indicator based on the loadings value. I present The financial institutions stress index in Figure 1.4.

Table 1.9: KMO Statistic for Financial Institutions Block

Variable	KMO (Kaiser-Meyer-Olkin measure of sampling adequacy)
Return on Asset	0.8557
Return on Equity	0.856
Net Interest Margin	0.8643
Capital Adequacy Ratio	0.8996
Leverage Ratio	0.9269
Z Score	0.7569
Wholesale Funding	0.9245
Credit to Deposit Ratio	0.8589
Fx Liabilities to Total Liabilities	0.8102
Non-performing Loan Ratio	0.8196
Change in Non-performing Loan Ratio to Change in Credits	0.669
Non-performing Loan to Equity	0.8293
Provisions to Average Loans	0.6356
Receivables From Financial Inst and Payables to Financial Institutions to Total Assets	0.6769
Overall	0.8489

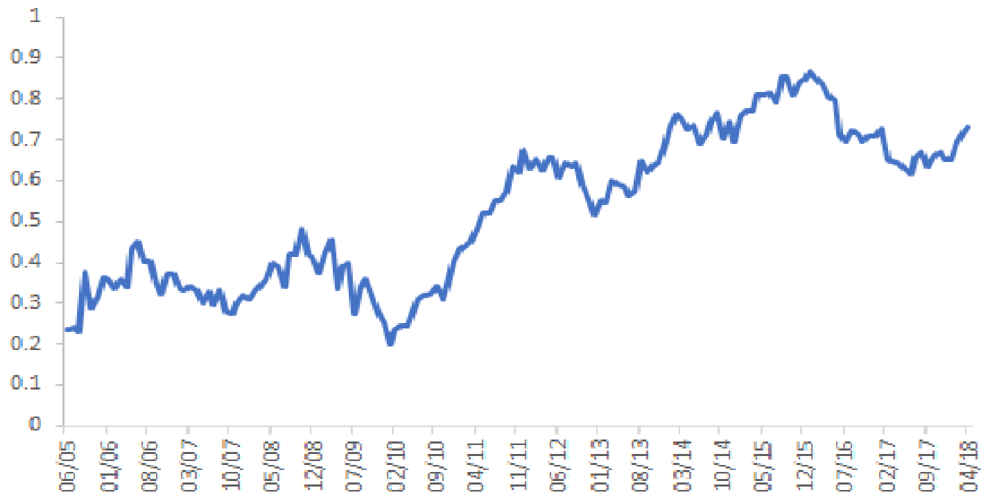
Table 1.10: PCA output for Financial Institutions Block

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	8.2231	6.22197	0.5874	0.5874
Comp2	2.00113	0.871279	0.1429	0.7303
Comp3	1.12985	0.413097	0.0807	0.811
Comp4	0.716755	0.122249	0.0512	0.8622
Comp5	0.594506	0.122558	0.0425	0.9047
Comp6	0.471947	0.127793	0.0337	0.9384
Comp7	0.344155	0.178687	0.0246	0.963
Comp8	0.165468	0.0496965	0.0118	0.9748
Comp9	0.115771	0.037102	0.0083	0.983
Comp10	0.0786691	0.00506729	0.0056	0.9887
Comp11	0.0736018	0.0214944	0.0053	0.9939
Comp12	0.0521074	0.0291958	0.0037	0.9976
Comp13	0.0229116	0.0128844	0.0016	0.9993
Comp14	0.0100271	.	0.0007	1

Table 1.11: Factor Loadings for Financial Institutions Block

	Comp. 1	Comp. 2	Comp. 3	Uniqueness	Communality
Return on Asset	0.34	-0.09	0.05	0.05	0.95
Return on Equity	0.33	-0.05	0.06	0.08	0.92
Net Interest Margin	0.32	0.06	-0.08	0.12	0.88
Capital Adequacy Ratio	0.32	0.02	0.09	0.15	0.85
Leverage Ratio	0.32	-0.01	-0.07	0.16	0.84
Z Score	-0.17	0.32	0.39	0.39	0.61
Wholesale Funding	0.30	0.17	-0.07	0.20	0.80
Credit to Deposit Ratio	0.32	-0.16	-0.13	0.09	0.91
Fx Liabilities to Total Liabilities	0.29	-0.14	0.10	0.26	0.74
Non-performing Loan Ratio	-0.25	-0.40	0.09	0.15	0.85
Change in Non-performing Loan Ratio to Change in Credits	0.07	0.03	0.83	0.18	0.82
Non-performing Loan to Equity	0.25	-0.42	0.17	0.09	0.91
Provisions to Average Loans	0.13	0.56	-0.18	0.21	0.79
Receivables From Financial Inst and Payables to Financial Institutions to Total Assets	0.13	0.40	0.19	0.51	0.49

Figure 1.4: Stress Index for Financial Institutions with PCA Method



For the financial markets block, I present the results for KMO, PCA results (eigenvalues and proportion of variance) and factor loadings in Tables 1.12 to 1.14. I place supplementary graphs and tables such as correlation matrix, scree plot and PCA weights for the financial markets stress index in Appendix. Since the KMO values of all indicators are greater than 0.5, I include all indicators in the analysis. By using the Kaiser criterion which provides suggestions to extract all the factors with an eigenvalue greater than 1, I extract four factors. The scree plot also supports the number of factors extracted. I obtain the weights of indicators for each of the sub-financial market segments from PCA results based on their proportions of variance. After that, for each factor, I remove the loadings (correlation coefficient) value which is lower than 0.3. I assign each indicator to a certain factor based on its maximum absolute factor loading. Then I calculate the weights of the indicators based on the loadings value. I present the financial markets stress index in Figure 1.5.

Table 1.12: KMO Statistic for Financial Markets Block

Variable	KMO (Kaiser-Meyer-Olkin measure of sampling adequacy)
Weighted TL Collapse	0.7005
Implied FX Volatility	0.7902
Realized FX Volatility	0.8112
USD TRY 25 Delta Risk Reversal	0.8281
USD TRY 3 Month Forward and Spot Rate Difference	0.6265
Weighted Equity Collapse	0.697
Stock Index and Bond Return Correlation	0.7316
Stock Index Realized Volatility	0.705
Price Equity Ratio	0.6202
Interbank Repo Rate	0.7965
Bank Bond Yield Difference	0.6351
Volume of Benchmark Bond Traded	0.8596
Public Debt Premium	0.5215
Yield Curve Slope Difference	0.5253
Realized Volatility of 2 Year Government Bond	0.6963
CDS	0.7558
Overall	0.7062

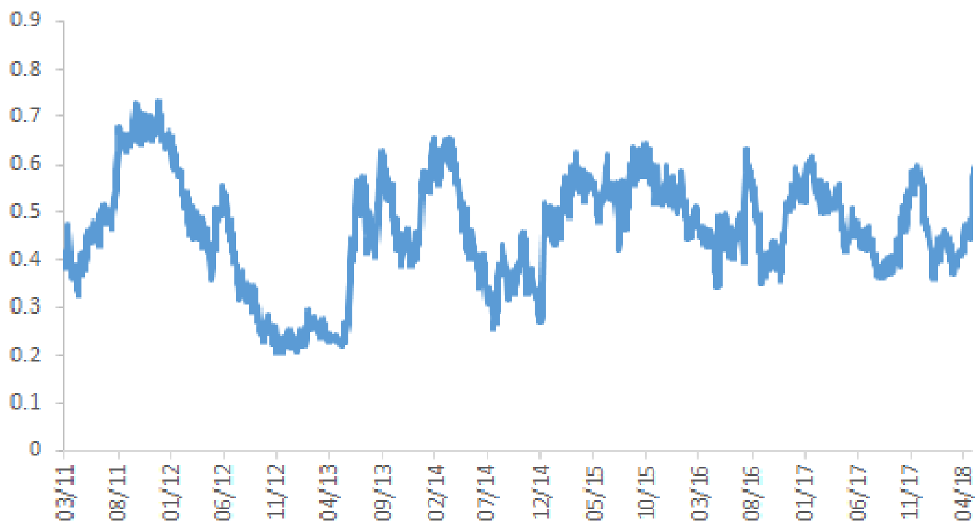
Table 1.13: PCA output for Financial Markets Block

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	5.47529	2.36238	0.3422	0.3422
Comp2	3.11291	1.6786	0.1946	0.5368
Comp3	1.43431	0.411989	0.0896	0.6264
Comp4	1.02232	0.102154	0.0639	0.6903
Comp5	0.92017	0.0123362	0.0575	0.7478
Comp6	0.907834	0.236756	0.0567	0.8046
Comp7	0.671077	0.102244	0.0419	0.8465
Comp8	0.568833	0.0182131	0.0356	0.882
Comp9	0.55062	0.197426	0.0344	0.9165
Comp10	0.353194	0.0338876	0.0221	0.9385
Comp11	0.319307	0.00727686	0.02	0.9585
Comp12	0.31203	0.17351	0.0195	0.978
Comp13	0.13852	0.0302757	0.0087	0.9867
Comp14	0.108244	0.0411388	0.0068	0.9934
Comp15	0.0671057	0.0288793	0.0042	0.9976
Comp16	0.0382264	.	0.0024	1

Table 1.14: Factor Loadings for Financial Markets Block

	Comp. 1	Comp. 2	Comp. 3	Comp. 4	Uniqueness	Communality
Weighted TL Collapse	0.32	-0.07	-0.20	-0.02	0.37	0.63
Implied FX Volatility	0.40	0.02	0.00	-0.01	0.13	0.87
Realized FX Volatility	0.35	0.02	0.10	-0.03	0.31	0.69
USD TRY 25 Delta Risk Reversal	0.35	0.07	-0.09	-0.13	0.29	0.71
USD TRY 3 Month Forward and Spot Rate Difference	0.28	-0.40	0.07	0.02	0.06	0.94
Weighted Equity Collapse	0.27	0.31	0.05	0.07	0.28	0.72
Stock Index and Bond Return Correlation	-0.08	0.00	0.29	0.74	0.28	0.72
Stock Index Realized Volatility	0.21	0.37	0.16	-0.07	0.29	0.71
Price Equity Ratio	-0.26	0.13	0.37	0.09	0.37	0.63
Interbank Repo Rate	0.29	0.16	0.18	0.30	0.33	0.67
Bank Bond Yield Difference	-0.08	0.49	-0.15	0.23	0.15	0.85
Volume of Benchmark Bond Traded	-0.04	0.20	-0.24	0.08	0.78	0.22
Public Debt Premium	-0.03	0.15	-0.66	0.21	0.26	0.74
Yield Curve Slope Difference	0.13	-0.38	0.09	0.23	0.39	0.61
Realized Volatility of 2 Year Government Bond	0.03	0.32	0.36	-0.39	0.33	0.67
CDS	0.34	0.04	0.00	0.17	0.33	0.67

Figure 1.5: Stress Index for Financial Markets with PCA Method



For real sector block, I present the results for KMO, PCA results (eigenvalues and proportion of variance) and factor loadings in Tables 1.15 to 1.17. I place supplementary graphs and tables such as correlation matrix, scree plot and PCA weights for the real sector stress index in Appendix. Since the KMO values of some indicators are lower than 0.5, these indicators, such as employment ratio, labor force participation ratio, durables goods sales, I remove them from the analysis. By using the Kaiser criterion which provides suggestions to extract all the factors with an eigenvalue greater than 1, I extract two factors. The scree plot also supports the number of factors extracted. I obtain the weights of indicators for each of the sub-real sector segments from PCA results based on their proportions of variance. After that, for each factor, I remove the loadings (correlation coefficient) value which is lower than 0.3. I assign each indicator to a certain factor based on its maximum absolute factor loading. Then I calculate the weights of the indicators based on the loadings value. I present the real sector stress index in Figure 1.6.

Table 1.15: KMO Statistic for Real Sector Block

Variable	KMO (Kaiser-Meyer-Olkin measure of sampling adequacy)
Weighted TL Collapse	0.7005
Implied FX Volatility	0.7902
Realized FX Volatility	0.8112
USD TRY 25 Delta Risk Reversal	0.8281
USD TRY 3 Month Forward and Spot Rate Difference	0.6265
Weighted Equity Collapse	0.697
Stock Index and Bond Return Correlation	0.7316
Stock Index Realized Volatility	0.705
Price Equity Ratio	0.6202
Interbank Repo Rate	0.7965
Bank Bond Yield Difference	0.6351
Volume of Benchmark Bond Traded	0.8596
Public Debt Premium	0.5215
Yield Curve Slope Difference	0.5253
Realized Volatility of 2 Year Government Bond	0.6963
CDS	0.7558
Overall	0.7062

Table 1.16: PCA output for Real Sector Block

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.51718	1.22548	0.4195	0.4195
Comp2	1.29171	0.325065	0.2153	0.6348
Comp3	0.96664	0.388075	0.1611	0.7959
Comp4	0.578565	0.14155	0.0964	0.8923
Comp5	0.437014	0.228124	0.0728	0.9652
Comp6	0.20889	.	0.0348	1

Table 1.17: Factor Loadings for Real Sector Block

	Comp. 1	Comp. 2	Uniqueness	Communality
Non-farming Unemployment Ratio	-0.09	0.75	0.26	0.74
Unemployment Ratio	0.41	-0.43	0.33	0.67
Industrial Production Index	0.43	0.01	0.53	0.47
Capacity Usage Ratio	0.44	-0.15	0.48	0.52
Real Sector Confidence Index	0.46	0.43	0.23	0.77
Consumer Confidence Index	0.48	0.22	0.36	0.64

Figure 1.6: Stress Index for Real Sector with PCA Method

1.5.3 Portfolio Theory Method

I calculate the stress indices according to the portfolio theory method which I discuss in the "Methodology" section. I present the stress indices in Figures 1.7 to 1.9.

Figure 1.7: Stress Index for Financial Institutions with Portfolio Theory Method

Figure 1.8: Stress Index for Financial Markets with Portfolio Theory Method

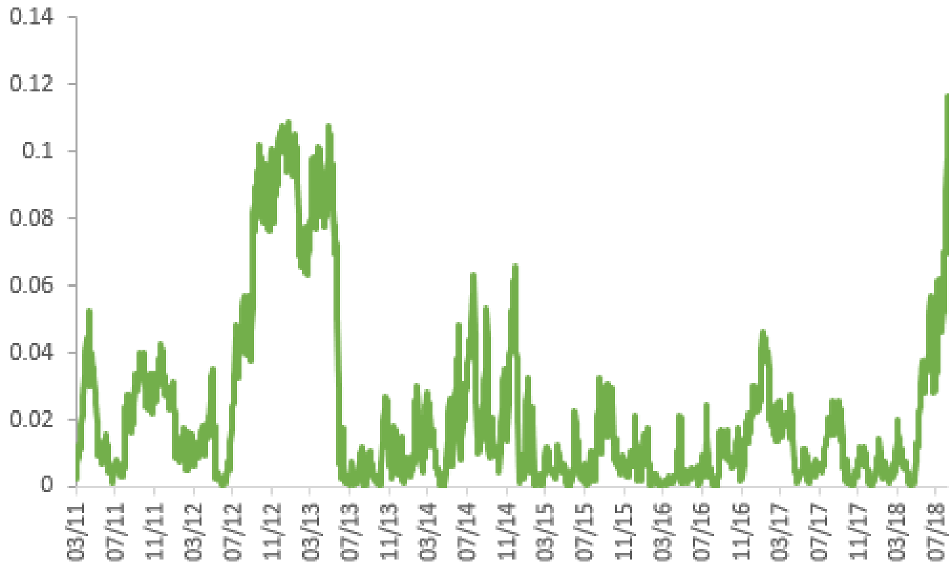
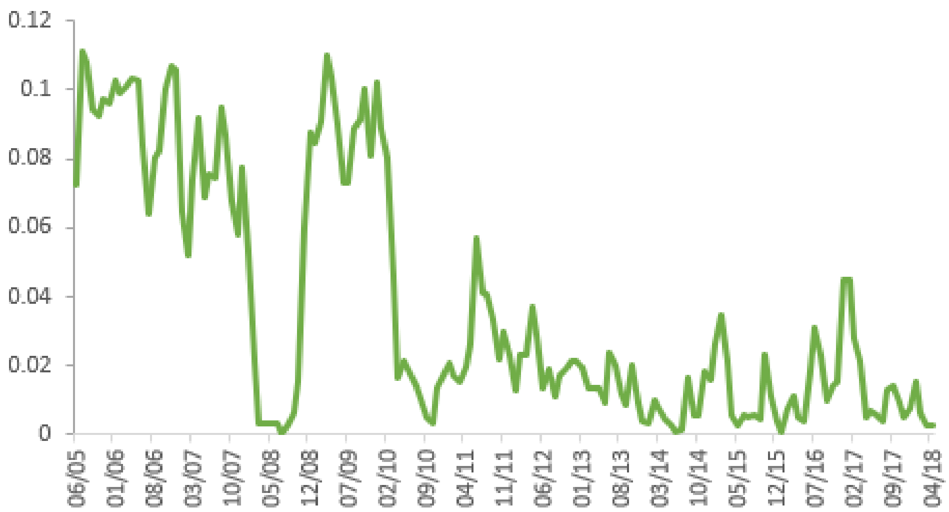


Figure 1.9: Stress Index for Real Sector with Portfolio Theory Method



1.6 Application of the Logit Model to the Stress Index

After getting the stress indices, by using the logit model, I aim to calculate the effects of the indicators on the probability of a crisis occurring for financial markets case. Due to the fact that the financial market data has a high frequency (daily basis), I can get more precise results in the financial market case. To identify the systemic events, I analyze the relationship between the Financial Stress Index and real effective exchange rate index. As it can be seen from Figure 1.10, the levels of the Financial Stress Index above the 80th percentile of the country distribution of the index anticipate median negative deviations of the real effective exchange rate index from its trend. Therefore, I mark the events exceeding the 80th percentile of financial institutions index as systemic events in this chapter. Then I implement the logit model to see the effects of the indicators on the probability of a crisis. I provide the results in Tables 1.18 and 1.19.

Figure 1.10: Percentiles of the Financial Stress Index and the Median Deviation of Real Effective Exchange Rate Index from Trend

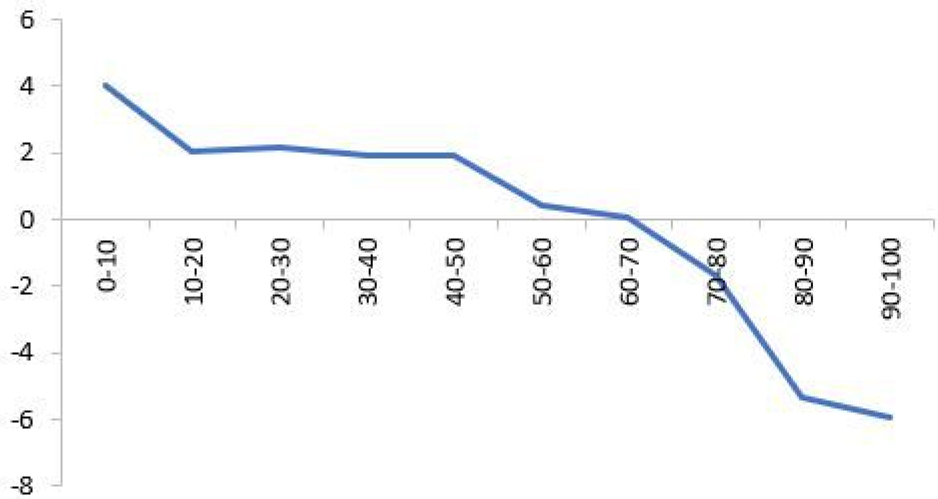


Table 1.18: Logit Model Results for Financial Markets Case

Crisis Status	Coef.	Std. Error.	z	P > |z|	[%95 Conf. Interval]	
Weighted TL Collapse	-2.83	14.66	-0.19	0.84	-31.57	25.90
Implied FX Volatility	0.26*	0.14	1.89	0.06	-0.01	0.54
Realized FX Volatility	0.69**	0.17	3.88	0.00	0.34	1.03
USDTRY Delta Risk Reversal	4.81**	0.94	5.11	0.00	2.96	6.66
USDTRY Forward&Spot Rate Difference	-40.48	37.82	-1.07	0.28	-114.60	33.64
Weighted Equity Collapse	-21.37**	8.77	-2.44	0.01	-38.57	-4.18
Stock Index Return and Bond Return Correlation	-7.55**	1.16	-6.49	0.00	-9.83	-5.27
Stock Index Realized Volatility	0.38**	0.10	3.55	0.00	0.17	0.59
Price – Equity Ratio	1.74**	0.71	2.43	0.01	0.33	3.15
Interbank Repo Rate	2.98**	0.67	4.39	0.00	1.64	4.31
Bank Bond Yield Difference	0.01	0.008	1.42	0.15	-0.004	0.02
The volume of benchmark bond traded	-3.01e-08**	5.84e-09	-5.15	0.00	-4.15e-08	-1.86e-08
Public Debt Premium	0.12**	0.02	5.84	0.00	0.08	0.16
Yield Curve Slope Difference	-0.06	0.58	-0.12	0.90	-1.22	1.08
Realized Volatility of 2-year government bond return	-0.02	0.04	-0.50	0.61	-0.10	0.05
CDS	0.05**	0.01	3.29	0.00	0.02	0.08

** $p<0.05$, * $p<0.1$, Pseudo $R^2 = 0.90$

Table 1.19: Marginal Effects in Logit Model

Delta Method						
Crisis Status	dy/dx	Std. Error.	z	P > |z|	[%95 Conf. Interval]	
Weighted TL Collapse	-0.19	0.10	-0.19	0.84	-0.21	0.17
Implied FX Volatility	0.001*	0.0009	1.93	0.053	-0.0002	0.003
Realized FX Volatility	0.004**	0.001	4.60	0.00	0.02	0.006
USDTRY Delta Risk Reversal	0.033**	0.005	6.49	0.00	0.23	0.043
USDTRY Forward&Spot Rate Difference	-0.27	0.25	-1.08	0.28	-0.78	0.227
Weighted Equity Collapse	-0.14**	0.05	-2.56	0.01	-0.26	-0.03
Stock Index Return and Bond Return Correlation	-0.05**	0.005	-9.36	0.00	-0.63	-0.04
Stock Index Realized Volatility	0.002**	0.0006	3.81	0.00	0.001	0.003
Price – Equity Ratio	0.01**	0.004	2.57	0.01	0.002	0.02
Interbank Repo Rate	0.02**	0.003	5.27	0.00	0.01	0.02
Bank Bond Yield Difference	0.00008	0.00005	1.45	0.14	-0.00003	0.0001
The volume of benchmark bond traded	-2.08e-10**	3.13e-11	-6.63	0.00	-2.69e-10	-1.46e-10
Public Debt Premium	0.0084**	0.0001	7.80	0.00	0.0006	0.001
Yield Curve Slope Difference	-0.0004	0.004	-0.12	0.90	-0.084	0.007
Realized Volatility of 2-year government bond return	-0.0001	0.0002	-0.50	0.61	-0.007	0.0004
CDS	0.003**	0.0001	3.62	0.00	0.001	0.0005

** $p<0.05$, * $p<0.1$

In the first table, I provide the results in the case of applying the logit model. In this table, I can interpret only the direction of effect, not the magnitude. Estimated coefficients do not quantify the influence of the indicators on the probability. The indicators which I denote by one star, are significant at the 0.1 level, the indicators which I denote by two stars are significant at the

0.05 level. The indicators who do not have any star, are not significant. For example, when the realized volatility increases, this leads to an increase in the probability of a crisis occurring with a 0.05 significance level or when the implied volatility rises, this leads to an increase in the probability of a crisis occurring with a 0.1 significance level.

