Louvain School of Management

What variables should be included in a dynamic EWS to have the best fitting model for financial crises (currency, banking, and debt crises)?

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Introduction

Unlike the financial crises of past centuries and decades, the systemic risk of current crises is significantly higher due to extensive globalization and the deep interconnections of global economies.

But it is important to know that the sooner a financial crises is suspected, the quicker solutions can be implemented to either prevent it or at least mitigate its consequences. It is in this context of prevention that the Early Warning System (EWS) models were developed.

In 2024, a stable and growing economy is a major factor in a country's well-being. In this context, the Early Warning System (EWS) plays firstly a crucial role in prospering in a healthy economy. The results of these EWS can be used to assess monetary policies and government decisions in order to avoid social catastrophes such as famine, revolutions, etc.

It is in this context that we have decided to take an interest in this model because it means more than a simple mathematical code. We are both passionate about finance and the impact of the economic world on our daily lives. It was, therefore, logical for us to turn to a subject for our master's thesis that was linked to our passions. We wanted to grasp the model but also understand what impact the different variables would have on it.

Our research question is : **What variables should be included in a dynamic EWS model in order to have the best fitting model for financial crises (currency, banking and debt crises) ?**

In our study, we will try to identify the most significant variables for each type of crises. We will cover the following 12 countries: Argentina, Brazil, Finland, Greece, Japan, Mexico, Poland, Portugal, Turkey, Spain, South Africa and USA.

Our work will be divided into 2 parts. The first one is a literature review in which we will review all the theoretical concepts that we will use in the second part.

In this first part, we will explain what a crises is and what its characteristics are, depending on the type of crises. We will focus on 3 types of crises banking, currency and debt. Next, We will define what an EWS model is and why we decided to use a dynamic one.

The second section is an empirical research. We will first review the methodology and the variables we used. Next, we will focus on the relation between variables. 3 tests were used: bivariate regression, correlation tests and multicollinearity tests.

After excluding certain variables using the 3 tests above. We will run the Logit estimation model for each country and each crises to determine the most significant variables. When these have been chosen, we will forecast the crises probability with these most significant variables and analyse whether certain countries are currently in crises or are in the process of becoming so.

Finally, we will evaluate our model and explain the limitations we faced during our work.

Literature review

To fully comprehend our subject and address our research question, we will take up with a literature review. Our aim in this section is to delve into essential theoretical concepts that will underpin our upcoming work. Let's begin with the definition of a financial crisis.

1 Definition financial crises

The term financial crisis is subject to various interpretations making it challenging to formulate a precise and comprehensive definition. However, the International Monetary Fund's (1998) defines it as potentially severe disturbances in financial markets that can have significant and adverse consequences on the real economy.

According to Mishkin (1992), a financial crisis drives the economy away from its stability where financial markets function efficiently towards a state where the market declines. During financial crisis, moral hazard and adverse selection are becoming much worse problems, making it challenging for markets to allocate properly funds to the ones with the most productive investment opportunities.

Financial crisis could trigger an economic recession, marked by declines in consumption and investments influenced by macroeconomic decisions. Furthermore, the term *financial crises* encompasses various specific crises, including currency, banking, and debt crises (Aziz et al. 2000, p.5).

In the following section, we will define these different types of crisis, beginning with the banking one.

1.1 Banking crises

Banking crisis can be conceptualized as a time when a notable portion of the banking system experiences either illiquidity or insolvency events (Beck et al., 2000).

Solvency crises occur when a bank's liabilities surpass the present value of its assets, rendering the bank effectively bankrupt. The liability approach emphasizes the liabilities listed on banks' balance sheets (Beck et al., 2000).

Very often, a banking crisis emerges from several factors, each contributing to the crisis on its own scale. Therefore, it makes sense that some factors have a more pronounced influence than others. Based on their causes, banking crises are generally categorized into two types: microeconomic or macroeconomic (Quintyn and Hoelsher, 2003) .

Crises stemming from microeconomic causes are attributed to uncontrolled practices and lenient policies within certain banks, such as excessive lending. Lax lending methods can contribute to the formation of asset price bubbles or lead to an excessive concentration in bank portfolios. The predominant cause often lies in risk management. Fragile systems are at the root of many microeconomic banking crises, leading to deficient balance sheets. Banks with deficiencies in their balance sheets are vulnerable to any shock, and even relatively minor external events can be enough to trigger a loss of confidence and a widespread flight (Quintyn and Hoelsher, 2003).