In the second table, I calculate the marginal effects of the logit model. So, I can interpret both the direction of the effect and magnitude of the effect by looking at the coefficients. If the average implied FX volatility increases an infinitely small amount, the probability of a crisis occurring rises by 0.2%.

I also check whether my model meets the assumptions of logistic regression. First of all, logistic regression requires there to be little or no multicollinearity among the independent variables. I used the vif command after the regression to check for multicollinearity. Variance inflation factor (VIF) quantifies how much the variance is inflated when multicollinearity exists. In particular, the variance inflation factor for the *jth* predictor is: $VIF_j = \frac{1}{1-R_j^2}$ where R_j^2 is the R^2 value obtained by regressing the *jth* predictor on the remaining predictors. As a rule of thumb, a variable whose VIF values are greater than 10 may merit further investigation. I present the results in Appendix. I conclude that my model does not have multicollinearity problem from the results. Secondly, I check whether my model has an specification error or not. I present the results in Appendix by employing linktest. The test is based on the idea that if a regression equation is properly specified and no additional independent variables should be significant above chance. The link test looks for a specific type of specification error which is called link error. The link test adds the squared independent variable to the model and tests for significance versus the nonsquared model. A model without a link error will have a nonsignificant t-test versus the unsquared version. I present the results of this test in Appendix. Because of the fact that the squared version of the model insignificant, I used the original model.

Next, I utilize ordered logit models by identifying three categories, such as high, medium and low stress. Ordered logit models explain variation in an ordered categorical dependent variable as a function of one or more independent variables. These models do not require that the distance between the categories be equal. Ordered logit models are typically used when the dependent variable has more than two categories. To identify the categories, I analyze the relationship between the Financial Stress Index and real effective exchange rate index. When the percentile is below 50%, I identify it as low stress due to the stable relationship between these two variables. When the percentile is between 50% and 70%, I label it as medium stress due to the inverse relationship observed between these two indicators. When the percentile is above 70%, I name it as high stress because it anticipates median negative deviations of the real effective exchange rate index from its trend.

Table 1.20: Logit Model Results for Financial Markets Case

Crisis Status	Coef.	Std. Error.	z	P > |z|	[95% Conf. Interval]	
Weighted TL Collapse	-4.73256	4.712816	-1	0.315	-13.9695	4.504392
Implied FX Volatility	0.563896	0.101995	5.53	0	0.363989	0.763803
Realized FX Volatility	0.746232	0.062356	11.97	0	0.624018	0.868447
USDTRY 25 Delta Risk Reversal	2.519849	0.324472	7.77	0	1.883897	3.155802
USDTRY Forward&Spot Rate Difference	-17.2925	18.44651	-0.94	0.349	-53.447	18.86194
Weighted Equity Collapse	-33.8587	2.824185	-11.99	0	-39.394	-28.3234
Stock Index Return and Bond Return Correlation	-5.86707	0.391907	-14.97	0	-6.6352	-5.09895
Stock Index Realized Volatility	0.056663	0.027851	2.03	0.042	0.002075	0.11125
Price – Equity Ratio	1.320677	0.195029	6.77	0	0.938428	1.702926
Interbank Repo Rate	2.057278	0.222556	9.24	0	1.621076	2.493479
Bank Bond Yield Difference	0.000554	0.004356	0.13	0.899	-0.00798	0.009091
The volume of benchmark bond traded	-1.29E-08	1.06E-09	-12.14	0	-1.49E-08	-1.08E-08
Public Debt Premium	0.065409	0.006349	10.3	0	0.052966	0.077853
Yield Curve Slope Difference	-0.35259	0.193259	-1.82	0.068	-0.73138	0.026187
Realized Volatility of 2 year government bond return	0.183289	0.016626	11.02	0	0.150703	0.215876
CDS	0.040168	0.004274	9.4	0	0.031791	0.048545

Table 1.21: Marginal Effects for the Low Stress Category

Delta Method						
Crisis Status	dy/dx	Std. Error.	z	P > |z|	[95% Conf. Interval]	
Weighted TL Collapse	0.113101	0.11314	1	0.317	-0.10864	0.334845
Implied FX Volatility	-0.01348	0.00361	-3.73	0	-0.02056	-0.0064
Realized FX Volatility	-0.01783	0.00382	-4.67	0	-0.02532	-0.01035
USDTRY 25 Delta Risk Reversal	-0.06022	0.01303	-4.62	0	-0.08576	-0.03468
USDTRY Forward&Spot Rate Difference	0.413265	0.45638	0.91	0.365	-0.48123	1.30776
Weighted Equity Collapse	0.809172	0.16915	4.78	0	0.477634	1.14071
Stock Index Return and Bond Return Correlation	0.140214	0.02816	4.98	0	0.085028	0.195401
Stock Index Realized Volatility	-0.00135	0.0007	-1.94	0.052	-0.00272	0.000012
Price – Equity Ratio	-0.03156	0.00756	-4.18	0	-0.04637	-0.01675
Interbank Repo Rate	-0.04917	0.01148	-4.28	0	-0.07167	-0.02666
Bank Bond Yield Difference	-1.3E-05	0.0001	-0.13	0.898	-0.00022	0.00019
The volume of benchmark bond traded	3.08E-10	0	4.9	0	1.80E-10	4.30E-10
Public Debt Premium	-0.00156	0.00033	-4.67	0	-0.00222	-0.00091
Yield Curve Slope Difference	0.008427	0.00473	1.78	0.075	-0.00085	0.017704
Realized Volatility of 2 year government bond return	-0.00438	0.00092	-4.78	0	-0.00618	-0.00258
CDS	-0.00096	0.00022	-4.4	0	-0.00139	-0.00053

Table 1.22: Marginal Effects for the Medium Stress Category

Delta Method						
Crisis Status	dy/dx	Std. Error.	z	P > |z|	[95% Conf. Interval]	
Weighted TL Collapse	-0.10556	0.10561	-1	0.318	-0.31256	0.101429
Implied FX Volatility	0.012578	0.0034	3.7	0	0.005922	0.019234
Realized FX Volatility	0.016645	0.00361	4.61	0	0.009573	0.023718
USDTRY 25 Delta Risk Reversal	0.056207	0.01219	4.61	0	0.03231	0.080104
USDTRY Forward&Spot Rate Difference	-0.38572	0.42707	-0.9	0.366	-1.22277	0.451329
Weighted Equity Collapse	-0.75524	0.15956	-4.73	0	-1.06798	-0.44251
Stock Index Return and Bond Return Correlation	-0.13087	0.02652	-4.93	0	-0.18285	-0.07889
Stock Index Realized Volatility	0.001264	0.00065	1.95	0.051	-4.70E-06	0.002532
Price – Equity Ratio	0.029459	0.00709	4.16	0	0.015568	0.04335
Interbank Repo Rate	0.045889	0.01087	4.22	0	0.02459	0.067188
Bank Bond Yield Difference	1.24E-05	0.0001	0.13	0.898	-0.00018	0.000202
The volume of benchmark bond traded	-2.87E-10	0	-4.86	0	-4.00E-10	-1.70E-10
Public Debt Premium	0.001459	0.00032	4.62	0	0.000841	0.002077
Yield Curve Slope Difference	-0.00786	0.00442	-1.78	0.075	-0.01653	0.000802
Realized Volatility of 2 year government bond return	0.004088	0.00087	4.72	0	0.002391	0.005785
CDS	0.000896	0.00021	4.36	0	0.000493	0.001299

Table 1.23: Marginal Effects for the High Stress Category

Delta Method						
Crisis Status	dy/dx	Std. Error.	z	P > |z|	[95% Conf. Interval]	
Weighted TL Collapse	-0.00754	0.00781	-0.97	0.335	-0.02285	0.007771
Implied FX Volatility	0.000898	0.00033	2.74	0.006	0.000255	0.001541
Realized FX Volatility	0.001189	0.00039	3.06	0.002	0.000428	0.001949
USDTRY 25 Delta Risk Reversal	0.004014	0.00139	2.88	0.004	0.001283	0.006744
USDTRY Forward&Spot Rate Difference	-0.02754	0.03026	-0.91	0.363	-0.08686	0.031771
Weighted Equity Collapse	-0.05393	0.01767	-3.05	0.002	-0.08855	-0.01931
Stock Index Return and Bond Return Correlation	-0.00934	0.00305	-3.06	0.002	-0.01532	-0.00337
Stock Index Realized Volatility	9.03E-05	0.00006	1.63	0.103	-1.8E-05	0.000199
Price – Equity Ratio	0.002104	0.00075	2.82	0.005	0.000639	0.003568
Interbank Repo Rate	0.003277	0.00109	3.02	0.003	0.001148	0.005405
Bank Bond Yield Difference	8.82E-07	0.00001	0.13	0.899	-1.3E-05	0.000015
The volume of benchmark bond traded	-2.05E-11	0	-3.04	0.002	-3.40E-11	-7.30E-12
Public Debt Premium	0.000104	0.00003	3	0.003	0.000036	0.000172
Yield Curve Slope Difference	-0.00056	0.00035	-1.61	0.107	-0.00125	0.000121
Realized Volatility of 2 year government bond return	0.000292	0.0001	3.07	0.002	0.000105	0.000479
CDS	0.000064	0.00002	2.97	0.003	0.000022	0.000106

In Table 1.20, I only interpret the direction of the effect, such as the probability of being in low stress is higher with an increase in weighted TL collapse. To quantify the magnitude, I calculate the marginal effects of the logit model. In Tables 1.21 to 1.23, I demonstrate the marginal effects. In these tables, I can interpret both the direction and the magnitude of the effect by looking at the coefficients, such as a unit increase in realized FX volatility is associated with 2% less likely being in the low stress category.

1.7 Comparison of Three Methods

1.7.1 Comparison of Three Methods - Stress Events

Before starting the comparison of these three methods, I quantify the correlation between stress indices in each method. To measure the correlation between stress indices, by using the Jarque-Bera test, I first identify whether the stress series are normally distributed or not. Jarque–Bera test is a goodness-of-fit test of whether sample data have the skewness and kurtosis matching a normal distribution. The null hypothesis is a joint hypothesis of the skewness being zero and the kurtosis being three. I present the results of the Jarque-Bera test in Table 1.24. If the p-values are higher than 0.05, then the series are normally distributed, otherwise they are not. While the real sector and the financial institutions data are normally distributed, the financial markets data are not. Then, I use the Pearson correlation coefficient if both of the series are normally distributed. The Pearson correlation coefficient measures the strength of the linear relationship between normally distributed variables. If either one of the series is not normally distributed, I use the Spearman rank corrrelation method. I demonstrate the correlation between the stress indices in Table 1.25.

The correlation between financial markets and financial institutions are positive. I can explain this through two channels. When the realized FX volatility and the implied FX volatility rises, the liabilities of banking sector spike due to the fact that the high share of the FX deposits in total deposits and syndicated loans obtained from foreign creditors. The other channel is related with the CDS premium. When CDS premium rises, the cost of syndicated loans which is the sum of LIBOR or the FED policy rate and CDS premium will be higher. The weighted cost of liabilities in the banking sector will rise and the profitability will decline. The correlation between the financial institutions and real sector is positive. I can interpret it in two ways. The real sector obtains the required funds to continue its operations from the financial institutions. If the credit conditions are tight and the profitability in the financial system is low, then the real sector and the households cannot obtain the required funds to make investments and consumption. It also has a feedback effect on financial institutions in terms of increasing the non-performing loan ratio. The correlation between the financial markets and the real sector is so low and statistically insignificant.

Table 1.24: Jaque Berra Test Results

	Financial Institutions	Financial Markets	Real Sector
Jaque Berra - p-values	0.56	0.01	0.21

Table 1.25: Correlation Between the Stress Indices

	Financial Institutions - Financial Markets		Financial Markets – Real Sector		Real Sector – Financial Institutions	
	Correlation	p-value	Correlation	p-value	Correlation	p-value
Pearson Correlation Coefficient			-0.07	0.72		
Spearman rank corrrelation	0.25	0.02			0.14	0.07

Although financial stress indices can be obtained through various approaches and methods, the performance assessment of calculated stress indices is seen as the most challenging stage of the process. This difficulty stems from the fact that objective criteria have not yet been developed in order to evaluate the performance of financial stress indices. Therefore, as in the studies of Illing and Liu (2006) and Huotari (2015), I evaluate the financial stress indices based on their reactions or levels based on stress events. For this purpose, I make the stress levels in these three methods comparable by utilizing the following formula.

$$Norm\,(x_i) = \frac{x_i - I_{min}}{I_{max} - I_{min}}$$

where I_{min} and I_{max} stand for the minimum and maximum value of the index, respectively and x_i denotes the value of the index at the respective date.

After making comparable the stress indices in these three methods, I classify the stress events into two categories: systemic and non-systemic events. Systemic event is associated with either the entire market or a particular segment of the market. It is caused by economic, political, and sociological changes, and is beyond the control of investors or the sovereign. For instance, the great recession of 2008 is a key example of systemic risk. It led to the collapse of various financial institutions. However, a non-systemic event refers to the risk associated with a specific instrument, firm or sector and internal factors are responsible for non-systemic events. It affects only a specific firm or sector. Municipality elections or presidential elections are examples of non-systemic events.

After determining the systemic and non-systemic events which are peculiar to the Turkish economy, I compare these three methods in terms of capturing these events. I present the results in Figures 1.11 to 1.13. In all figures, while the red line and blue line respectively show the stress indices obtained by using the equal variance weighting method and the principal component analysis method, the green line reflects the stress indices obtained by using the CISS method. The vertical lines indicate stress events. I present the systemic and non-systemic events related to stress indices below the chart, respectively. I have two observations from these figures. First, while the CISS method captures systemic events, the PCA method and EVW method appear to be able to accurately reflect non-systemic events. The reason for this conclusion lies in the fact that with the addition of the correlation between the sub-markets in the calculation of the stress index, the method provides more weight to the stress that occurs in more than one sub-market, it brings a 'systemic' feature to the index. Second, the stress levels in the real sector case, increase considerably relative to financial institutions case during the global financial crisis. In this specific period, although the soundness of financial institutions was not affected much by the global financial crisis, the crisis affected the real sector heavily. Because of the fact that the Turkish financial system lacks the same kind of subprime credits that lead to a mortgage crisis in the USA, it prevented experiencing the same kind of problems faced in the USA financial markets. Due to the fact that the measures taken after the banking crisis occurred in 2001, the financial structure of the banking sector has been strengthened and the banking sector was not affected too much from the global financial crisis. Moreover, the banking sector, which carefully applied the Basel criteria, has made significant improvements in the issue of financial stability. However, the same is not valid for the real sector. The real sector suffered great losses due to many other reasons such as shrinking global credit taps, increasing credit costs, decreasing demand in EU countries, the high share of the external debt in total debt of the real sector, and the heavy burden of interest payments on real sector causing the substantial rise in current account deficit. For example, as a result of the global financial crisis, there was a significant decrease in the growth rate from the last quarter of 2008 to the first quarter of 2010. Turkish economy contracted by 4.7% in 2009 when the actual effects of the crisis were deeply felt. The phenomenon of crisis led to a large increase in unemployment with a decline in production.

It is also important to understand the economic intuition behind the differences in methods in terms of capturing systemic and non-systemic events. The "saving ratio" is an important metric for financing growth. However, developing countries need external borrowing due to inadequate savings to finance investment. External borrowing comes through mainly two ways. 1- Foreign Direct Investment (FDI) : It is an investment made by a firm or individual in one country into business interests located in another country. Generally, FDI takes place when an investor establishes foreign business operations or acquires foreign business assets in a foreign company. In Turkey, FDI mostly occurs in the form of brownfield investment in which a company or government entity purchases or leases existing production facilities to launch a new production activity. 2- Foreign Portfolio Investment (Capital Flows): It refers to the purchase of securities and other financial assets by investors from another country. Examples of foreign portfolio investments include stocks, bonds, mutual funds, exchange - traded funds. This kind of investment typically has a shorter time frame for investment return than direct investment. As with any equity investment, foreign portfolio investors usually expect to realize a profit quickly on their investments and the investors can transfer the realized profits to the home country.

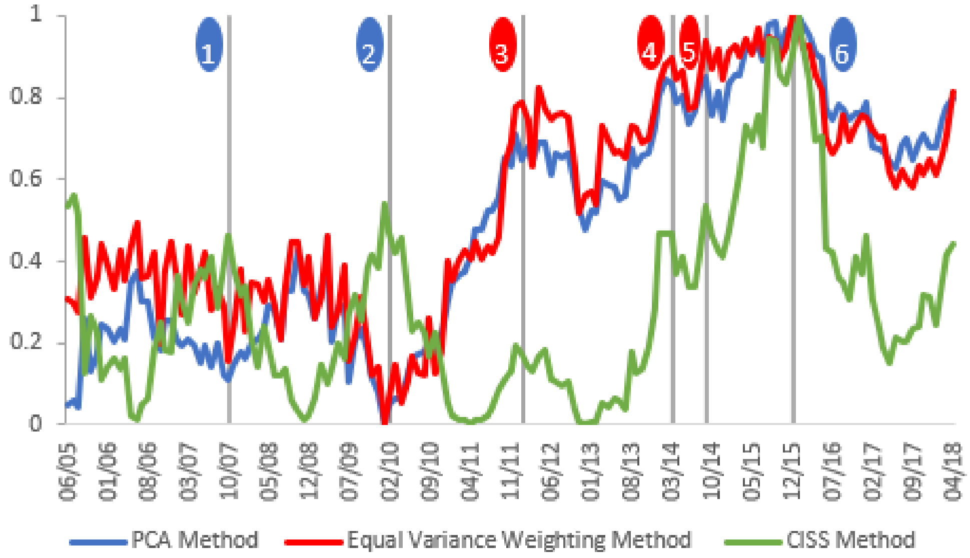
During the global financial crisis, the reversal of capital flows in the form of profit transfers led to exchange rate risk and a decrease in Central Bank reserves. It also resulted in a rise in CDS premium and an increase in the debt burden. From the viewpoint of financial institutions, it caused an increase in dollarization and current account deficit. It also pressured the non-performing loan ratio to rise because of the decline in economic activity. This led to a decline in capital adequacy ratio (CAR) which is calculated by dividing regulatory capital by risk-weighted assets. The rise in the non-performing ratio has a direct negative impact on CAR. Because of the exchange rate risk, funding costs of financial institutions rose and profitability ratios were affected negatively. Because of creating high stress in the credit losses block and capital block simultaneously, the CISS puts more weight on situations in which high stress prevails in several market segments at the same time.

The volatility of the stock exchange market index rose due to the negative impact of the European debt crisis, foreigners who invested in the stock market started to withdraw their funds and bring back to the their home country. Because of the rise in US/EUR nominal exchange rate and weakness in external demand mainly driven by Eurozone countries, the current account deficit widened. It pressured the exchange rate to rise. Because of creating high stress in the FX market block and stock market block simultaneously, the CISS puts more weight on situations in which high stress prevails in several market segments at the same time.

Non-systematic events, such as municipality elections and presidential elections are under the control of investors or sovereigns and, they are expected events. In these cases, the risk does not jump suddenly, the stress level starts to accumulate from a certain period of time before. Election results affect all the blocks the same way because all uncertainty disappears about what economic policies of the ruling party will be.

Another important finding that I can extract from these graphs is that non-systemic events are more relative to systemic events. There are mainly two reasons that can explain this phenomenon. Firstly, expansionary monetary policy implemented by Central Bank resulted in low interest –high exchange rate policy. One of Turkey's main problem basically stems from imports of the investment and consumption goods and the use of imported intermediate goods and raw materials by the sectors making production for the domestic market. Given the fact that a large part of imports consists of raw material, intermediate goods and investment goods, with the increase of production in Turkey, imports of intermediate goods and raw materials also increase, which cause an increase in the current account deficit. The depreciation in local currency increases the cost of production via pass-through effect and it is ultimately reflected in the final price that the consumers face. Policies implemented to decrease the interest rate lead to rise in savings gap. Due to the lack of adequate domestic savings, Turkish economy heavily relies on external funding to realize the desired growth rate. Secondly, political instability, increased uncertainties because of generally having early elections, the disharmony between fiscal policy and monetary policy, the deterioration in the independence of economic institutions and political pressures coming from the ruling party on the issue of determination of interest rates, change in economic policies in the term of office period of each new minister resulted in having more non-systemic events relative to systemic ones. I can also justify this by using some important metrics. I can use the share of FX deposits in total deposits and rollover ratio in public sector for providing base for this claim. The share of foreign currency deposits in total deposits is 54%, which is an key metric indicating that the society does not trust local money. In such an environment, the stabilizing the value of local currency and keeping inflation under control are uneasy job. At the same time, rollover ratio is over 100%, which means that public sector borrows more than domestic debt payments. As a result of the increase in the domestic debt rollover ratio, the private sector borrows less and invests less. Because the public sector demands most of the loanable funds and causes the interest rates to rise. This indicates that the most powerful anchor of the Turkish economy, which is public fiscal discipline is deteriorating.

Figure 1.11: Comparison of Three Methods for Financial Institutions Case



Corr($PCA_t, EVW_t = 0.95$), Corr($PCA_t, CISS_t = 0.41$), Corr($PCA_t, CISS_t = 0.42$)

Systemic Events for Financial Institutions Case

1- October 2007 - As a result of the negative effects of the problems that started in the field of housing finance in the United States on the world economy and financial sector, the economic activity slow down. Non-performing loan ratio rises and capital adequacy ratio declines

2- February 2010 - The negative effect of the global financial crisis

6- December 2015 - Shrinking "the ratio of the net interest income to the net income" leads to a decline in profitability due to the increase in the federal funds rate for the first time since 2006

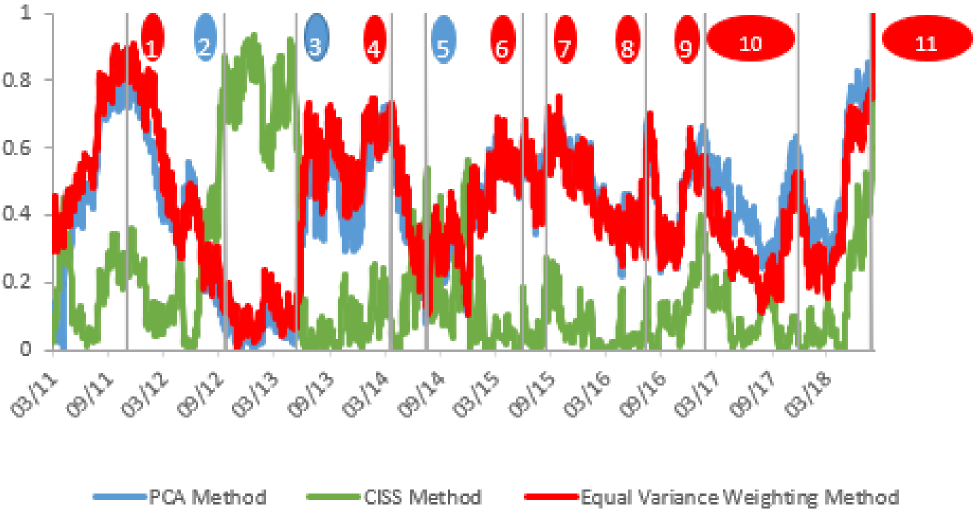
Non-systemic Events for Financial Institutions Case

3- January 2012 - Because of expansionary monetary policies implemented by CBRT, wholesale funding increased

4- March 2014 - Municipality Elections

5- August 2014 - Presidential Elections

Figure 1.12: Comparison of Three Methods for Financial Markets Case



Corr($PCA_t, EVW_t = 0.90$), Corr($PCA_t, CISS_t = -0.40$), Corr($PCA_t, CISS_t = -0.47$)

Systemic Events for Financial Markets Case

2- 27 November 2012 - Deepening of European debt crises

3- 21 May 2013 - Taper Tantrum

5- 24 June 2014 - Capital flows reversed in July, August, and September after the FED announced that it would stop giving liquidity in October

Non-systemic Events for Financial Markets Case

1- 15 November 2011 - Current account deficit reached record levels

4- 30 March 2014 - Municipality election

6- 7 June 2015 - Turkish general election

7- 25 August 2015 - Unsuccessful attempts to form a coalition government resulted in a snap general election

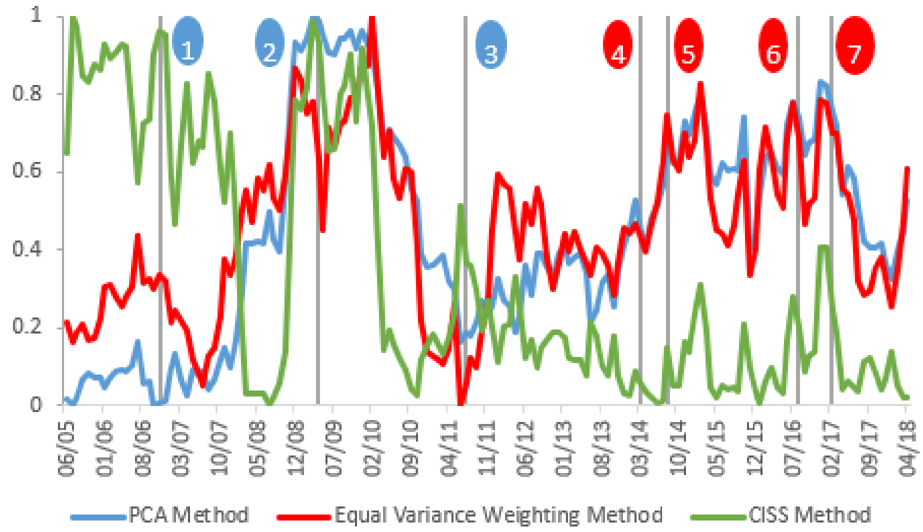
8- 15 July 2016 - Coup Attempt

9- 27 January 2017 - Downgrading Turkey credit note under investment grade by Fitch

10- 4 December 2017 - Inflation reaches double digits after a long time due to the high depreciation of the Turkish lira, the rise in import prices, the tax increase in tobacco and alcoholic beverages, the strong course in economic activity, and the deterioration in pricing behavior

11- August 1, 2018 - Sanctions imposed by the U.S. Department of Treasury on top Turkish government officials who were involved in the detention of Andrew Brunson

Figure 1.13: Comparison of Three Methods for Real Sector Case



Corr($PCA_t, EVW_t = 0.85$), Corr($PCA_t, CISS_t = -0.11$), Corr($PCA_t, CISS_t = -0.19$)

Systemic Events for Real Sector Case

1- October 2006 - FED increased its interest rates by 5.25 percent until the end of June

2- March 2009 - Contraction of 6.2% in the last quarter of 2008 which was announced (Effect of global financial crises)

3- June 2011 - European Debt Crisis

Non-systemic Events for Real Sector Case

4- March 2014 - Municipality Elections

5- August 2014 - Presidential Elections

6- July 2016 - Coup Attempt

7- January 2017 - Downgrading Turkey credit note under investment grade by Fitch

1.7.2 Comparison of Three Methods - Stress Levels

The second metrics for evaluating performance of the methods is to look whether they accurately reflect the stress level related to the stress event examined or not. To that end, using the approach developed by Duprey et al. (2015) and establishing preliminary expectations through the link between real sector stress index and economic activity, financial sector stress index and non-performing loan ratio. I select two sample events for financial institutions and real sector case. As it is seen in Figure 1.11, portfolio method shows the normalization of monetary policy of the FED as a higher stress period relative to global financial crisis for the financial institutions case. As it is seen in Figure 1.13, portfolio method represents global financial crisis as a higher stress period relative to European debt crisis for real sector case. For the first case, I present non-performing loan ratio (NPL) response for the 12 months following the selected stress periods in Figure 1.14. For the second case, I present GDP response for the 12 months following the selected stress periods in Figure 1.15.

The interpretation of these two figures can be done as follows:

1 - The rise in NPL ratio continued for 12 months following the second stress period contrasted to global financial crisis. It is an evidence of having low stress level in global financial crisis period.

2- When I look at the reaction in real GDP after the date when the stress event hitted the economy worst, it recovered more relative to European debt crisis in the following 12 months because of the low base effect. The real side of the economy heavily affected from global financial crisis so that the base year growth was very low relative to the European debt crisis.

Figure 1.14: Non-Performing Loan Ratio Response For 12 Months Following Selected Stress Periods

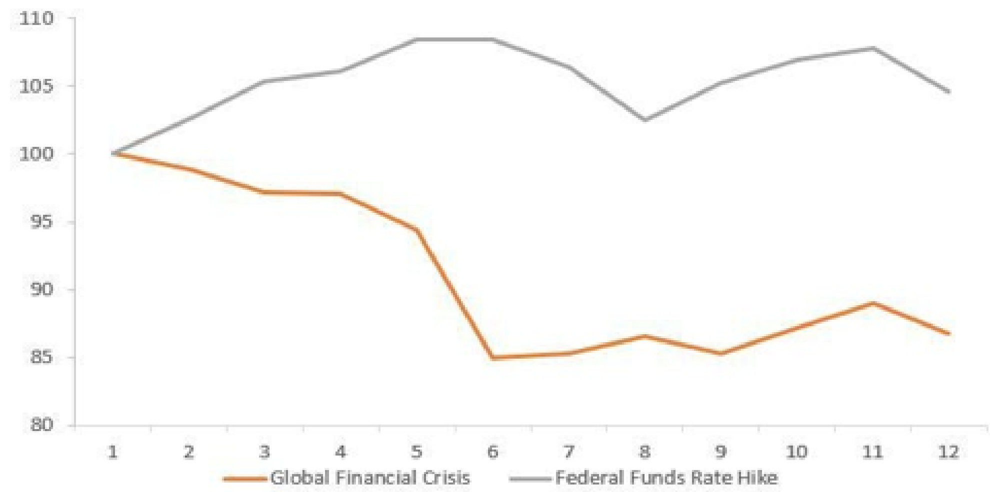
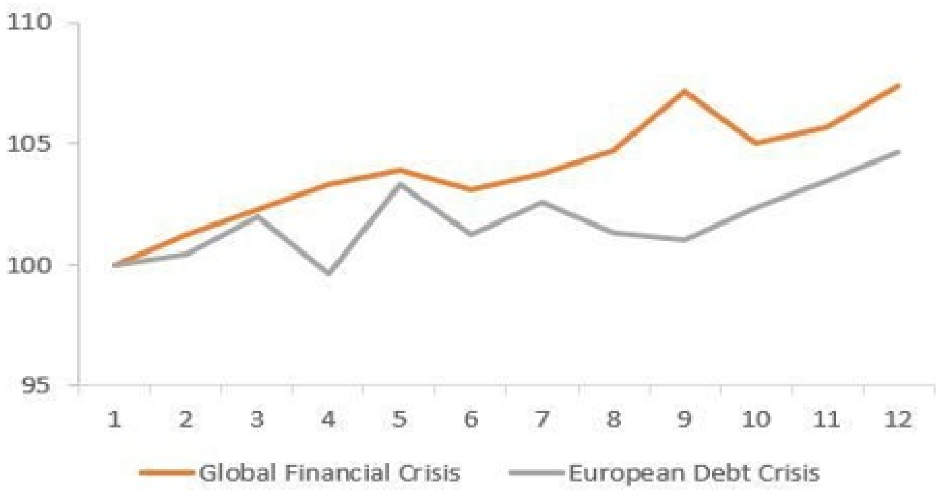


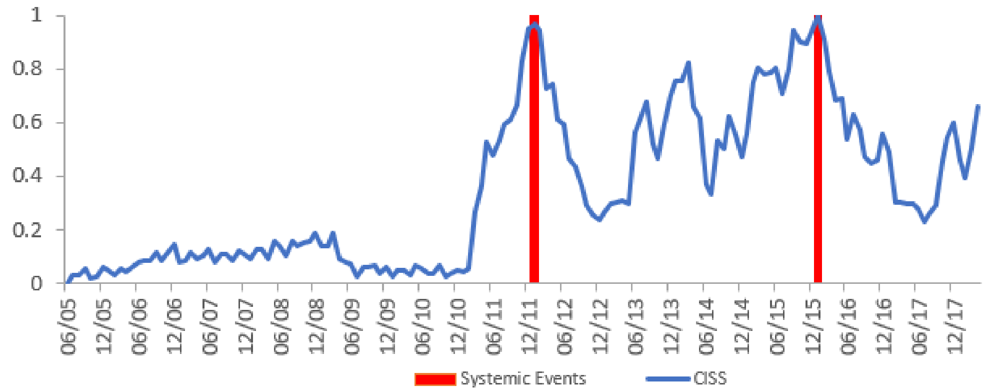
Figure 1.15: Real GDP Response For 12 Months Following Selected Stress Periods



1.8 A Unified Stress Index

In this part of the chapter, I create a composite index by employing all the variables used to develop the earlier three indices. I utilize 'Portfolio Theory' to create this index and present it in Figure 1.16. The red vertical lines represent two major systemic events that the index captures. The first one is related with the European debt crisis which was deepen in 2012. Many European countries are technically in recession, and the indebtedness and unemployment rates of developed countries have increased. Economic crisis in the Eurozone area leads to shrink in external demand and reduce the Turkey's export to this area. The second one is related to the normalization of the FED monetary policy, namely, the rise in the FED policy rate for the first time over 9 years in December 2015. It has an big impact on the emerging markets due to the exit of short-term capital flows. So, the depreciation of the local currency and the rise in policy rate of Turkey had pressure on banking sector profitability and capital adequacy ratio.

Figure 1.16: Composite Stress Index



1.9 Conclusion

In this chapter, I try to answer these questions: Is there a way to construct stress indices for three blocks such as financial institutions, financial markets, and the real sector? Which method is better in terms of capturing systemic and non-systemic events? Which indicators are significant in terms of predicting financial market crashes? My contribution to the literature is twofold. First, I come up with three different indices with three different methods by using rich data set relative to other indices constructed specifically for Turkey. Secondly, I try to calculate the impacts of the indicators on the probability of financial market crashes occurring. At the end of this chapter, I come up with these results. While the CISS method captures systemic events better than the other two methods, the PCA method and EVW method appear to be able to capture non-systemic events. Second, USD/TRY Delta Risk Reversal, Weighted Equity Collapse, Realized FX Volatility, CDS and Public Debt Premium are the statistically significant indicators in terms of predicting the probability of financial market crashes occurring.

1.10 References

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1.11 Appendices

1.11.1 Scree Plots

Figure 1.17: Scree Plot for Financial Institutions Block

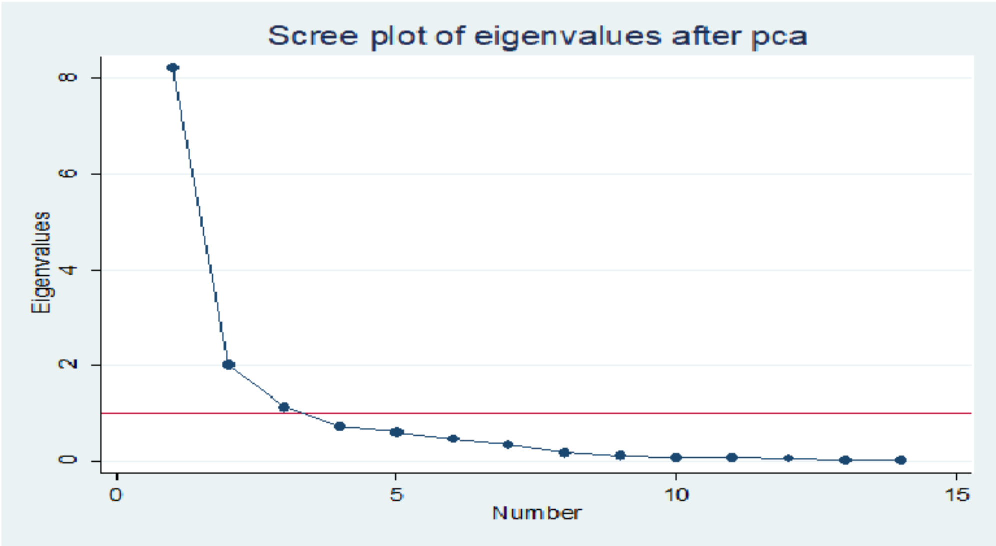


Figure 1.18: Scree Plot for Financial Markets Block

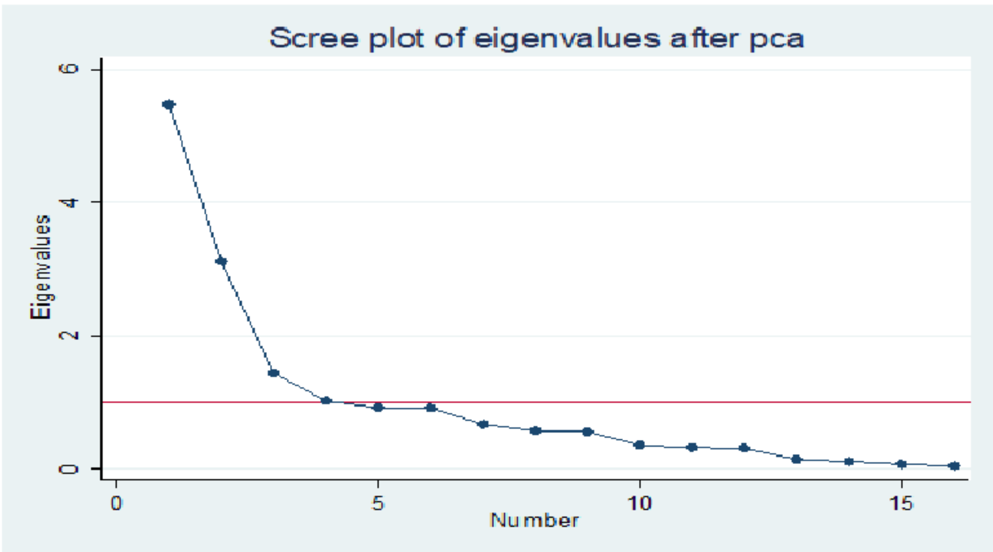
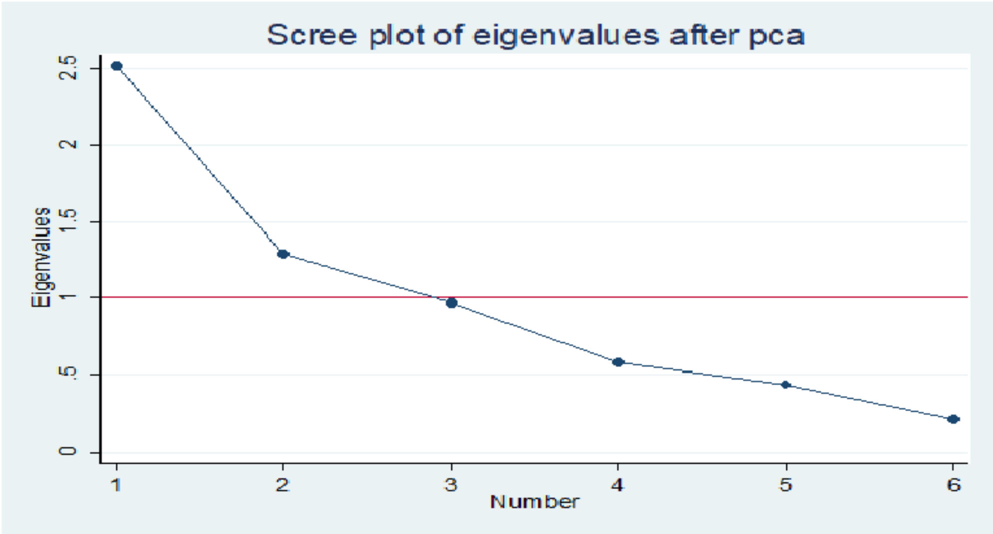


Figure 1.19: Scree Plot for Financial Markets Block



1.11.2 PCA Weights

Table 1.26: Scree Plot for Financial Institutions Block

Sub-Financial Institutions Index	**Weight in the PCA**
Capital and Profitability	0.724
Loan Losses and Interconnectedness	0.176
Default Risk	0.100

Table 1.27: Scree Plot for Financial Markets Block

Sub-Financial Market Index	**Weight in the PCA**
FX Market	0.474
Stock and Bond Market	0.299
Funding Cost	0.125
Credit Risk Indicators	0.102

Table 1.28: Scree Plot for Financial Markets Block

Sub-Financial Institutions Index	**Weight in the PCA**
Expectations and Production	0.661
Labor Market	0.339

1.11.3 Logit Model Assumption Checking

Table 1.29: Multicollinearity

Variables	VIF	1/VIF
Weighted TL Collapse	3.96	0.25
Implied FX Volatility	9.56	0.10
Realized FX Volatility	3.97	0.25
USD TRY 25 Delta Risk Reversal	4.19	0.24
USD TRY 3 Month Forward and Spot Rate Difference	9.61	0.10
Weighted Equity Collapse	3.87	0.26
Stock Index and Bond Return Correlation	1.11	0.90
Stock Index Realized Volatility	3.65	0.27
Price Equity Ratio	4.02	0.25
Interbank Repo Rate	1.98	0.51
Bank Bond Yield Difference	5.04	0.20
Volume of Benchmark Bond Traded	1.08	0.93
Public Debt Premium	2.16	0.46
Yield Curve Slope Difference	3.11	0.32
Realized Volatility of 2 Year Government Bond	2.16	0.46
CDS	3.32	0.30

Table 1.30: Specification Error

Logistic Regression					Number of Obs.	1941
Log Likelihood	-59.19				LR chi2(2)	1195.08
					Prob > chi2	0.00
					Pseudo R2	0.91
Crisis Status	**Coefficient**	**Std. Errors**	**z**	**P > IzI**	**%95 Conf. Interval**	
_hat	0.99	0.13	7.47	0.00	0.73	1.25
_hatsq	0.00	0.00	1.05	0.29	0.00	0.01
cons	0.03	0.24	0.13	0.90	-0.44	0.51

Chapter 2

Financial Stress and Effect on Real Economy: The Turkish Experience

2.1 Introduction

The Global Financial crisis earmarked a new era of banking supervision in recent times. It underlined the greater role of financial risk on real economy. The crisis started from the mortgage market of the United States and translated into a full blown financial market collapse by September 2008. With the collapse of Lehman Brothers, the stock market plummeted drastically and US economy slipped into an economic depression. Unemployment level reached a record level and US households suffered a drastic loss of their wealth as asset price crashed. In short, the Global Financial Crisis underlined the rippling effect of financial stress on real economic activities. Following the collapse of global financial market during the global financial crisis, macro-financial linkage became a major area of analysis and understanding the role of financial stress on real economic activities captured the headline of central bank research. Turkey's experience was no exception. In this chapter, we analyze the impact of financial stress on real economic activities through the lens of Turkish economy using threshold vector auto regression model and Markov Switching Model.

This chapter evaluates the role of financial stress on real economic activities and thereby contributes to broadly three strands of literature. The primary contribution of the chapter is focused on empirical evaluation of the relationship between financial stress and real economy. We used a noble financial institution stress index (following Yildirim (2021)) to quantify the historical stress levels in financial sector. The spillover analysis of financial stress are motivated by the financial friction literature. The chapter analyzes the economic impact of financial friction through real GDP, consumption, investment, and unemployment growth. The empirical framework uses threshold vector autoregression model (TVAR) highlighting the role of non-linearity in spillover of financial shock. Such non-linear trade-off emphasises the importance of non-linearity in financial friction mechanism. For that, the existence of threshold is established and threshold VAR model is used to model the impact of financial stress under low stress and high stress regimes. The VAR model uses quarterly data since 2002 onwards. The impact of financial stress is visualized using impulse response function under both regimes. However the robustness of threshold VAR models can be compromised due to lack of data availability. Hence we introduce linear projection estimation methodology for checking the robustness of the findings. The local projection estimation approach in TVAR model is relatively new. We use the local projection approach of Miranda Agrippino in the TVAR model. The threshold estimate is carried out using Markov Switching model on financial stress index following Hamilton (1989). Following the literature of financial friction, this chapter analyzes the impact of financial stress on real GDP, consumption, investment, and unemployment for Turkey. The chapter observes asymmetric effect of financial stress on overall growth and domestic demand. Financial stress is found to impart significant moderation of real GDP growth when the stress level is already high. The effect is found to be muted in lower stress regime. This observation follows the financial friction models. Further, the forecast error decomposition reveals that the forecast error of real GDP growth is contributed by the financial stress during high stress regime.