Crises resulting from macroeconomic perspective causes are quite different from the preceding ones. They are initiated by external aggregates to the banking system. Well-managed banking systems, within a robust legal framework, can be overwhelmed by the effects of faulty macroeconomic policies. Well-managed banks can absorb certain shocks, but irrational monetary, exchange, or fiscal policies can create financial tensions that compromise the solvency of banks or push them into risky operations. Here are some examples that weaken banks and make them more vulnerable: too much exposure to the government, often the result of high returns on public bonds, the dollarization of financial contracts, and high and volatile interest rates (Quintyn and Hoelsher, 2003).

1.1.1 Systemic vs non systemic crises

Systemic and non-systemic crises damage the real economy by hindering the normal flow of credit from savers to entrepreneurs and other businesses, while also making risk distribution more difficult or costly. Given the harm that financial crises can inflict, researchers and policymakers are keenly interested in their causes and consequences (Ozili,2020).

A systemic crisis occurs when issues within one or more banks reach a severity that significantly harms the real economy. This is because financial instabilities become so pronounced that they affect the entire financial system, particularly at the aggregate level (economic indicators). Such a crisis typically involves a mass withdrawal of creditors and depositors from both financially stable and insolvent banks, posing a threat to the entire banking sector. The panic is driven by concerns that obtaining the means of payment will become impossible at any cost. In a fractional reserve banking system, this triggers a rush for high-powered money and a withdrawal of external credit lines (Quintyn and Hoelsher, 2003).

At the heart of systemic risk lies contagion, *"In economics and finance, a contagion can be explained as a situation where a shock in a particular economy or region spreads out and affects others by way of, say, price movements"* (The Economic Times, s.d.).

In financial systems, the transmission of shocks and crises can occur through multiple channels of contagion, ultimately contributing to systemic crises. One significant channel is liquidity hoarding, where banks adopt precautionary measures by holding onto liquidity reserves rather than lending them out. This behavior can exacerbate financial stress by reducing the availability of funds for borrowing and investment, thereby tightening credit conditions and potentially triggering broader economic downturns. Another channel of contagion is through direct cross-exposures in interbank markets. Financial institutions often have interconnected relationships, and distress in one institution can quickly spread to others through these linkages, leading to a domino effect of financial instability. Additionally, fire sale externalities present another avenue for contagion. When distressed assets are sold at discounted prices, it can trigger a downward spiral in asset values as other market participants mark down the value of their holdings, creating a feedback loop of declining market confidence and further distress (Aldasoro et al., 2017).

A non-systemic crisis can be defined as a crisis that does not have a widespread impact across multiple banks or on the macroeconomic aggregates of a country. It typically involves specific sectors such as savings or loans. However, this type of crisis can escalate and become fatal as it may trigger a domino effect, dragging other sectors along with it (Quintyn and Hoelsher, 2003).

1.2 Currency crises

Intuitively we link currency crises with a strong and drastic depreciation of the nation's currency. Nevertheless a clear and universal definition of currency crises does not exist. But most of the researchers agree on the fact that a currency crisis happens when investors fear that a currency becomes weaker (Krugman, 2007).

That speculative attack could either result in a sharp depreciation as mentioned previously, or it could force the authorities to use macro-economic tools, such as raising the interest rates, force capital control or using high amounts of international reserves, in order to avoid a currency crisis (Claessens et al., 2013).

The origin of a currency crisis can be divided into two clear categories. The first generation crisis explains how a currency crisis arises from the mishandling of macroeconomic fundamentals. In contrast, the second generation suggests that crisis emergence is due to factors not directly related to macroeconomic fundamentals.
Lets develop those concepts in the following parts.

1.2.1 First generation crises

A first-generation currency crisis, outlined by Flood and Graber (1984), arises due to mismanagement of macroeconomic fundamentals, particularly in the management of the domestic money market.