This chapter also compares the estimates with the other leading papers, which highlight the relation between financial stress and economic activity. By using regime switching model for US economy, David and Hakkio (2010) presented that the effect of positive one standard deviation of change in financial stress during the normal stress periods decreases the economic activity, which is measured via Chicago Fed National Activity Index, by 0.05 standard deviations from the average level of economic activity. However, the effect rises to 0.25 standard deviations during the high stress perods. Their results are consistent with the Bernanke, Gertler, and Gilchrest model, namely that the effect is larger and longer-lasting in the distressed regime. Our findings also stress the importance of financial friction mechanism which is proposed by the BGG model. Afonso et al. (2011) highlighted that the effect of positive one standard deviation of change in financial stress has different magnitude of impact for four developed economies which are USA, UK, Germany and Italy. The common feature of the findings for these economies is that the effect on output growth of increased financial stress is larger in the high stress regime than in the low stress regime. When we take the average of the impact on output growth during the high stress regime, it overlaps with our magnitude for Turkey. Hollo et. al. (2012) applied TVAR model for Eurozone countries by creating two stress regimes, namely, high and low stress regimes. They found that during the high stress regime, the maximum impact is reached after four months, when annual output growth has been reduced by about 2.7% in response to an initial shock in the financial stress index by positive one standard deviation. Some papers such as Elekdag and Kanli (2010), Cevik et al. (2012) utilized the standard VAR model to analyze the interaction between economic activity and financial stress. Elekdag and Kanli (2010) found that the industrial production index declines by 3 percent in response to positive one standard deviation in financial stress. Cevik et al. (2012) analyzed the dynamic relationships between Turkish Financial Stress Index and measures of economic activity are examined by means of unrestricted vector autoregression (VAR) models. Their measures of economic activity are the 12-month growth rate of the industrial production index (GIP), the 12-month growth rate of foreign trade (sum of merchandise exports and imports-GFT) and 12- month growth rate of gross fixed capital formation (with constant prices-GGI) in Turkey. They found that the effect of positive one standard deviation of change in financial stress declines the investment growth by 50 percent.

The bottom line of this discussion is that it is hard to compare our results with the literature for two reasons. First of all, all papers highlighted in this section use financial stress indices formed by different indicators and weighting methods. Secondly, the country sets analyzed are different. Depending on the variation in the financial, legal and social institutional framework , demographic structure, applied macro policies, each country's economy reflects different characteristic features.

The relation between financial sector stress and economic activities can be explained using three broad channels namely borrower financial conditions, banks' balance sheet position and liquidity channel. The importance of these channels are aptly described under financial friction theory. As the financial stress builds up, the cost of borrowing exerts bindings impact on real economic activities. The financial accelerator theory thereby combines the higher cost of borrowing with lesser investment and hurting growth potential. On the contrary, the economic activities are not impacted by financial sector stress when the level of stress is benign. Bernanke et al. (1998) (*hereafter referred as the BGG model*), Carlstrom and Fuerst (1997) proposed the workhorse model of financial friction where the firms with higher debt pays premium while borrowing for fresh investment under stress scenario. The borrowing constraint which creates the wedge between highly leveraged and low leveraged firms, binds only when the financial institutions face stress. Using asset value as collateral, Kiyotaki and Moore (1997) (*hereafter referred as the KM model*) explained the relationship between credit constraint and economic growth in financial friction. They highlighted the role of collateral in accessing credits. The collateral constraint is amplified during recession as value of collateral depreciates. The importance of bank lending channel was highlighted in financial accelerator model of Holmström and Tirole (1997). Stein (1998) and Van den Heuvel (2002) provided insight about the role of bank's financial condition in overall credit supply. Another aspect of bank lending channel may arise due to the monetary and macro prudential policy. Lowe and Borio (2004), Goodhart et al. (2004) showed the importance of bank's balance sheet impact due to such policies. Finally, Fisher (1933) described the transmission of bad asset sales and its impact on overall credit supply using liquidity channel. Other noted work on this topic are Diamond and Dybvig (1983) model where he highlighted bank run as a possible mechanism under liquidity channel, impairing the overall credit conditions. Diamond and Rajan (2005) magnified the interaction between bank's health and solvency problem. In this chapter, we consider all these three channels towards possible transmission mechanism of financial stress shock. However no conscious is made to disentangle the relative importance of these channels.

This chapter also contributes to the empirical literature on financial stress and real economic activities. Empirical evidences of financial shocks impacting real economic activities are also vastly available across literature. Sufi (2005) observed bank's line of credit as significant source of debt financing for the firms. Gan (2007) established the impact of real estate sector stress on the health of domestic banks in Japan. Almeida et al. (2009) analyzed the effect of financial contracting on the behaviour of firm investment during global crisis for the leveraged firms using COMPUSTAT data. Sufi (2009) observed significant moderation of credit line access when the firms' profitability are hit adversely. Ivashina and Scharfstein (2010) found increasing reliance on firm's line of credit at the time of global financial crisis. Paravisini et al. (2011) observed impact of financial crisis on working capital finance. Extending the analysis beyond investments, Benmelech et al. (2011) observed significant impact of liquidity shocks on employment decisions. Acharya et al. (2013) observed that firms facing exogenous liquidity shocks often move out of credit lines at the instance of downgrade.

The third strand of literature, in which this chapter fits, is the financial stress index and its importance in policy making. Drawing experience from the recent financial crisis, the central banks around world started developing financial stress index for assessing the financial market conditions. These financial stress indices were found to have feedback mechanism with real economic activities like real GDP growth (Hakkio and Keeton, 2009). The nexus between financial stress and monetary stability is found to be influencing growth prospects (Granville and Mallick, 2009; Sousa, 2010). Castro (2011) observed that financial stress modulates the domestic demand during different phases of business cycle. Highlighting the importance of credit condition, Jermann and Quadrini (2012) observed that the financial stress led to economic downturn due to constrained credit condition.

The remaining of the chapter is organized as follows - Section 2 briefly describes the relevant literature, section 3 documents the transmission mechanism and empirical framework. Section 4 focus on data description and stylized facts. The empirical findings are listed in Section 5, followed by concluding remarks in Section 6.

2.2 Literature Review

In this section, we briefly review the economic literature on this topic, focusing on studies that allow for linear and non-linear relationships between financial stress and the real economy. We can group these studies into two main headings. The first group of papers use descriptive statistics, such as correlation, mean to highlight the relation between financial stress and economic activity. For example, Illing and Liu (2006), who are among the main studies examining the relationship between financial stress and economic activity, statistically demonstrated that financial stress has devastating effects on economic activity if financial stress deviates by one or two standard errors from its historical average. Although the method used in the study provides the opportunity to compare the current financial stress level and its effects on economic activity with a historical perspective, it has some disadvantages. While standardizing the variables, it is accepted that the financial stress index has a normal distribution and the change in the sample mean and standard deviation with each stress period added to the sample causes the reclassification problem. Another criticism of the method is that the method ignores the specific characteristics and effects of stress events, in other words, assumes all stress events as the same.

As an alternative to this method, the second group of studies utilize the empirical models that examine the relationship between financial stress periods and economic activity. Claessens et al. (2008) examined the relationship between macroeconomics and financial variables during periods of financial stress and economic recession on 21 OECD countries. Their results indicated that economic contractions experienced after high financial stress periods are longer and deeper than those experienced after low stress periods. Hakkio and Keeton (2009) argued that there is a negative relationship between industrial production and financial stress for the US economy and concluded that the negative correlation between the two variables increased in the post-crisis period compared to the pre-crisis period. Davig and Hakkio (2010) examined the interaction between financial stress and the real economy depending on the stress regime in their studies and concluded that the contraction in the real economy is more severe in times of high stress. Elekdağ et al. (2010) examined the relationship between financial stress and economic activity from the perspective of developing countries and revealed the negative effects of financial stress on economic activity as a result of the VAR analysis they applied.

When we look at the studies done specific for Turkey, Çevik et al. (2013) comes into prominence. By using the financial stress index created for Turkey, they looked at the relationship between financial stress and economic activity through unrestricted VAR analysis and stated that economic activity displays statistically significant negative responses to financial stress shocks.

In addition to these empirical studies, the number of studies examining the relationship between financial stress and economic activity with nonlinear models has increased in recent years. The basic idea behind this approach is to model the interaction of financial system dynamics with the real economy in multiple equilibrium conditions, depending on the stress regime the economy is in. Hubrich and Tetlow (2012) analyzed the interaction of economic activity with the financial sector through the markov regime switching vector autoregression (MSVAR) model and revealed the sensitivity of economic activity to the change in the financial stress regime. Afonso et al. (2011) examined the relationship between financial stress and macroeconomics through threshold VAR (TVAR) model and concluded that there is a non-linear relationship between economic activity and financial stress and that economic contraction is relatively stronger in high stress periods. Hollo et al. (2012) also came up with different stress regimes for the Eurozone countries with the stress threshold calculated internally by the means of TVAR model.

2.3 Transmission Mechanism and Empirical Framework

The link between financial stress and real sector of economy can be examined by the macro-financial linkages. The relation between real and financial sector can be drawn from real business cycle models (RBC). As the macroeconomic condition deteriorates due to productivity shock, the household savings are affected adversely resulting in low savings and low investment. Further, as the economic downturn realizes, households and firms default, leading to Bank's asset-liability mismatch and the bank run. Hence the financial sector suffers as a result of macroeconomic downturn. Following RBC models, the linkage between financial sector and real sector is, therefore, one-directional. The implications of financial shocks on real sector is drawn from financial friction model. Following the friction literature, any financial shock can impact real economic activities through two major channels - (i) balance sheet effect of borrower and (ii) balance sheet effect of banks and other financial institutions. Apart from these two channels, the liquidity channel is another channel which creates a wedge between credit supply to different firms and households.

The financial friction literature came into prominence by the works of BGG and KM around 1997. These models established significant influence of firm's financing decision, contrary to the view proposed by Modigliani-Miller. The balance sheet effect of the firms and the banks were found to amplify the financial shocks as credit condition worsens. The borrower balance sheet effect is likely to hurt households and firms due to lender's inability to screen borrower's profile, their investment pattern and inability to enforce repayment of debt fully. The BGG model proposed costly state verification in the RBC model which resulted in borrower's paying higher risk premium at the time of borrowing. The risk premium which varies inversely with the networth of the borrower, provides incentive to the borrowers to undertake risky propositions. In this mechanism, the financial stress will result in devaluation of borrower's networth and thereby restricts credit supply. Another strand of models which deals with the financial linkages with real sector, is the Kiyotaki and Moore (1997) model *(hereafter referred as the KM model).* Unlike risk premium, the KM's model links the borrowing limit with the asset value as collateral. The lenders, in this model, can force the borrower to repay by enforcing a limit to borrowing and that limit is determined by the underlying value of the asset. In case of any adverse shock, the collateral loses value leading to strict borrowing constraint. As credit constraint binds, the borrowers faces lack of credit supply and investment goes down. The feedback mechanism between financial sector and real sector of the economy comes into play.

The bank balance sheet channel, on the other hand, focus on the importance of financial health of banks and financial institutions. There are two broad sub-components which can trigger bank balance sheet effect - (i) bank lending channel and (ii) bank capital channel. The traditional bank lending channel links the domino effect of any shock on the liability side and the asset side of the banks. Following Bernanke and Blinder (1988), the bank lending channel can invoke as contractionary monetary policy affect bank's balance sheet from asset and liability side. The bank balance sheet effect can also emerge in case of bank's capital loss. Holmström and Tirole (1997) showed the impact of bank capital on amplification of the effectiveness of bank lending channel as banks use their own capital to finance credit supply. Any credit crunch, therefore, leads to lack of credit supply and as credit supply moderates, the aggregate demand also moderates. Following Stein (1988), capital rich banks takes due diligence to underwrite the borrowers and monitor their loans. Hence the capitalized banks will be able to raise non-deposit funds at relatively lower cost.

Finally, the liquidity channel concentrates on the banks' liquidity condition in addressing credit demand. Following seminal work of Fisher (1933), the banks opt for fire sale of their assets in case of any solvency shocks. The fire sale reduces the asset price which further shrinks banks' assets leading the banks to more asset sales. The bank run model proposed by Diamond and Dybvig (1983), highlighted the impact of the liquidity channel at the event of bank run. On similar lines, Diamond and Rajan (2005) proposed the interaction of liquidity shortage and solvency in case the depositors start asking for deposits back from the banks. Following Brunnermeier and Pedersen (2009), The liquidity channel can be further segregated into funding liquidity and market liquidity components. The funding liquidity impacts the liability side of banks' balance sheet and it depends upon bank's ability to raise new funds by asset sales and net borrowing. The market liquidity component addresses the ease of trading any asset and thereby links the asset side of bank balance sheet.

We combine these three channels of transmission to assess the impact of financial stress using financial stress index, credit supply and real GDP/ consumption/ investment/ unemployment growth as endogenous variables. The other endogenous variable is domestic inflation which contains direct impact of financial stress on domestic price movements and indirect proxy of asset prices. The price impact of financial stress can be linked with asset price channel. Elevation in financial stress leads to asset price movements. Baker and Wurgler (2006) observed significant movement in stock prices due to investors' sentiment which are often linked to financial stress. Following long run risk (LRR) framework proposed by Bansal and Yaron (2004), He and Zong (2021) observed financial stress influencing asset prices by inducing consumption volatility and market volatility. While the causality between asset prices and financial stress can be bi-directional in nature, Hakkio and Keeton (2009) observed that financial stress impacts fundamentals of asset prices in statistically significant manner. As the asset price changes in response to the financial stress level, the size of balance sheet changes for the borrowers and lenders. The impact of high financial stress, thereby, is expected to translate into moderation of growth following financial friction mechanism. Further the asset price movements can become inflation in the presence of nominal rigidity. Following Assenza et al. (2010), the cost channel of monetary policy augments the Phillips Curve with asset price. In view of the above mechanisms, we postulate a four variable vector auto-regression model with financial stress, credit supply, domestic inflation and real economic activity to assess the impact of financial stress.

2.3.1 Threshold VAR Model

Following the financial friction literature, the financial frictions amplifies the economic downturn when the borrowing constraint binds. Higher financial stress is expected to amplify the asset price movements and thereby may result into balance sheet impact. However the same mechanism may not be true for regimes with low financial stress. In particular, low financial stress may not evoke the adverse asset price movements and thereby the financial friction mechanism is likely to be absent. With this background, we rule out the linearity assumption for assessing the impact of financial stress and introduce non-linearity in VAR model. The simplistic VAR model with non-linear trade-off can be achieved using threshold VAR model. The threshold VAR model inhibits multiple different VAR models depending upon the regimes. In a two regime model, the regimes are defined in terms of a threshold variable. When the threshold variable crosses a particular threshold, then the data generating process moves into high regime and VAR model from high regime is used to explain the endogenous interactions among variables. The threshold variable can be endogenous or exogenous in nature. In this chapter, we propose to use the level of financial institution stress to determine the regimes. This assumption helps to make intuitive interpretation about the regimes.

Further to the threshold variable, the subjectivity lies with the choice of optimal number of regimes. We follow the extension proposed by Lo and Zivot based on Hansen (1996) approach to determine the optimal number of regimes from the data. We test for linearity vs 2 regimes and linearity vs 3 regimes with optimal lag length of 1 quarter [1]. The optimal number of regimes is found to be 2 from our data. Following the choice of number of regimes, the threshold VAR model for consumption, investment, real GDP, and unemployment growth can be written in following way where Δ stands for quarter-on-quarter growth.

[1] We consider lag length of 1 following quarterly frequency of our data and to accommodate higher number of regimes

$$
\begin{bmatrix} \Delta FISI_t \\ \Delta Credit_t \\ \pi_t \\ \Delta C_t \end{bmatrix} = \begin{cases} \phi_0^L + \Phi_1^L \begin{bmatrix} \Delta FISI_{t-1} \\ \Delta Credit_{t-1} \\ \pi_{t-1} \\ \Delta C_{t-1} \end{bmatrix} + \epsilon_t^L & \text{if } FISI_{t-1} < F\bar{I}SI \\ \phi_0^H + \Phi_1^H \begin{bmatrix} \Delta FISI_{t-1} \\ \Delta Credit_{t-1} \\ \pi_{t-1} \\ \Delta C_{t-1} \end{bmatrix} + \epsilon_t^H & \text{if } FISI_{t-1} \geq F\bar{I}SI \end{cases}
$$

$$
\begin{bmatrix} \Delta FISI_t \\ \Delta Credit_t \\ \pi_t \\ \Delta Y_t \end{bmatrix} = \begin{cases} \phi_0^L + \Phi_1^L \begin{bmatrix} \Delta FISI_{t-1} \\ \Delta Credit_{t-1} \\ \pi_{t-1} \\ \Delta Y_{t-1} \end{bmatrix} + \epsilon_t^L & \text{if } FISI_{t-1} < F\bar{I}SI \\ \phi_0^H + \Phi_1^H \begin{bmatrix} \Delta FISI_{t-1} \\ \Delta Credit_{t-1} \\ \pi_{t-1} \\ \Delta Y_{t-1} \end{bmatrix} + \epsilon_t^H & \text{if } FISI_{t-1} \geq F\bar{I}SI \end{cases}
$$

$$
\begin{bmatrix} \Delta FISI_t \\ \Delta Credit_t \\ \pi_t \\ \Delta I_t \end{bmatrix} = \begin{cases} \phi_0^L + \Phi_1^L \begin{bmatrix} \Delta FISI_{t-1} \\ \Delta Credit_{t-1} \\ \pi_{t-1} \\ \Delta I_{t-1} \end{bmatrix} + \epsilon_t^L & \text{if } FISI_{t-1} < F\bar{I}SI \\ \phi_0^H + \Phi_1^H \begin{bmatrix} \Delta FISI_{t-1} \\ \Delta Credit_{t-1} \\ \pi_{t-1} \\ \Delta I_{t-1} \end{bmatrix} + \epsilon_t^H & \text{if } FISI_{t-1} \geq F\bar{I}SI \end{cases}
$$

$$
\begin{bmatrix} \Delta FISI_t \\ \Delta Credit_t \\ \pi_t \\ \Delta U_t \end{bmatrix} = \begin{cases} \phi_0^L + \Phi_1^L \begin{bmatrix} \Delta FISI_{t-1} \\ \Delta Credit_{t-1} \\ \pi_{t-1} \\ \Delta U_{t-1} \end{bmatrix} + \epsilon_t^L & \text{if } FISI_{t-1} < F\bar{I}SI \\ \phi_0^H + \Phi_1^H \begin{bmatrix} \Delta FISI_{t-1} \\ \Delta Credit_{t-1} \\ \pi_{t-1} \\ \Delta U_{t-1} \end{bmatrix} + \epsilon_t^H & \text{if } FISI_{t-1} \geq F\bar{I}SI \end{cases}
$$

where $FISI_t$ is the financial stress index from Yildirim (2021); $Credit_t$

represents total credit supply to commercial sector; π_t is the domestic inflation proxy by GDP deflator; C_t is the consumption at time t, I_t is the real investment at time t, Y_t is the real GDP at time t, and U_t is the unemployment at time t. The threshold VAR model is estimated using conditional least square approach.

As indicated previously, the impact of financial stress is examined using impulse response function. Impulse response analysis in VAR models calculates the expected values of the variables defined in the system in the face of an external shock. In order to describe the effect of shocks, the system must be defined as a vector moving average (VMA) model which is presented as follows:

$$Y_t = \mu + \varepsilon_t + \sum_{i=1}^{\infty} \Psi_i(L)\epsilon_{t-i}$$

However, under the regime change, the VMA model cannot be modeled linearly in terms of shocks. Therefore, impulse response analysis should be calculated with the magnitude and direction (whether they are positive or negative) of the shocks as well as the initial period information set. The impulse response function for the non-linear model is conditional on the entire past history of the variables and the size and direction of the shock. To that end, we decide to use the method developed by Balke (2000) that calculates nonlinear generalized impulse-response functions under alternative regimes using bootstrap simulations. The algebraic form of this method is as follows:

$$IRF_k = E\left[Y_{t+k} \mid \Omega_{t-1}, e_t\right] - E\left[Y_{t+k} \mid \Omega_{t-1}\right]$$

Here, Y_{t+k} is the vector of endogenous variables in the period k and Ω_{t-1} is the information set before the period when the t shock is applied. The formula indicates that the impulse response function depends on the initial conditions and there is no limit on the symmetry of shocks.

2.3.2 TVAR with Local Projection

One of the major disadvantages of threshold VAR model is that the model parameters increase exponentially as regimes increase. Hence it requires longer history of variables to obtain robust estimate of the parameters. In view of the lack of quarterly data for our analysis, we use local projection approach to estimate the threshold VAR model at different horizons. The local projection estimation of threshold VAR model is done using ordinary least squares for each horizon. An example of TVAR with local projection for consumption is presented in Eq. 2.1.

$$\begin{aligned}\begin{bmatrix}\Delta FISI_{t+k}\\ \Delta Credit_{t+k}\\ \pi_{t+k}\\ \Delta C_{t+k}\end{bmatrix} &= \phi_0^L \mathbf{1}_{FISI<\bar{FISI}} + \phi_1^L \begin{bmatrix}\Delta FISI_{t-1}\\ \Delta Credit_{t-1}\\ \pi_{t-1}\\ \Delta C_{t-1}\end{bmatrix} \mathbf{1}_{FISI<\bar{FISI}} \\ &+ \phi_0^H \mathbf{1}_{FISI\geq\bar{FISI}} + \phi_1^H \begin{bmatrix}\Delta FISI_{t-1}\\ \Delta Credit_{t-1}\\ \pi_{t-1}\\ \Delta C_{t-1}\end{bmatrix} \mathbf{1}_{FISI\geq\bar{FISI}} + \epsilon_t \;\forall k = 0,1,2,....H\end{aligned} \tag{2.1}$$

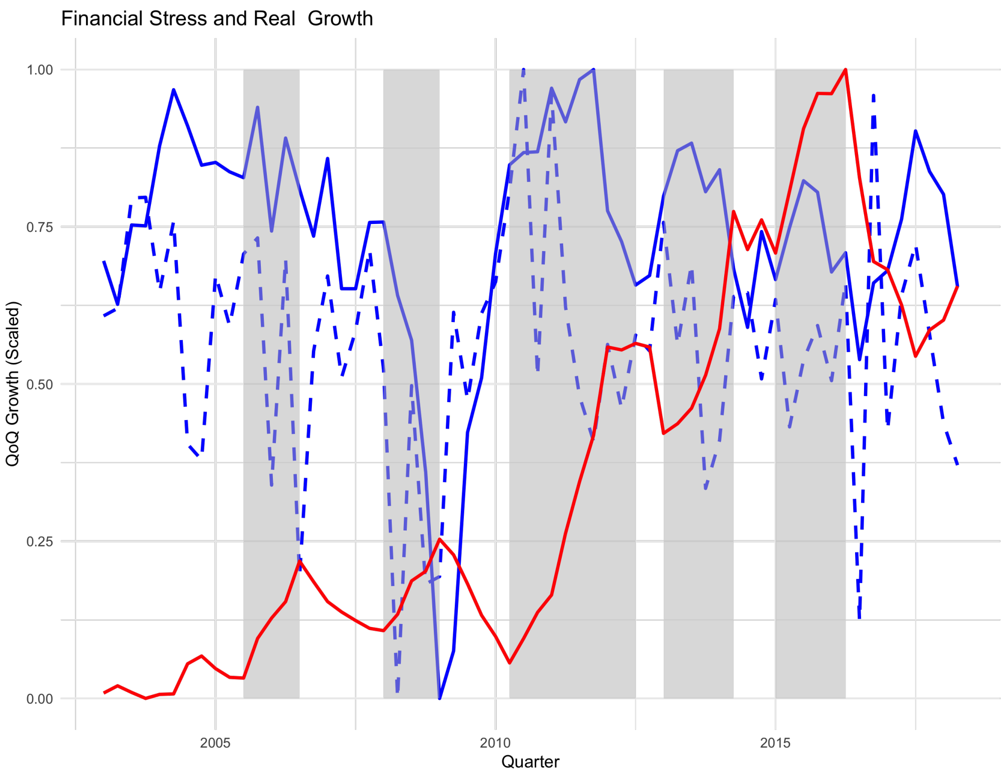
Eq. 2.1 is estimated for every horizon k (k=0,1,,,,H). In view of the quarterly frequency of our data, we restrict H to 8 quarters.

2.4 Data and Stylized Facts

We take consumption, real GDP, investment, and unemployment as a measure of economic activity. We obtained the data from Turkish Statistical Institute (TUIK) for the period of 2002:12–2018:03 in quarterly frequency. To measure the financial stress, we use the stress index which we develop by using the Portfolio Theory. The main characteristic of this method that it takes into account the systemic component of stress. The index has a structure that gives more weight to the financial stress that occurs in several sub-markets at the same time as a result of taking time dependent cross-correlations between sub-indices into account when aggregating sub-indices. We also use the credit growth and domestic inflation rate to provide a plausible linkage between the financial stress and economic activity.

The effect of financial stress is visualized on the consumption growth and real GDP growth. Due to possible non-linearity in the trade-off between financial stress and real economy, we analyze the growth pattern different phases of financial stress. The turn around points of financial stress is identified using Harding-Pagan approach for quarterly data. The growth patterns are then analyzed for the phases when financial stress moved from peak to trough and trough to peak. The shaded regions in Figure 2.1 represents the trough to peak transition of financial stress i.e. these episodes signify the period when financial stress moved from low stress to high stress regimes. While the movement in financial stress is represented by the red line, the change in real GDP and consumption growth is characterized by solid and dashed blue lines, respectively. As the stress moved from low to higher level, both real GDP growth and consumption growth moderated visibly. This supports our hypothesis of possible non-linearity in the trade-off between financial stress and economic activities. In the next section, we try to establish the differential impact of financial stress on real GDP and consumption growth using econometric models.

Figure 2.1: Real GDP and Consumption growth during financial stress cycle [2]



2.5 Findings

We use the threshold VAR model on the quarterly data to assess the impact of financial stress on real economy using quarterly data since 2003. For that, the optimal number of thresholds is determined using Hansen test. The threshold variable is considered as level of financial stress with delay of 1 quarter.

[2]The red line represents financial stress level and blue line is consumption growth and real GDP growth. The shaded area denotes turn around point of financial stress.

We built three different models for financial stress impact on real GDP growth, consumption growth, and investment growth. For that, we compare the linear model vs two thresholds and three thresholds for VAR models with lag of 1 and 2 quarters. We restrict our model selection with minimum lag length and minimum number of regimes to ensure robustness in the estimates [3]. Following Table 2.1, we confine our model with 2 regimes and 1 quarter lag value.

Table 2.1: Threshold determination using LR test

	linear vs 2 regimes	**Linear vs 3 regimes**
	Lag length of 1 quarter	
Test Statistic	71.24*	4215.77***
p-value	(0.08)	(0.00)
	Lag length of 2 quarter	
Test Statistic	108.28***	4178.01***
p-value	(0.00)	(0.00)

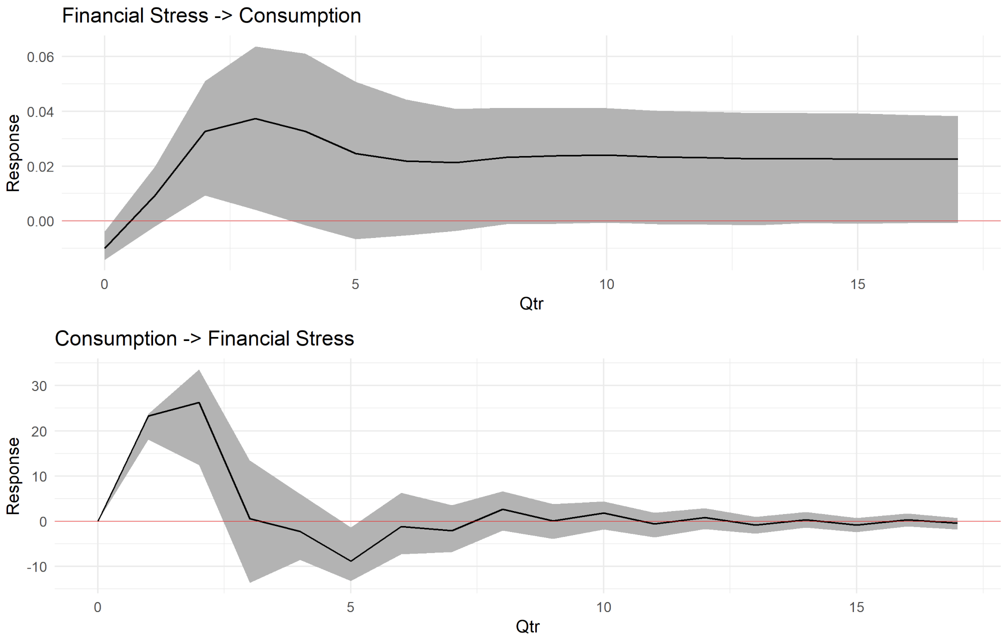
With the model selection, the parameters of endogenous variables were estimated for the two regimes (*We call these two regimes as high and low regime*). The threshold value of financial stress level was found to be 0.03 [4]. We start with the consumption and investment impact first since the friction channel of financial stress impacts the real economy through consumption and investment growth. Towards the end of the findings, we also focus on the overall impact of financial stress on real GDP growth and unemployment.

[3]The parameter space explodes as number of lags and number of regimes increase in a threshold VAR model, resulting in loss of degrees of freedom

[4]The threshold of financial stress index corresponds to scaled value of financial stress index. The scaling of financial stress index is done using Z-score of FISI index value over time

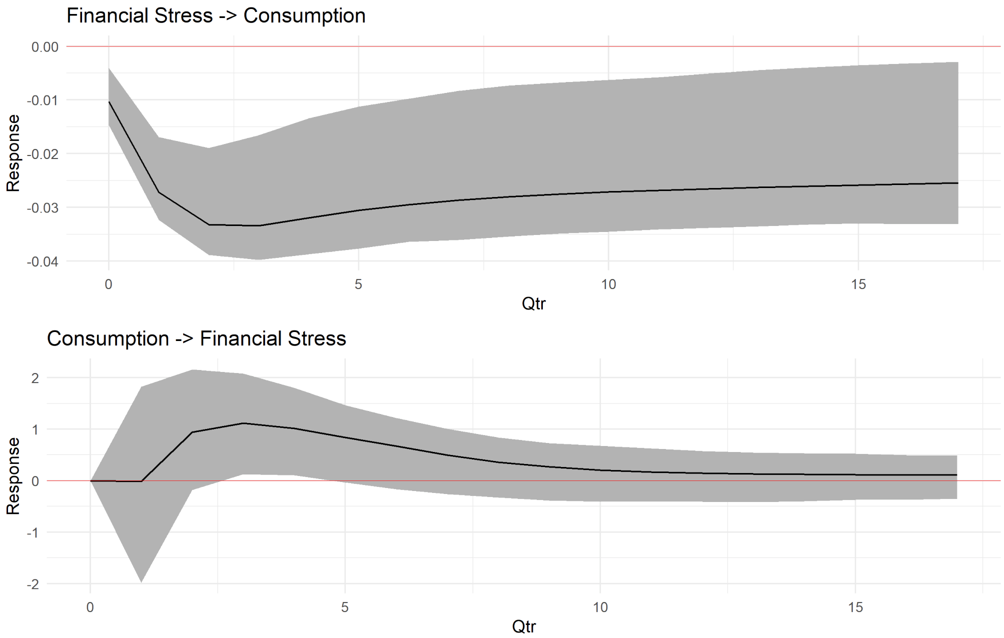
To understand the impact of the financial stress, we analyze the impulse responses by giving one standard deviation shock on the change of financial stress and consumption growth in high stress and low stress regimes. The first set of responses, drawn on consumption growth and financial stress growth, reveals the dynamics between economic growth and stress in low stress regimes. Figure 2.2 illustrates the response of consumption growth and financial stress on each other in a low stress regime. This response functions provide us insight about the possible feedback mechanism happening between financial stress and consumption growth. When the overall stress level is low, the consumption growth appears to increase as financial stress increases and the effect is found to be statistically significant at 95% confidence. The response of consumption growth to one standard deviation shock in the change of financial stress reaches its maximum level, which is 4 percent, and it lasts for about 5 quarters during the low stress period. On the other hand, increase in consumption growth appears to be elevating the stress level. The effect of financial stress shock influences consumption growth for at least 5 quarters whereas the effect of consumption growth is much short lived. This phenomenon follows a typical business cycle model where higher financial stress does not impede real economic activities as the overall stress level remains low. The financial friction mechanism remains absent in this process as the borrowing constraint does not bind.

Figure 2.2: Impulse response from TVAR for lower regime



Contrary to low stress regime, the impact of financial stress on higher regime imparts contractionary effect on consumption growth and the effect stays for longer period of time. The response of consumption growth to one standard deviation shock in the change of financial stress hits its maximum level, which is 3 percent, and it lasts for at least 10 quarters during the high stress period. When the consumption shock is applied during high stress regime, the financial stress elevates further and the effect is statistically significant after 3 quarters of lag (refer to Figure 2.3). The contraction in consumption due to high financial stress is justified through the lens of financial friction models when the stress level is already high. Higher financial stress indices the financial institutions to provide strict borrowing constraint. As the borrowing constraint binds, the financial friction kicks in, moderating the consumption growth.

Figure 2.3: Impulse response from TVAR for upper regime



Next, we move to the forecast error variance decomposition in the high stress and low stress regime for consumption growth and financial stress. The forecast error of consumption growth is contributed by the financial stress significant extent over different forecast horizons when the stress level is already high. In fact, the contribution of financial stress outpaces the contribution of credit growth and domestic inflation, implying the dominant effect of binding constraint during the high stress regime (refer to Figure 3.5) [5]. On the contrary, the dominance of financial stress on consumption growth is lost when the financial stress level is relatively lower. Credit supply appears to be the dominant factor contributing to higher stress level during low stress regime. Shifting to forecast error variance of financial stress, the effect of consumption growth is noticeable when the stress level is higher. Similar phenomenon is absent when

[5] Here we focus on the contribution of the endogenous variables excluding self impact of consumption lags

the stress is lower. This findings corroborates with the credit channel effect of financial friction models (refer to Figure 2.5). The lingering effect of financial stress on consumption growth implies that binding nature of the borrowing constraint remains effective as higher stress forces financial institutions to maintain strict borrowing constraint.

Figure 2.4: Forecast Error Variance Decomposition of Consumption Growth

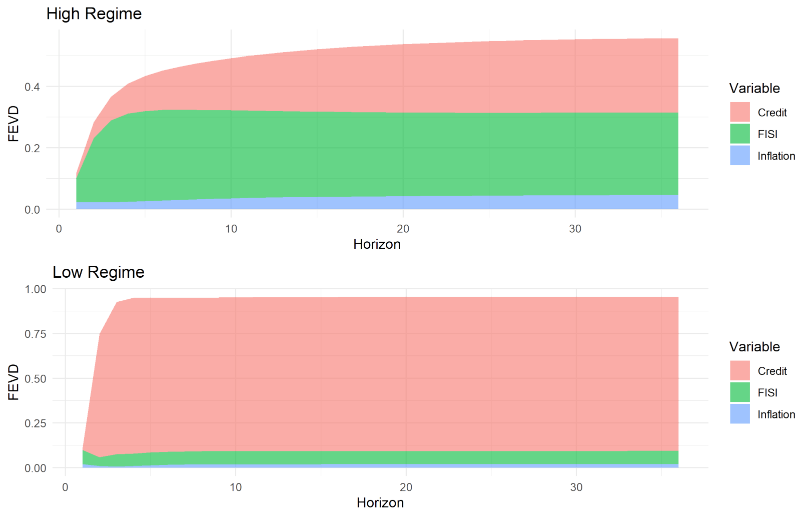
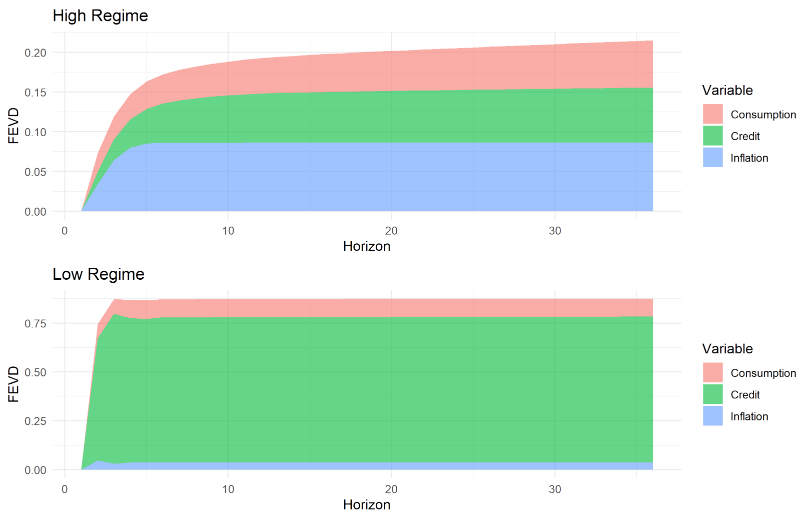


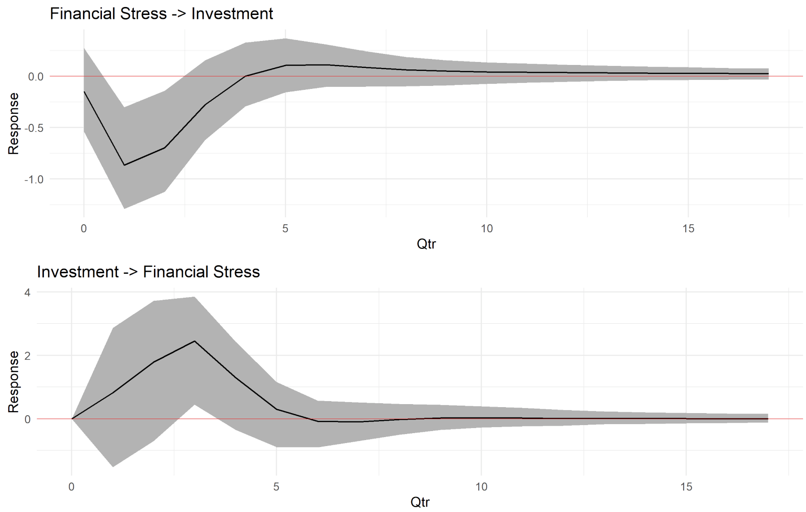
Figure 2.5: Forecast Error Variance Decomposition of Financial Stress



We conduct similar analysis on investment growth also. The model selection criteria remains same as before. The impact of financial stress is analyzed using impulse response function analysis and forecast error variance decomposition. As indicated previously, the impulse response plots (refer to Figure 2.6 for lower regime and Figure 2.7 for higher regime) represent the response of investment growth and change in financial stress in response to one standard deviation shock on financial stress and investment growth respectively. The impact of financial stress hurts investment growth adversely when the financial stress level is already high. During the high stress regime, the effect of one standard deviation shock in the change of the financial stress on the investment growth reaches its maximum value, almost 100 percent, with a lag of 3 quarter. On the other hand, the impact of higher investment growth increases financial stress further but with a lag of 3-4 quarters during high stress regime.

Figure 2.6: Impulse response from TVAR for lower regime

Figure 2.7: Impulse response from TVAR for upper regime



The forecast error variance decomposition of investment growth displays similar pattern like consumption growth. The contribution of financial stress is found to be significantly higher in high stress regime. On the other hand, domestic inflation dominates the forecast error of investment growth during lower stress regime (refer to Figure 2.8). Similar pattern is also observed in financial stress index (refer to Figure 2.9).

Figure 2.8: Forecast Error Variance Decomposition of Investment Growth

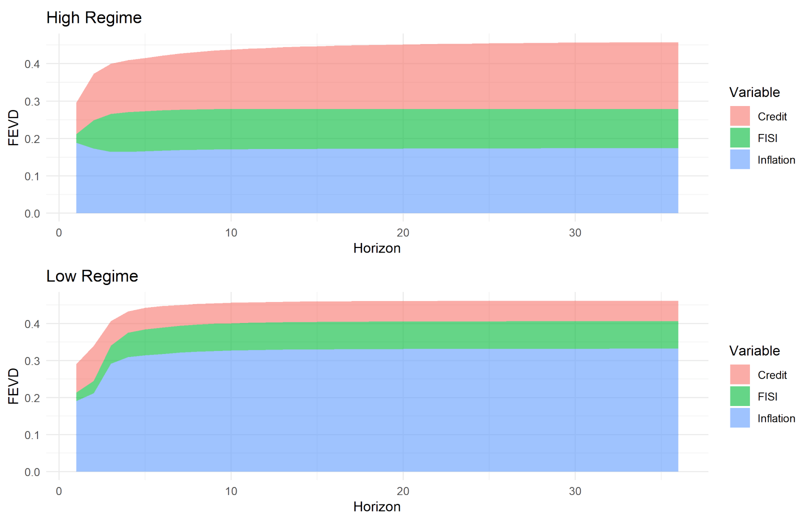
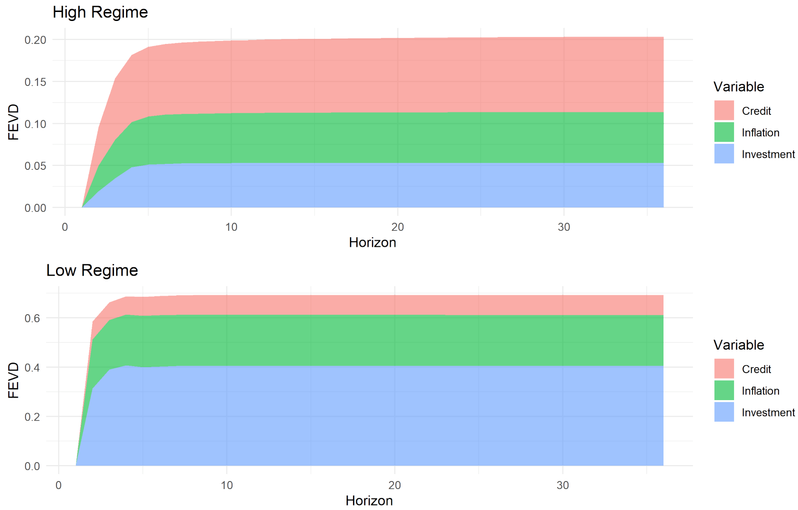


Figure 2.9: Forecast Error Variance Decomposition of Financial Stress



Then, we analyze the effect of financial stress on real GDP growth. The VAR structure remains same as before, we only replace the consumption growth by real GDP growth. The threshold level is determined and the impulse responses are derived for low and high financial stress regimes (refer to Figure 2.10 for low regime and Figure 2.11 for high stress regime). Real GDP growth is found to be impacted positively in response of increase in financial stress level during low financial stress regime. As seen in the upper part of figure 10, during the low stress regime, the impact reaches the top value immediately, when real GDP growth elevates about 15 percent in response to one standard deviation shock in the change of the financial stress. The opposite happens during the high stress regime when the real GDP growth contracts in response to higher financial stress. During the high stress regime, the effect of one standard deviation shock in the change of the financial stress on the real GDP growth reaches its maximum value, which is 15 percent, with a lag of 3 quarters. The explanation of real GDP growth response highlights the importance of financial friction during the high stress regime. The effect of real GDP growth increases financial stress in low and high risk regimes.

Figure 2.10: Impulse response from TVAR for lower regime

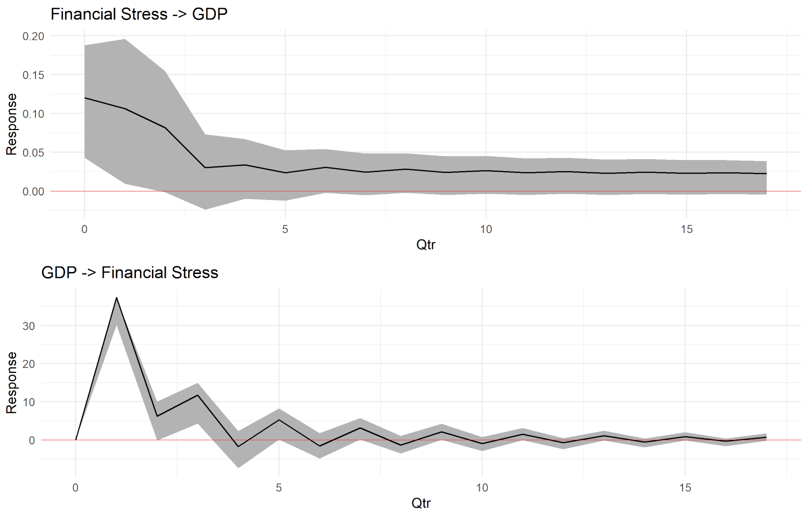
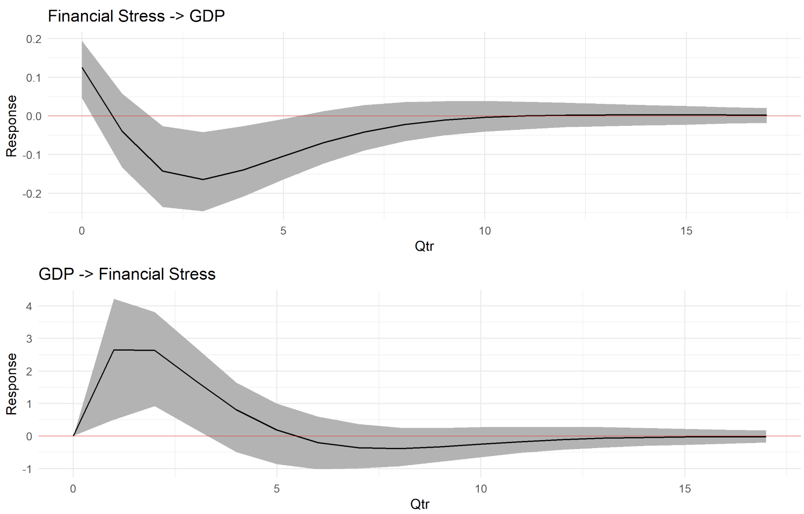


Figure 2.11: Impulse response from TVAR for upper regime



The forecast error decomposition of real GDP growth underlines the impact of financial stress on real growth of economy but the effect is more dominant during higher stress regime. Following the impact of financial stress on investment growth, the pattern appears to be self-explanatory. However unlike other components of real GDP, the contribution of domestic inflation also remains dominant on real GDP growth during higher stress regime (refer to Figure 2.12). On the other hand, forecast error of financial stress is contributed by real GDP growth, credit supply and domestic inflation over longer horizon when the stress is already at elevated level. On the other hand, real GDP growth dominates the movement of financial stress during low stress regime (refer to Figure 2.13).