Krugman (2001) added three key observations to take into account when defining a first generation crisis.
The first one being, as mentioned above, the root that causes a crisis is poor government policy. The increase in the shadow exchange rate is caused by the government's desire to create money, a concept known as seigniorage. The models indicate that addressing fiscal problems could prevent these crises. Secondly, although the crisis occurs suddenly, it is deterministic, which means it is inevitable given the existing policies. Theoretically, the timing of the occurrence of the crisis could be predicted, but in reality forecasting is quite challenging. Finally, first-generation crises seem to have limited consequences expect exposing existing economic problems. These crises serve more as a revelation of economic issues rather than initiate significant post-crisis downturns.

Flood and Marion (1999), in reference to Flood and Graber (1984), describe the mathematical model that explain the concept of the first generation model.

In this model we assume that a country fixes its currency exchange rate to that of a large foreign partner. The domestic money supply equilibrium is represented as follow :

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

where m is the domestic supply of high-powered money, p is the domestic price level, and i is the domestic interest rate.
The key components are the following :

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

So when a crisis happens, if the government finances deficits by increasing domestic credit, this leads to a loss of reserves (r' = -v), eventually forcing a departure from the fixed exchange rate.

1.2.2 Second generation crises

The second generation currency crises theory, introduced by Obstfeld in 1996, bifurcates from the traditional focus on macroeconomic fundamentals and highlights the role of market imperfections and investor behavior in generating currency crises (Flood and Marion, 1999).

The second generation model focuses on the non-linear behaviors of the economic agents. Unlike the first generation which is based on linear assumptions and policy mistakes. Here, the model highlights the significance of macroeconomic trade-offs, market perceptions, and self-fulfilling dynamics. Additionally, the model adds the concept of multiple equilibria where the economy could have different stable situations determined by the initial condition and the agents actions. For example, those multi-equilibria could result from the government's non-linear behaviors and could be influenced by various factors as extreme beliefs, information cascade, etc. (Flood and Marion, 1999).

The second generation model suggests that crises can arise suddenly, even in situations where no crisis seemed imminent, due to, once again, shifts in market perceptions and expectations. This indeterminacy underscores the importance of understanding market dynamics and expectations in predicting and managing currency crises (Krugman, 2001).

Let's now have a look into the mathematical model explained by Flood and Marion (1999), in reference to Obstfeld (1996).

This model considers that the government minimizes its loss function, which is calculated as follow:

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

$C(\varepsilon)$ refers to the cost when changing the exchange rate
$\varepsilon = e_t - e_{t-1}$ is the change in the exchange rate
y^* is the output target

The government chooses the exchange rate e after it has observed the negative supply shocks. But any variation in e changes $C(\varepsilon)$ which is included within $[\underline{C}, \bar{C}]$.

We will now combine the initial equation (1) with the Philips curve A.1.

$$L = [(\bar{y} - y^*) + \alpha(\varepsilon - \varepsilon^e - u]^2 + \beta\varepsilon^2$$

In order to minimize the function we want the partial derivative to be equal to 0 (the demonstration can be found in A.2).

$$Min_\varepsilon L(.) = \frac{\partial L(.)}{\partial \varepsilon} <=> \varepsilon = \frac{\alpha(y^* - \bar{y} + u) + \alpha^2\varepsilon^e}{\alpha^2 + \beta}$$

Thus, if y^* is $> \bar{y}$ it means that it is incentive to devaluate because $\varepsilon > 0$.

As we mentioned in the definition of the second generation crisis, it is a multi-equilibria model. In fact, it exists 3 equilibria that depends on the shocks (u). All the mathematical details for the equilibrium can be find in the appendix A.3. The 3 different equilibria are the following :

Equilibrium I :

$$E(\varepsilon) = \frac{\alpha}{\alpha^2+\beta}\Big\{[y^* - \bar{y} + \alpha\varepsilon^e][1 + \frac{\bar{u} - \underline{u}}{2\mu}] + \frac{\bar{u}^2 - \underline{u}^2}{4\mu}\Big\}$$

Equilibrium II :

$$E(\varepsilon) = (\frac{\mu - \bar{u}}{2\mu})(\frac{\alpha}{\alpha^2+\beta})[(y^* - \bar{y} + \alpha\varepsilon^e) + \frac{\mu - \underline{u}}{2}$$

Equilibrium III:

$$E(\varepsilon) = \frac{\alpha}{\alpha^2+\beta}(y^* - \bar{y} + \alpha\varepsilon^e) \;\; E(u) = 0$$

The following graph represents the multi-equilibria that the second generation model, established by Obstfeld, states. As we can see, if the initial situation is *Eq1* and a shock happens, then the only equilibrium that is stable is *Eq 3* which equals to a 100% probability of devaluation.