Figure 2.12: Forecast Error Variance Decomposition of real GDP Growth

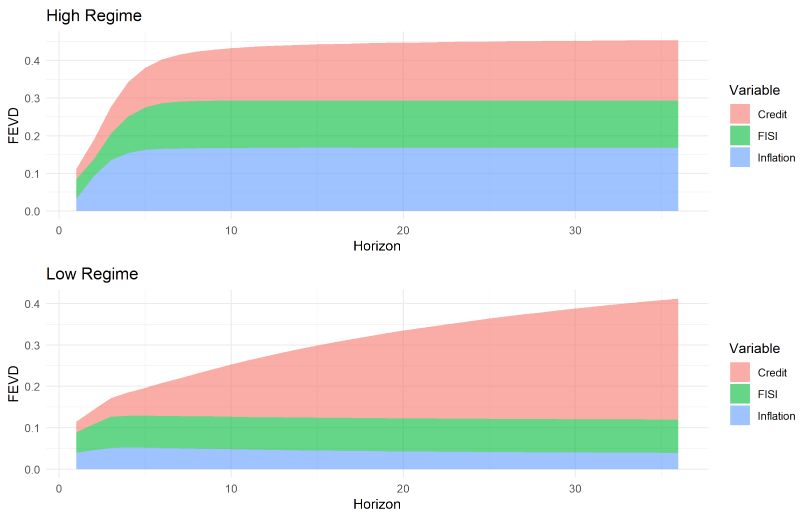
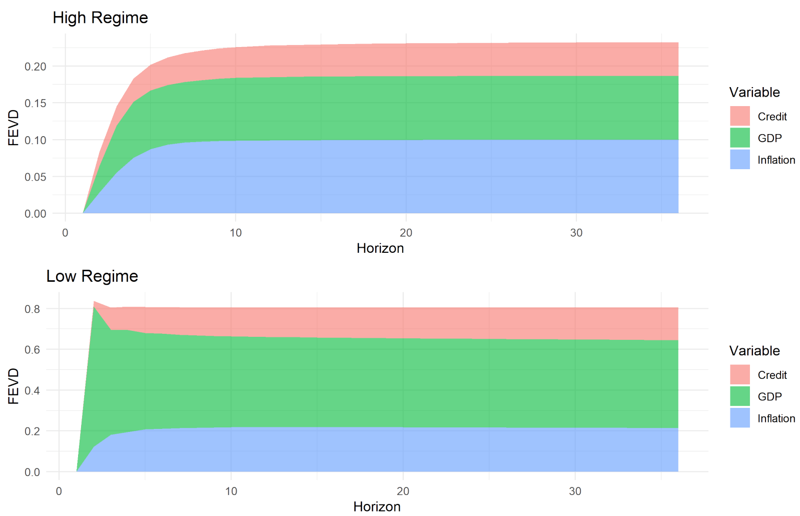


Figure 2.13: Forecast Error Variance Decomposition of Financial Stress



Lastly, we analyse the impact of financial stress on unemployment rate.

Unlike real GDP growth or its components, the effect of financial stress on unemployment rate remains less prominent. Following similar specifications of threshold VAR model, increase in financial stress moderates unemployment rate initially but thereafter increases over longer horizon when the stress level remains elevated. On the other hand, increase in financial stress soothes the unemployment rate initially when the financial stress level is lower. The effect of higher unemployment creates additional financial stress in both regimes (refer to Figure 2.14 for lower regime and Figure 2.15 for high risk regime).

Figure 2.14: Impulse response from TVAR for lower regime

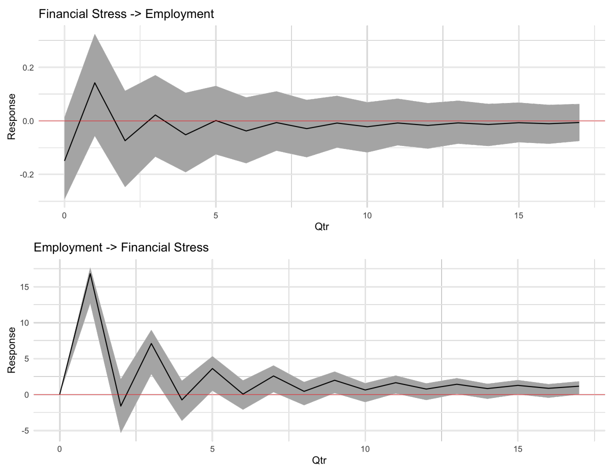
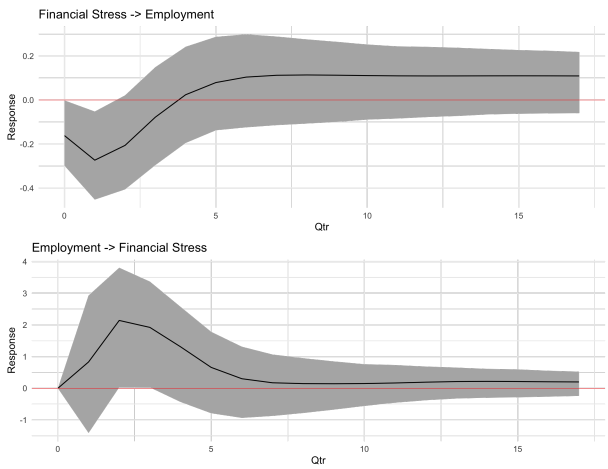
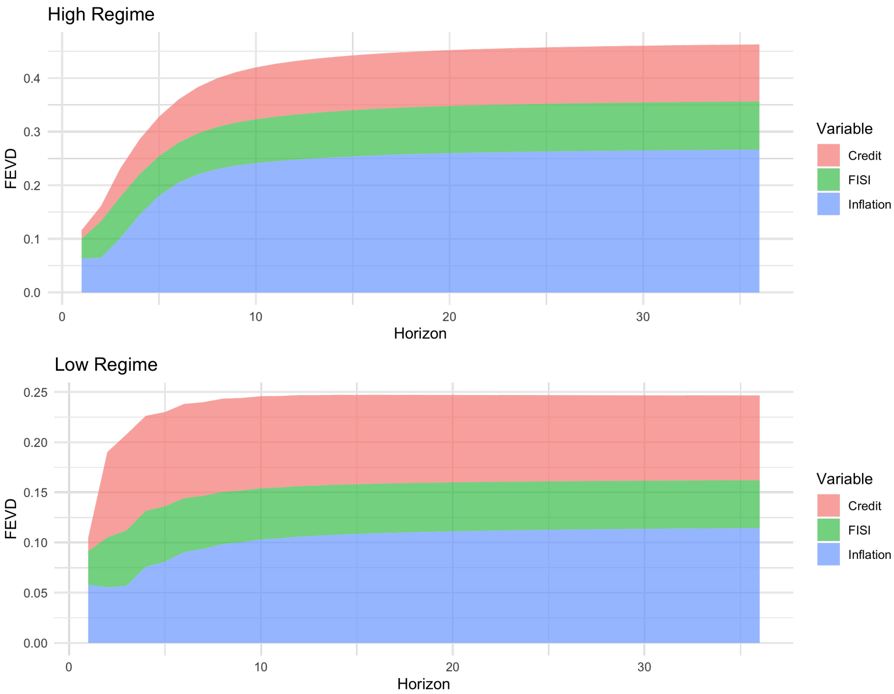


Figure 2.15: Impulse response from TVAR for upper regime



The forecast error variance decomposition of unemployment rate indicates range bound contribution of financial stress in both regimes which implies persistent direct effect from financial stress. On the other hand, the indirect effect resulting from domestic inflation contributes significantly in the unemployment rate over longer forecast horizon (Figure 2.16).

Figure 2.16: Forecast Error Variance Decomposition of Unemployment Growth



2.6 Robustness

In this section, we present the findings of threshold VAR estimates using local projection method. We estimate threshold level using Markov Switching model on financial stress and apply local projection method on threshold estimates. The estimation code of threshold VAR using the local projection (LP) method broadly follows Stock and Watson (2018) as well as Miranda and Agrippino (2021) using the threshold value from the Markov switching model. The basic idea behind local projections, as proposed by Jordà (2005), is to estimate the impulse responses separately at each horizon by a direct regression of the future outcome on current covariates opposite to the standard VAR models which estimates the impulse responses with respect to the a recursive orthogonalization of the reduced-form forecast errors. The benefit of using LP method is that it does not assume any structural assumption among the endogenous variables. However one of the major disadvantages of LP approach is that different parameter estimates for different horizons are based on the different number of data points. The impulse responses are derived from LP estimates for values above and below threshold. Here we present the parametric impulse responses for both regime in the case of consumption and real GDP [6].

The impulse response of LP estimates corroborates with the classical estimation. These impulse responses corresponds to 1 unit of positive shock on financial stress (compared to 1 standard deviation shock in previous analysis). Following Figure 2.17 for consumption effect, we observe that the consumption growth increases as financial stress remains low. The effect is contractionary in high stress regimes. Further the effect of financial stress appears to drag consumption growth till 4 quarters in higher stress regime. Similarly, the effect of financial stress on real growth is found to be negative in high stress regime as seen in the threshold VAR model. The effect of one standard deviation shock in the change of financial stress on the real GDP growth reaches its maximum value, which is 3 percent, with a lag of 4 quarters.

[6] We applied the non-parametric approach for estimating the impulse response function using wild bootstrap of residuals and the results are found to be in similar lines

Figure 2.17: Impulse response from TVAR for consumption

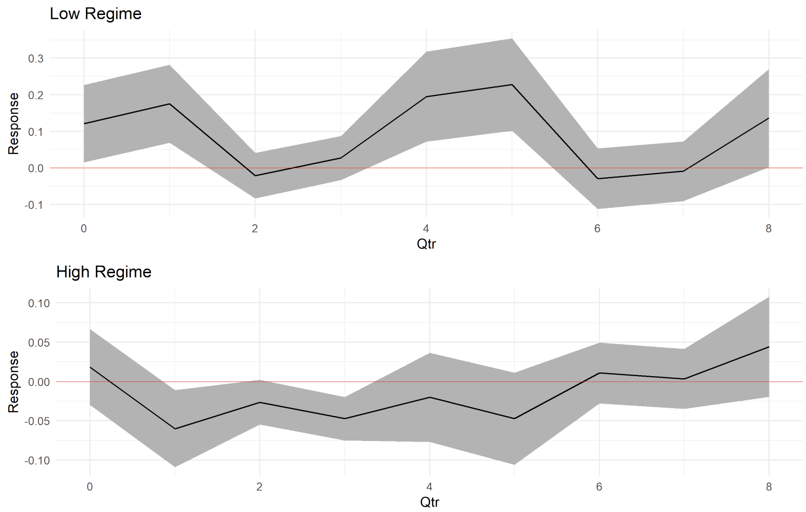
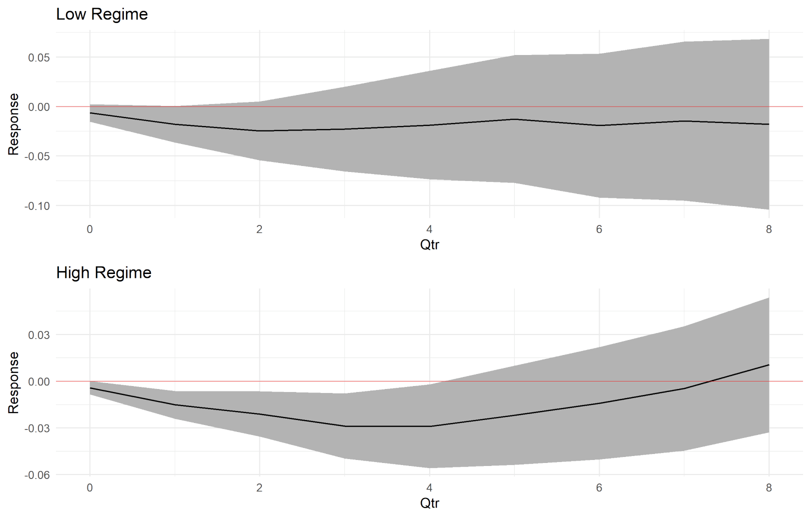


Figure 2.18: Impulse response from TVAR for real GDP



2.7 Concluding Remarks

The financial crisis, which emerged in the economies of developed countries in 2008 and spread to developing countries, once again proved the depth of the relationship between the financial sector and real economy. We investigate the nonlinear impact of financial stress on economic activity by looking at consumption, investment, real GDP, and unemployment responses to the financial stress shocks.

To that end, we start with the assumption that the effects of exogenous shocks on economic activity in upper stress periods may be reverse and significant relative to the lower stress periods. For this purpose, we utilize TVAR estimation which was developed to examine nonlinear relationships, including regime changes, multiple equilibria, and asymmetric responses to shocks.

In the first stage of the TVAR estimation, we test whether there is a threshold effect in the relationship between financial stress and economic activity. After finding the presence of the threshold effect, the TVAR method calculates the threshold stress value internally. Then, we present the nonlinear impulse-response functions of consumption, real GDP, investment, and unemployment depending on whether the economy is in a lower or upper stress period. We find that the financial stress affects the real GDP adversely during the upper and lower stress regime. The impact is more substantial and prolonged in the upper stress regime.

According to the main findings of this study, stress arising in financial markets can have a nonlinear impact on economic activity. This asymmetric reaction between economic activity and financial stress might highlight that when the overall stress level is high, the proper functioning of the financial system could be impaired. Then, the economy faces the risk of entering a vicious downward cycle with financial stress and economic activity reinforcing each other. Our results also support the RBC model propositions stating that financial variables have no impact on real activity in the case of no financial frictions. In this respect, we conclude that it would be more accurate to examine the effect of financial stress on economic activity depending on the stress regime.

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Chapter 3

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

3.1 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 chapter 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 chapter, further, looks at the signals of individual EWIs and the time profile of the signal strength. Lastly, the chapter combines the EWIs using linear combinations to validate the improvement of signaling due to combinations.

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. EWIs should provide signals at the right time, meaning that they should not be too early or late. 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(2014), we adopt three criteria for optimal EWIs of banking crises, including timing, stability, and interpretability.

The main contribution of this chapter 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 chapter 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 chapter observes that linear combination of these EWIs strengthens signal strength even further.

The rest of the chapter 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 chapter concludes by highlighting key findings in Section 6.

3.2 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.

3.3 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.

3.3.1 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).

3.3.2 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 chapter'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 3.1: 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 chapter. 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 3.2: 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

3.4 Methodology

3.4.1 Standalone Indicators

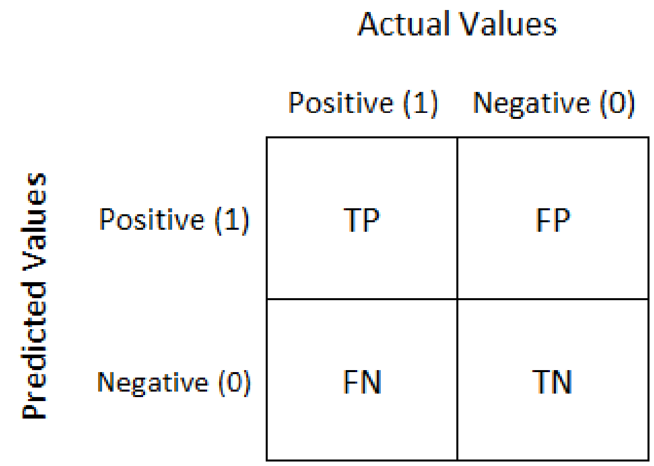
In this section, we discuss the receiver operating curve in general and how we may use it to compare the performance of the indicators in their standalone versions.

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, research 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 ROC curves, it is necessary to know what the following expressions mean.

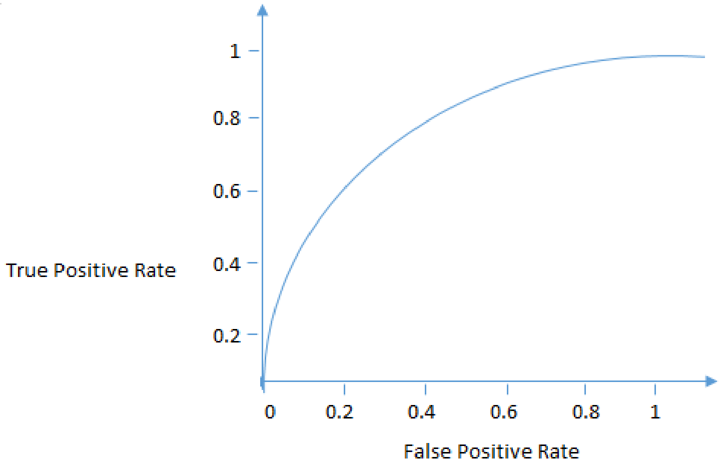
- Confusion Matrix is to show the current situation in the data set and the number of correct and incorrect predictions of our classification model. It is presented in Figure 3.1.
- True Positive (TP) : The model correctly predicted the positive class as a positive class.
- False Positive (FP) : The 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 3.1: Confusion Matrix



ROC curves display all possible cut-off 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 3.2. 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 via ROC analysis regarding its diagnostic success.

Figure 3.2: 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.

True Positive Rate = Sensitiviy = True Positives/(True Positives+ False Negatives)

False Positive Rate = 1 -Specificity = False Positives/(False Positives+True Negatives)

When establishing the cut-off 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;

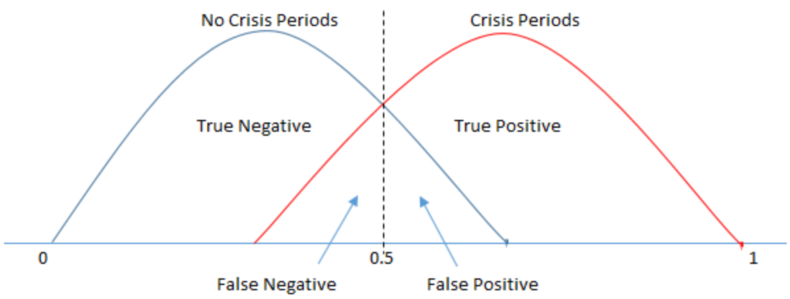
- There will be a record of all of the crisis moments.
- Some of the no crisis periods will be diagnosed as crisis (false positive).
- The sensitivity of the screening test will improve, resulting in a higher true positive rate.
- On the other side, the screening test's sensitivity will fall, increasing 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 3.3, 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 3.3: Intuition Behind the ROC Curve



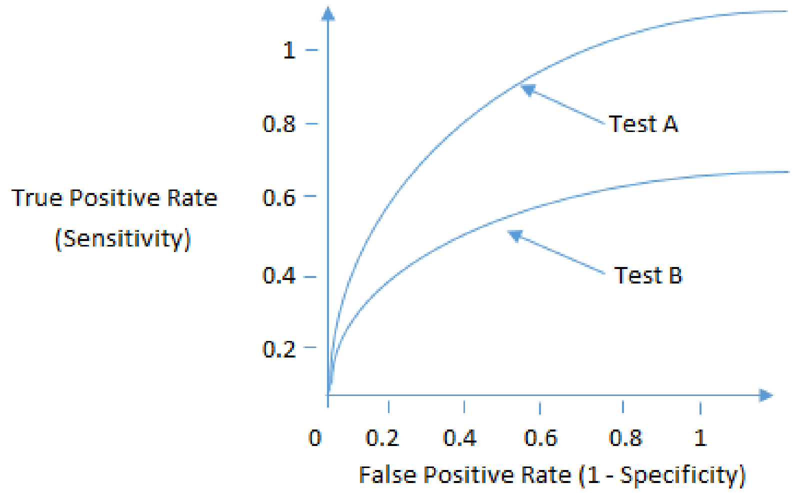
We can distinguish two extreme outcomes based on the ROC curve's discrimination power:

- 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 3.4, 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 3.4: Discrimination Power of ROC Curve - Area Under the Curve



After introducing the method which we employ in this chapter, 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:

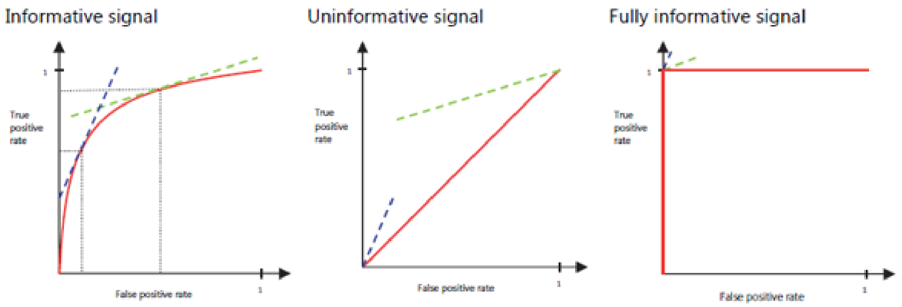
$$U_{11} > U_{01} \text{ and } U_{00} > U_{10}.$$

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 3.5 illustrate the trade-offs of three hypothetical variables.

Figure 3.5: Assessing Signal Quality



Note: Red line: ROC curve. Dotted lines: preferences of a policy maker who weights the expected costs and expected benefits linearly. The blue (green) line indicates high (low) costs relative to benefits.

Source: Drehmann & Juselius, 2014

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.

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

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 3.5 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 3.5 between the red and green or blue curves.

Unfortunately, determining the predicted costs and benefits of macro-prudential 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. We also explain all the highlighted criteria by using AUC metrics as follows:

Criterion 1:

If $AUC(S_{i,h}) > 0.5$ for some horizon h $\in$ [-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 dating 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.

3.4.2 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 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 chapter, we validate the combination of indicators using two approaches. The first approach combines indicators as combination of rank based classifiers on bi-variate indicators i.e. $\min(\mathbf{I}(EWI_i > \theta_i), \mathbf{I}(EWI_j > \theta_j))$. In the second approach, combination of indicators using a linear combinations i.e. $\sum_i \theta_i EWI_{it}$ has a natural appeal 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 hyperplane 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 elastic-net and can be illustrated as follows:

$$\mathbf{P}(I_{it} = 1) = \alpha_0 + \sum_{i=1}^{I} \sum_{l=L}^{20} \alpha_{il} EWI_{i,t-l} + \lambda_1 \sum_{i=1}^{I} \sum_{l=L}^{20} |\alpha_{il}| + \lambda_2 \sum_{i=1}^{I} \sum_{l=L}^{20} \alpha_{il}^2 + \epsilon_{it} \tag{3.1}$$

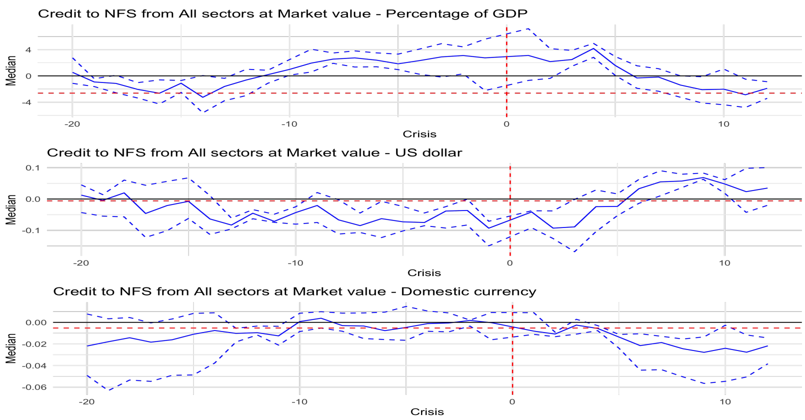
where λ_1 and λ_2 are penalizing parameters for L_1 and L_2 norms of parameters and these parameters will be used for restricting the size of the parameter space. Further, I is the number of indicators shortlisted, L is the lag selection. We consider all possible lags of the indicators from L quarters 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.

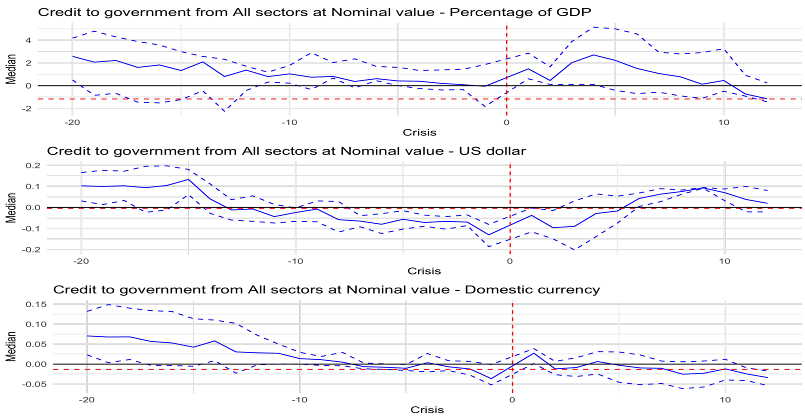
3.5 Empirical Results

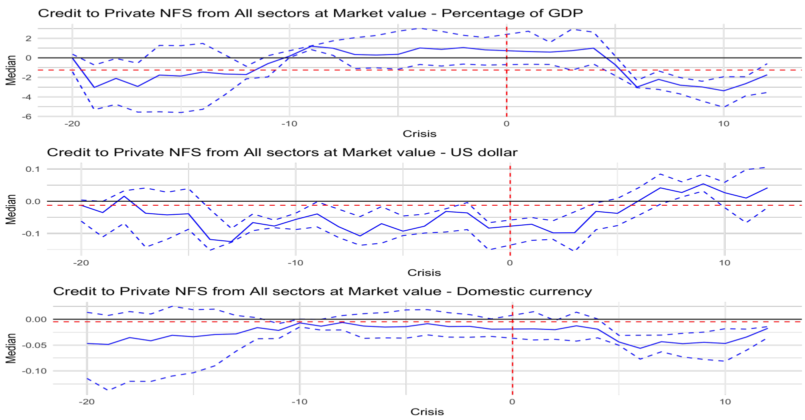
3.5.1 The Behaviour of Indicator Variables Around Systemic Crises

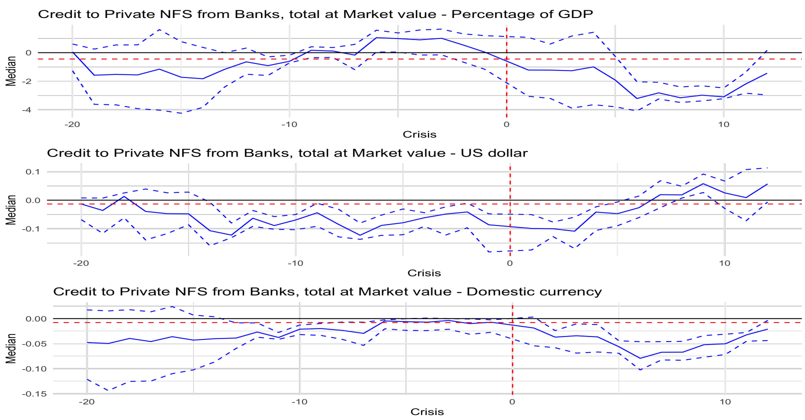
Before starting out the analysis, we first applied unit root tests in three forms (no-drift and no-trend, drift and no-trend, both drift and trend) to investigate whether the series are stationary or not. The list of abbreviations used to label the indicator and the unit root test results are presented 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 3.6 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.

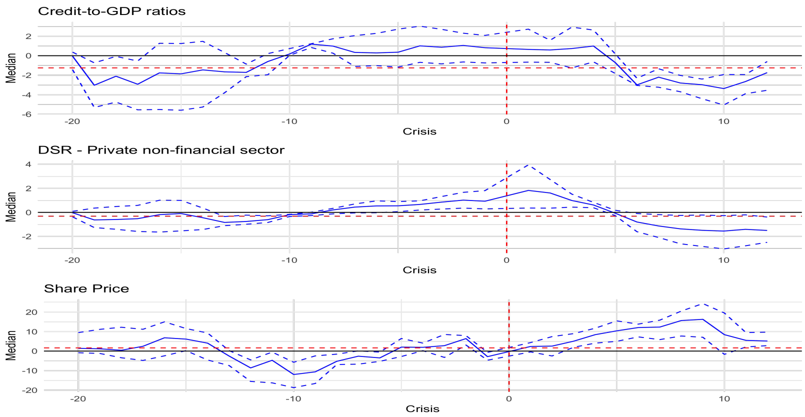
Figure 3.6: Indicator variables around Crises

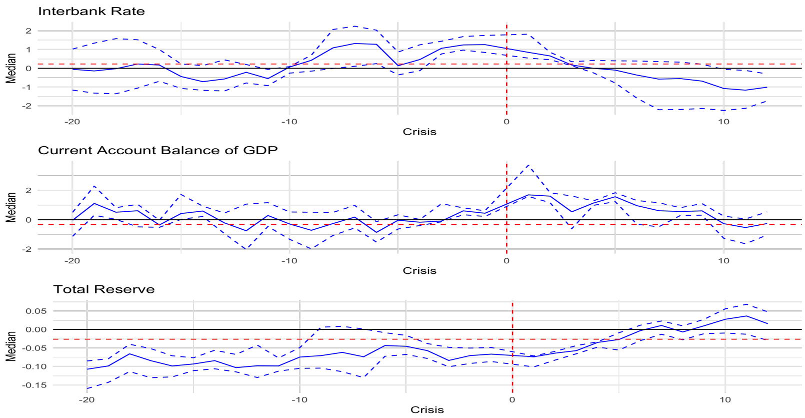


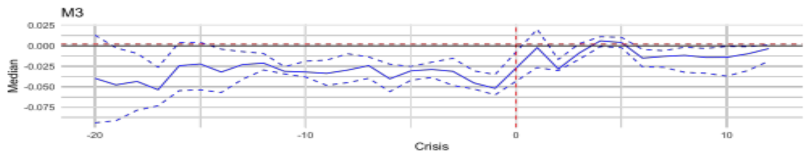

Credit to government from All sectors at Nominal value - Percentage of GDP
Median
Crisis
Credit to government from All sectors at Nominal value - US dollar
Median
Crisis
Credit to government from All sectors at Nominal value - Domestic currency
Median
Crisis


Credit to Private NFS from All sectors at Market value - Percentage of GDP
Median
Crisis
Credit to Private NFS from All sectors at Market value - US dollar
Median
Crisis
Credit to Private NFS from All sectors at Market value - Domestic currency
Median
Crisis


Credit to Private NFS from Banks, total at Market value - Percentage of GDP
Median
Crisis
Credit to Private NFS from Banks, total at Market value - US dollar
Median
Crisis
Credit to Private NFS from Banks, total at Market value - Domestic currency
Median
Crisis


Credit-to-GDP ratios
Median
Crisis
DSR - Private non-financial sector
Median
Crisis
Share Price
Median
Crisis


Interbank Rate
Median
Crisis
Current Account Balance of GDP
Median
Crisis
Total Reserve
Median
Crisis


M3
Median
Crisis

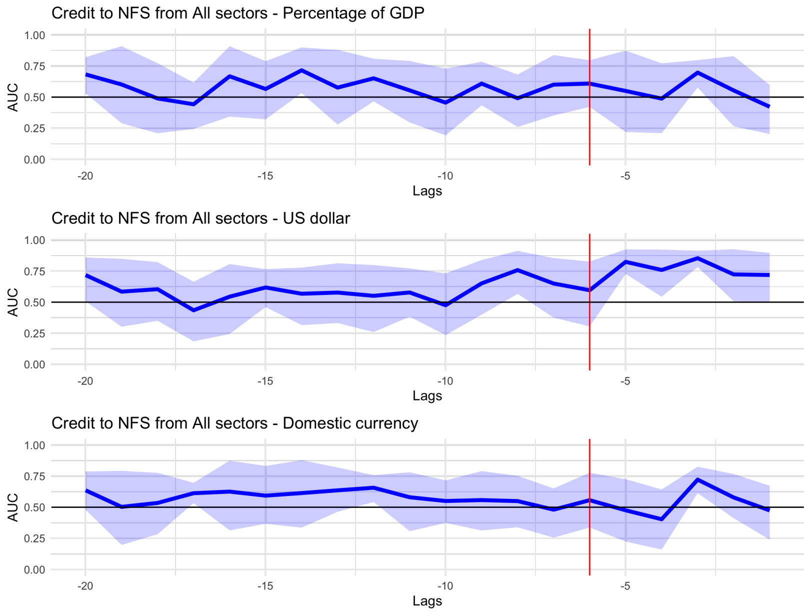
3.5.2 The Signalling Quality of Different Standalone EWIs

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 3.4. 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 3.7 - 3.12 (the AUC estimates with confidence bands are also provided numerically in the Appendix 3.8.4). 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 for the horizon of 8 quarters before the crisis are shown in Appendix 3.8.4.

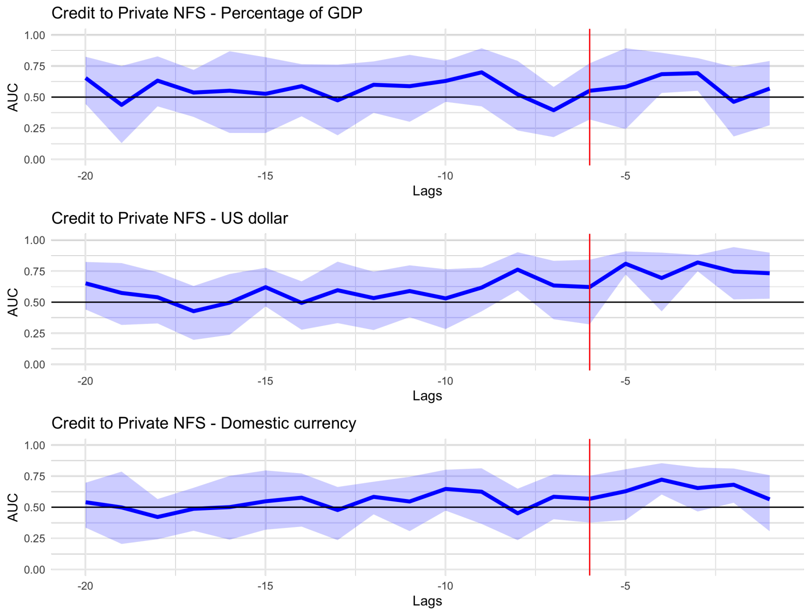
First, we evaluate the signal strength of credit variables. Following Figure 3.7, the credit to non-financial sectors showcase a consistent signal prior to 6 quarters of crisis as the AUC estimates of these variables stayed above the threshold value. Further, the strength of signal also remained steady 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 3.7: EWIs and policy requirements – AUCs over time



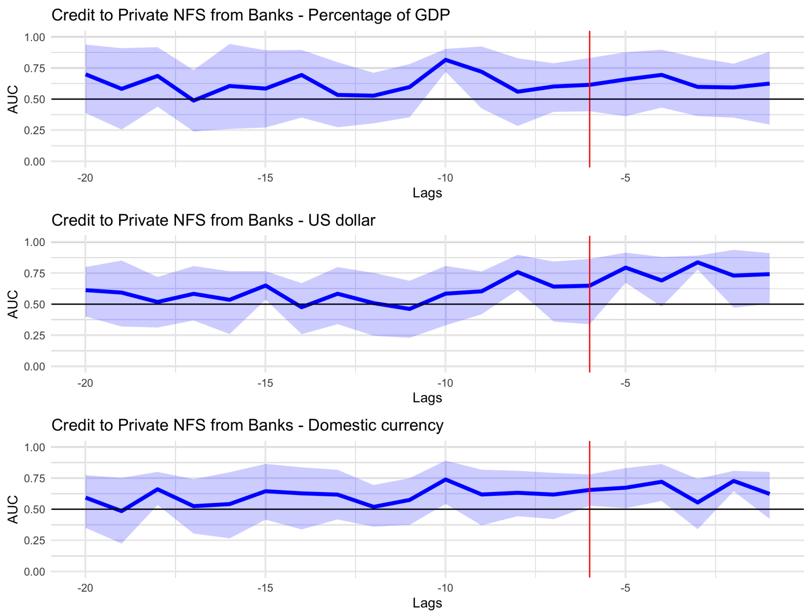
The signal strength of credit to private non-financial sector also demonstrated similar pattern. The credit to private non-financial sector scaled by GDP and dollar denominated credit value to private non-financial sector showed better signal strength among other components. The stability of signal strength was, however, remained elevated for dollar denominated credit amount to this sector (following Figure 3.8).

Figure 3.8: EWIs and policy requirements – AUCs over time



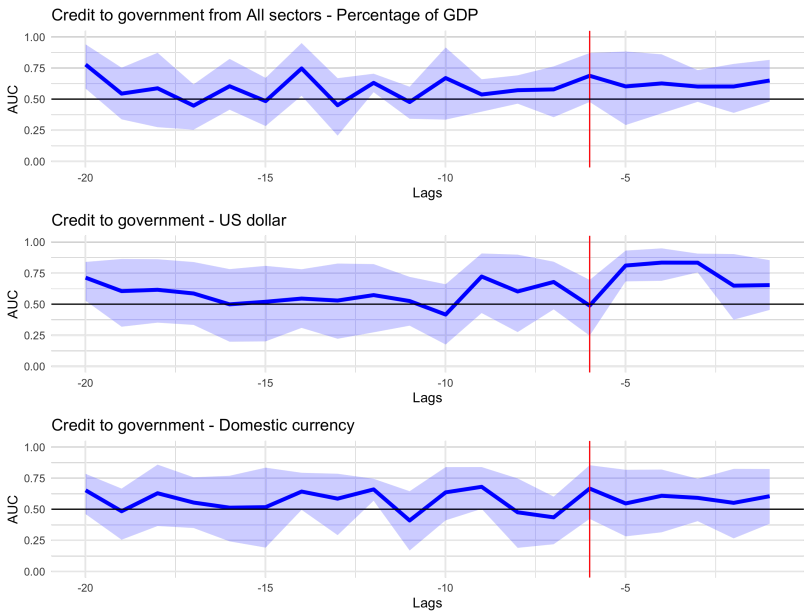
The credit disbursement to private non-financial sector from banks also showed strong signal prior to the crisis. The credit disbursed by the banks as percentage of nominal GDP exhibit better stability and robustness over the prediction horizons, prior to 6 quarters of the crisis. The absolute credit 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 3.9)

Figure 3.9: 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 Figure 3.10).

Figure 3.10: 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 3.11). Share price provided a mixed signal around prediction horizon of 16-20 quarters. However, the signal strength improved after that. The signal of interbank rate also remained stable over the prediction horizon. However current account balance (as % of GDP) remained unstable in signal strength (refer to Figure 3.12). Lastly, the total reserve appeared to be better indicator of systemic risk compared to money supply (refer to Figure 3.13).

Figure 3.11: EWIs and policy requirements – AUCs over time

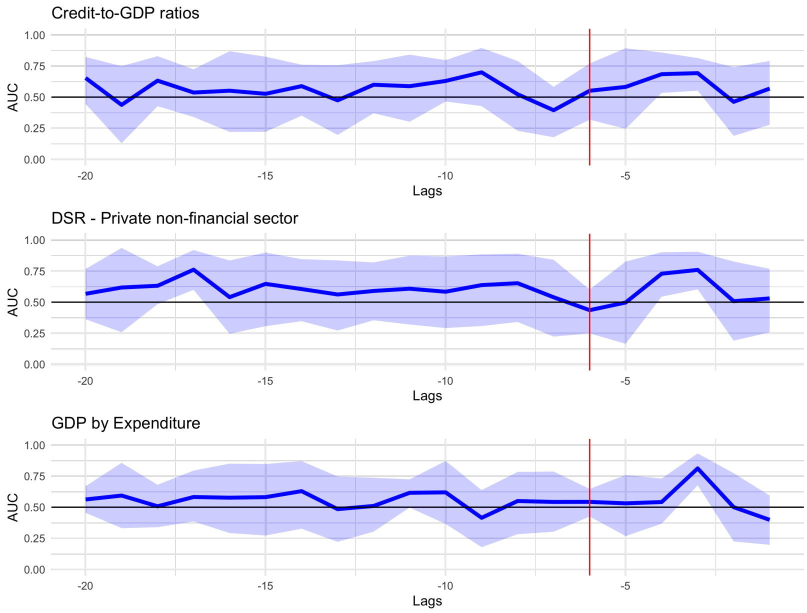


Figure 3.12: EWIs and policy requirements – AUCs over time

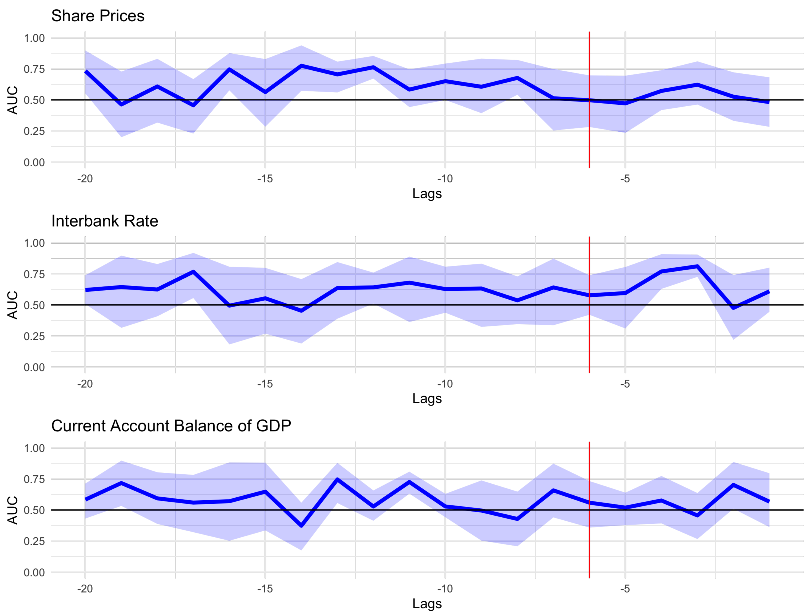
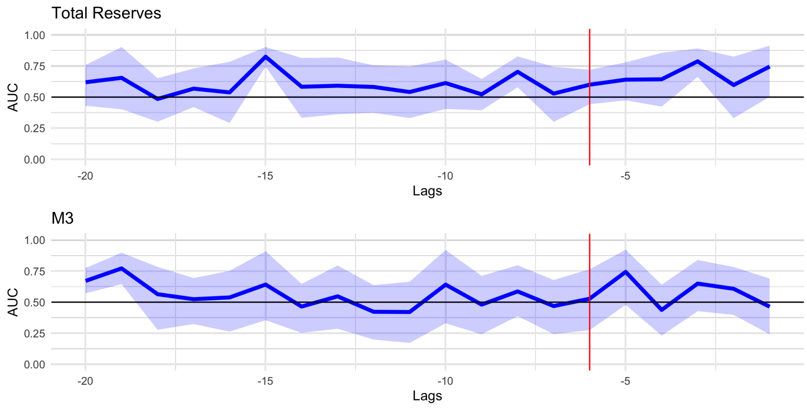


Figure 3.13: EWIs and policy requirements – AUCs over time



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 boosts 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 (2014), 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, their signal strength remained strong well before the crisis. 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.

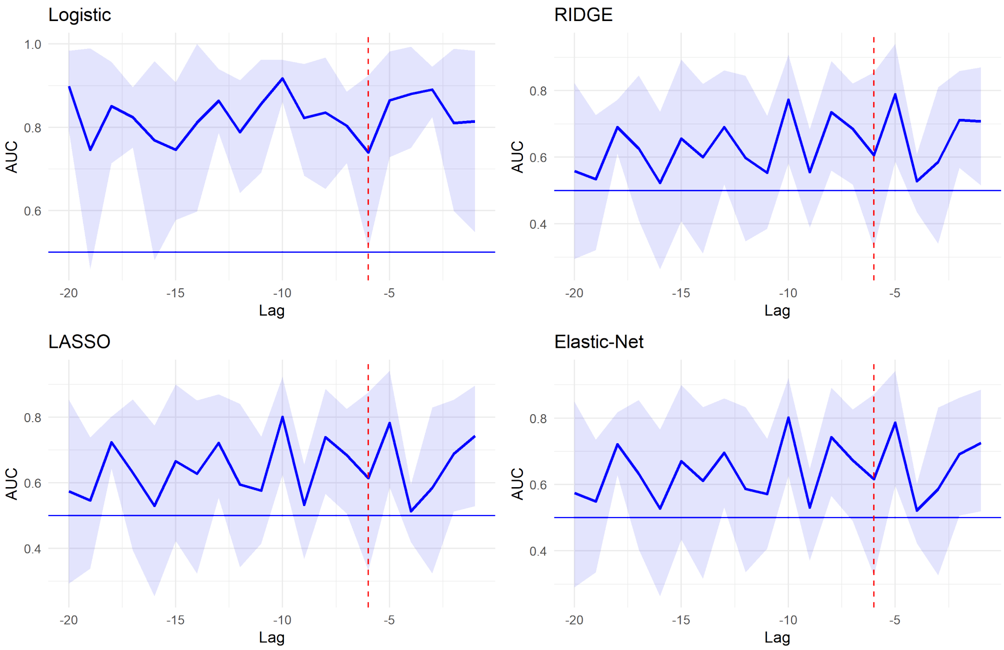
The lack of absolute supremacy of any particular indicator in terms of signal strength, rules out the possibility of single indicator based monitoring of systemic risk. Rather, it advocates for a combination of indicators to predict the systemic risk episodes. However, any combination of these indicators 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.

3.5.3 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.

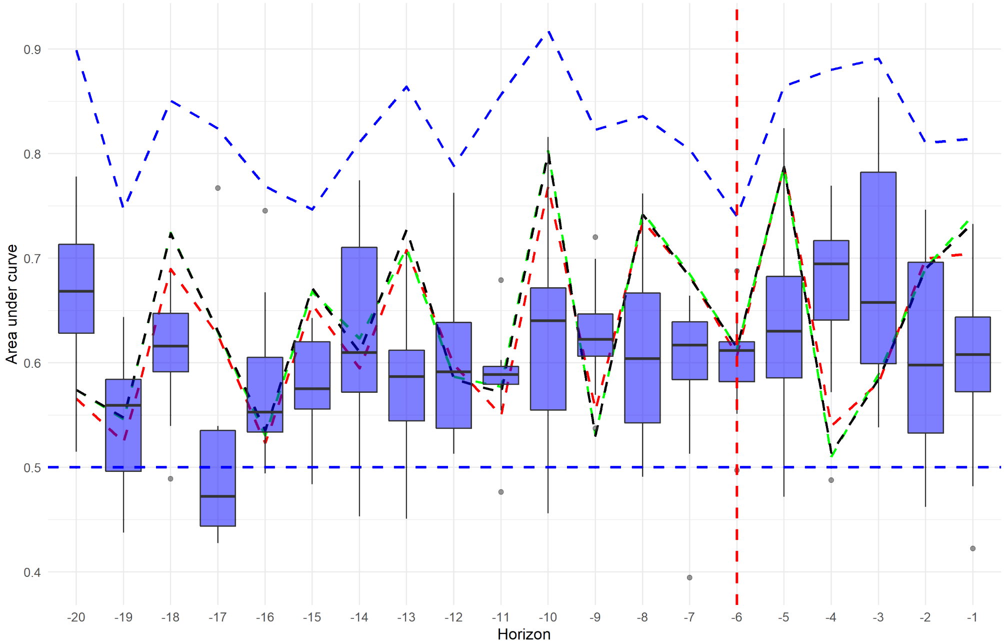
The combination of EWIs using logit model yields improvement of signal strength over all horizons. In particular, the signal of the EWI combinations remains at an elevated position compared to the threshold value of 0.5. However, the parameter space remains unrestricted in the logit regression due to 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 3.14).

Figure 3.14: 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 3.15). In the below figure, 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.

Figure 3.15: Comparison of signal strength



3.6 Concluding Remarks

This chapter tries to analyze the effectiveness of EWIs in capturing and predicting banking and currency crises in cross-country setup 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 chapter 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 chapter 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 chapter 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 chapter 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 chapter, 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 (2014). The limitation of the chapter 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 chapter attempts to address the concern using different choice of smoothing parameters and EWI combination models.

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3.8 Appendices

3.8.1 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

3.8.2 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

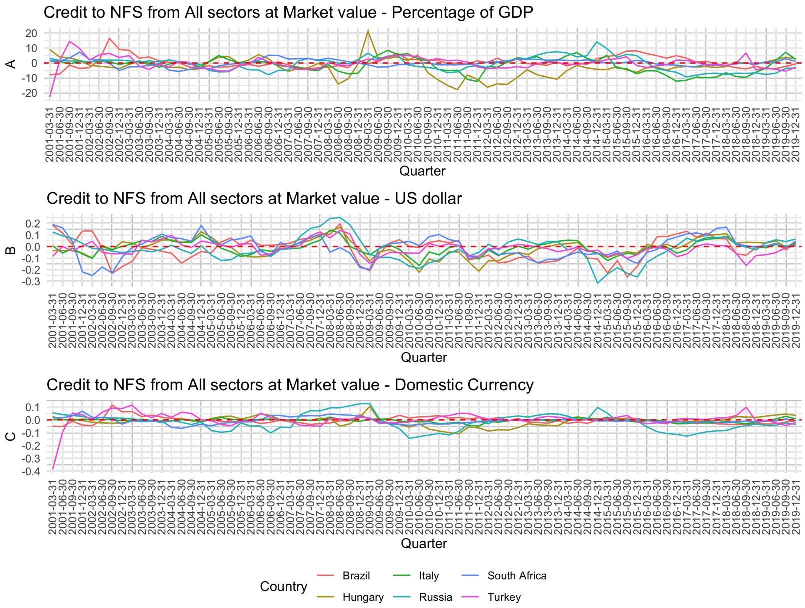
	Country	Variable	No-drift No-Trend	Drift-No Trend	Drift-Trend
1	South Africa	A	0.97	0.98	0.01
2	South Africa	B	0.95	0.45	0.47
3	South Africa	C	0.99	0.99	0.60
4	South Africa	D	0.93	0.99	0.44
5	South Africa	E	0.97	0.98	0.01
6	South Africa	F	0.98	0.91	0.35
7	South Africa	G	0.99	0.99	0.99
8	South Africa	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

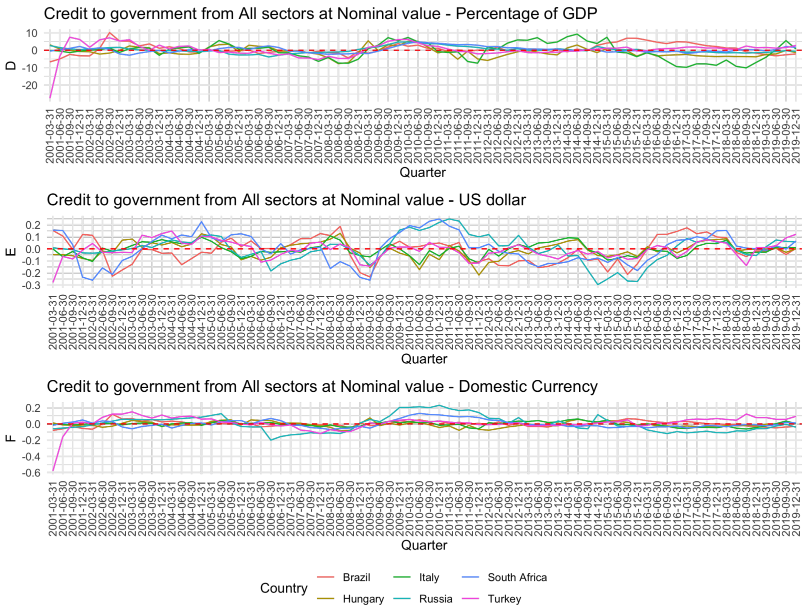
	Country	Variable	No-drift No-Trend	Drift-No Trend	Drift-Trend
1	Russia	A	0.85	0.84	0.37
2	Russia	B	0.85	0.66	0.29
3	Russia	C	0.98	0.99	0.53
4	Russia	D	0.01	0.01	0.01
5	Russia	E	0.85	0.84	0.37
6	Russia	F	0.76	0.67	0.45
7	Russia	G	0.99	0.99	0.67
8	Russia	H	0.94	0.60	0.49
9	Russia	I	0.83	0.64	0.35
10	Russia	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

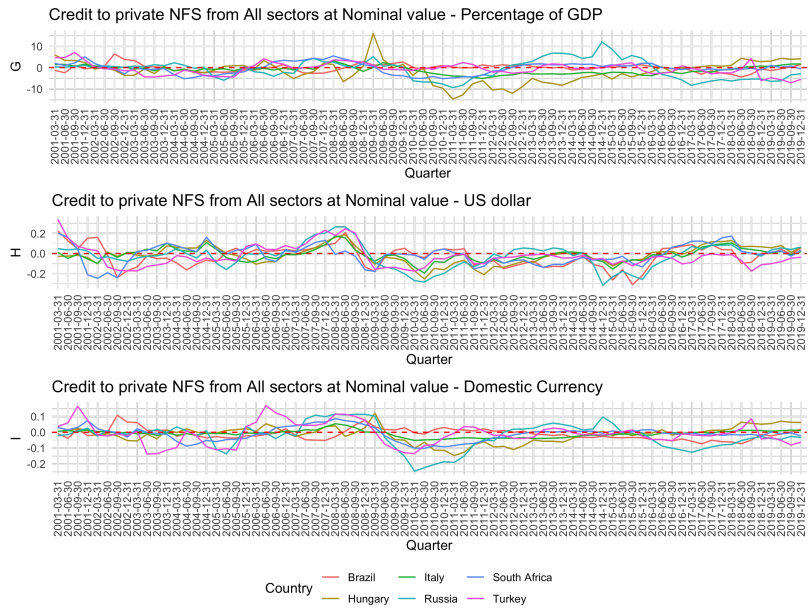
	Country	Variable	No-drift No-Trend	Drift-No Trend	Drift-Trend
1	Hungary	A	0.76	0.41	0.98
2	Hungary	B	0.81	0.11	0.73
3	Hungary	C	0.99	0.36	0.82
4	Hungary	D	0.76	0.42	0.96
5	Hungary	E	0.76	0.41	0.98
6	Hungary	F	0.89	0.08	0.54
7	Hungary	G	0.99	0.83	0.03
8	Hungary	H	0.70	0.50	0.96
9	Hungary	I	0.75	0.23	0.78
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

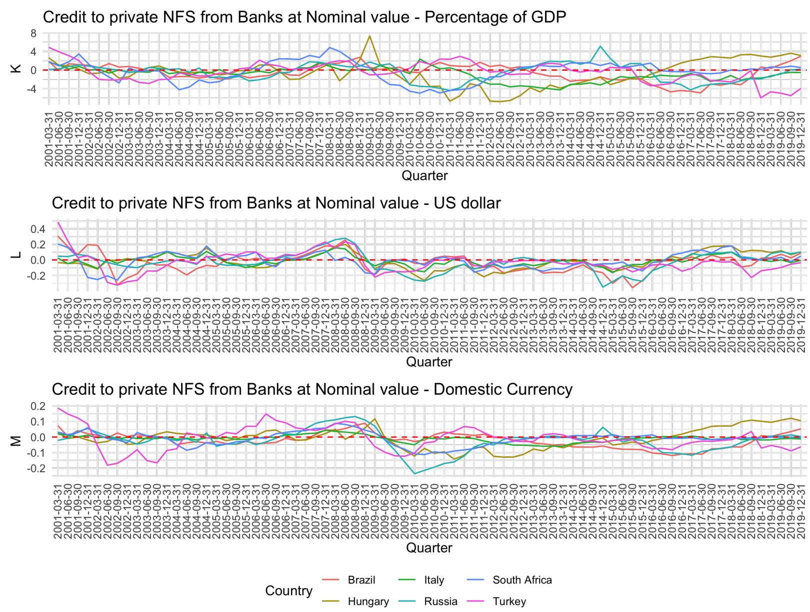
	Country	Variable	No-drift No-Trend	Drift-No Trend	Drift-Trend
1	Italy	A	0.95	0.50	0.91
2	Italy	B	0.87	0.08	0.61
3	Italy	C	0.99	0.15	0.94
4	Italy	D	0.91	0.81	0.55
5	Italy	E	0.95	0.50	0.91
6	Italy	F	0.91	0.16	0.25
7	Italy	G	0.99	0.92	0.44
8	Italy	H	0.80	0.02	0.99
9	Italy	I	0.76	0.14	0.77
10	Italy	K	0.86	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

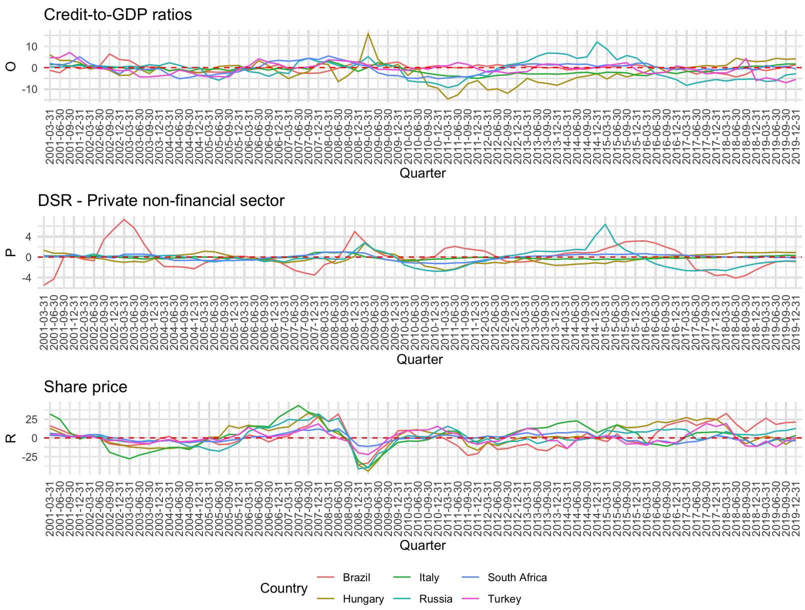
3.8.3 Detrending

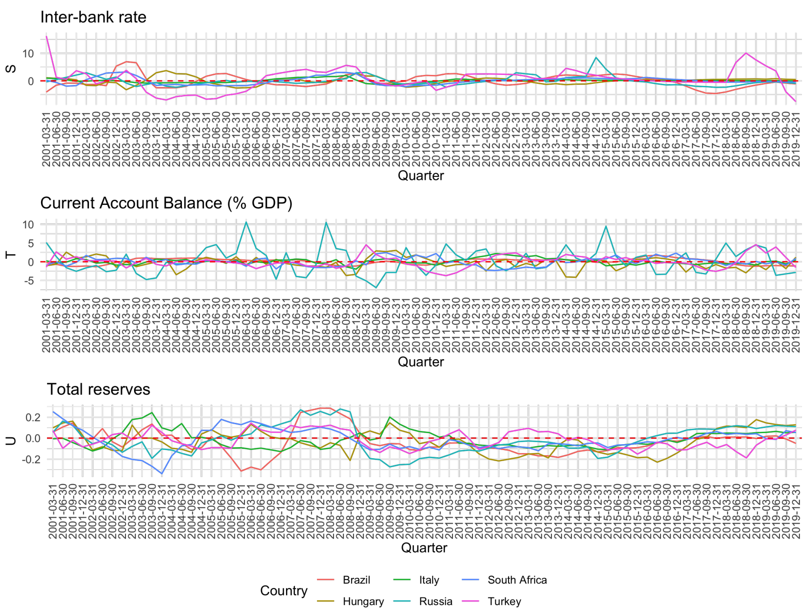




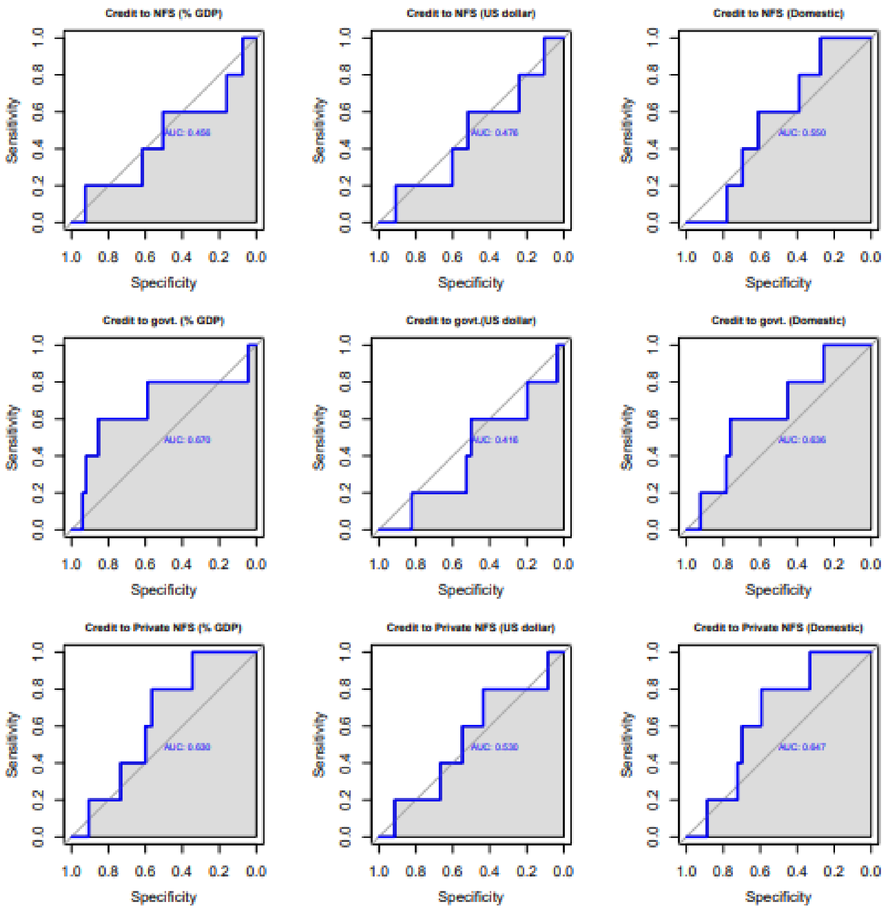

Credit to private NFS from All sectors at Nominal value - Percentage of GDP
G
Quarter
Credit to private NFS from All sectors at Nominal value - US dollar
H
Quarter
Credit to private NFS from All sectors at Nominal value - Domestic Currency
I
Quarter
Country
Brazil
Hungary
Italy
Russia
South Africa
Turkey

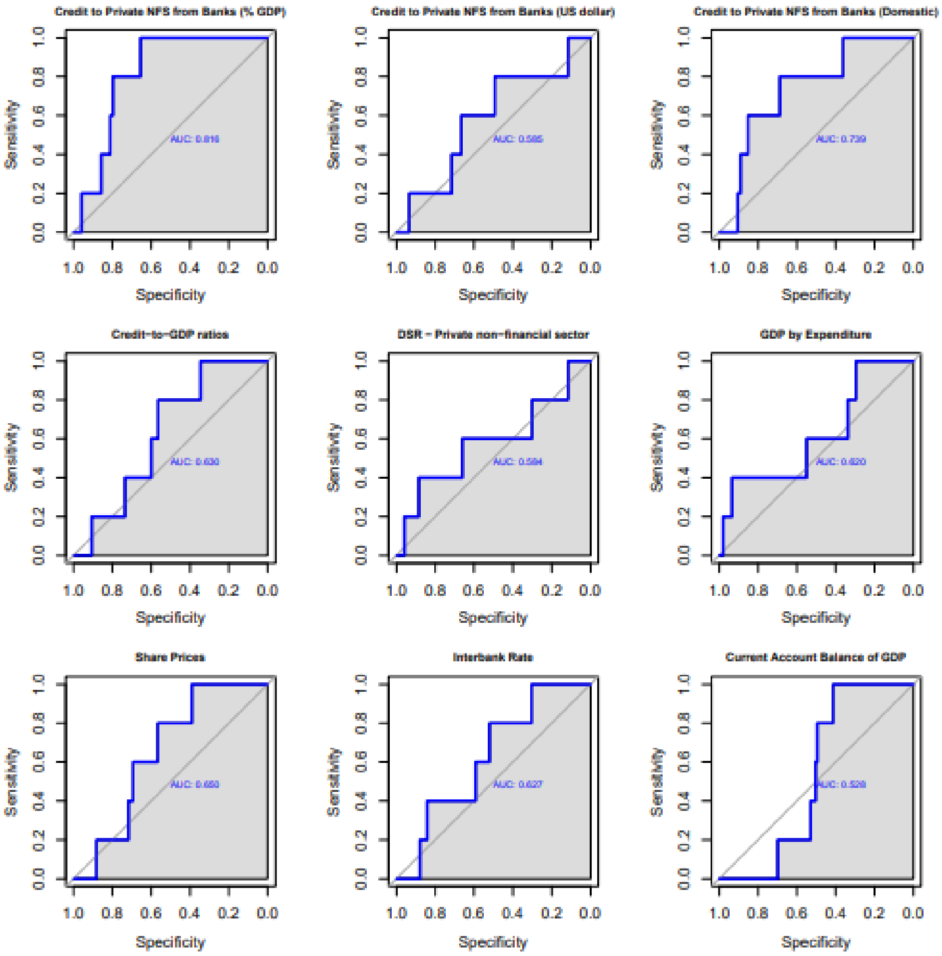

Credit to private NFS from Banks at Nominal value - Percentage of GDP
K
Quarter
Credit to private NFS from Banks at Nominal value - US dollar
L
Quarter
Credit to private NFS from Banks at Nominal value - Domestic Currency
M
Quarter
Country
Brazil
Hungary
Italy
Russia
South Africa
Turkey

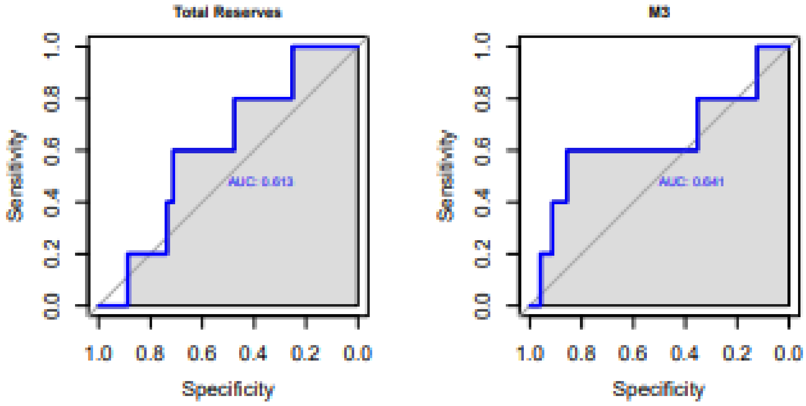

Credit-to-GDP ratios
O
Quarter
DSR - Private non-financial sector
P
Quarter
Share price
R
Quarter
Country
Brazil
Hungary
Italy
Russia
South Africa
Turkey


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

3.8.4 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
DSR – Private non-financial sector
GDP by Expenditure
Share Prices
Interbank Rate
Current Account Balance of GDP
Sensitivity
Specificity


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

Variable	Type	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
		Horizon																			
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
	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
Current Account Balance of GDP	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
	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
Total Reserves	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
	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
M3	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