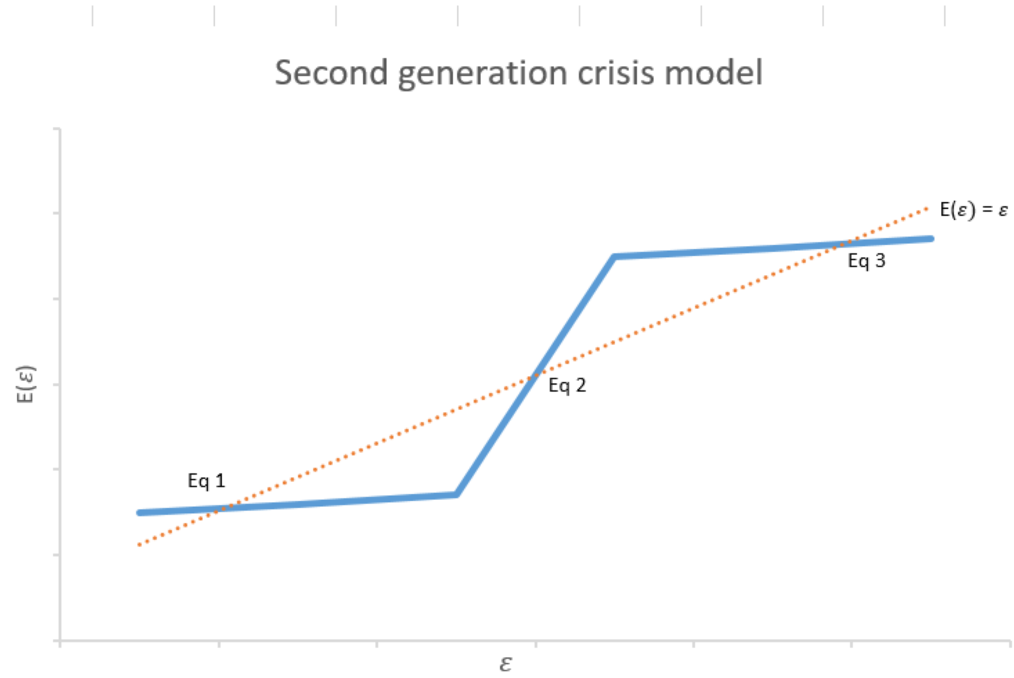


Figure 1: Second generation crises model

1.3 Debt crises

A debt crisis occurs when a country faces challenges or outright refusals in paying back its debt. This situation can emerge due to various reasons such as sudden drops in currency value, high inflation, or measures that limit financial freedoms (Claessens and Kose, 2013).

Delving deeper, Detragiache and Spilimbergo (2001) outlined two primary conditions that define a debt crisis. Firstly, it is when a country falls behind on paying back the principal or interest on its foreign debts to private lenders by more than 5% of its total external debt. Secondly, it occurs when there's a need to renegotiate or restructure debt with these private creditors. This definition specifically includes situations where a country takes steps to rearrange its debt payments before actually defaulting, while excluding minor payment delays. It's also worth noting that issues related to restructuring or delaying payments on government-held debt do not fall under this crisis category.

Moreover, it's crucial to differentiate between a new crisis and the extension of a previous one. According to Detragiache and Spilimbergo (2001), a crisis happening within four years of an earlier one is seen as a continuation.

Dornbusch (1989) identified several factors that play a role in the development of a debt crisis, highlighting the delicate equilibrium between creditors and debtors. These factors include:

1. An increase in real interest rates, which can worsen the financial situation if creditors are hesitant to provide additional funds.

2. A drop in the non-interest current account balance, which could result from domestic economic issues or external pressures like unfavorable trade conditions or lower demand for exports, leading to a financing gap.

3. A sudden rise in global inflation rates, which could lead to an increase in nominal interest rates and, consequently, cause cash flow problems for borrowers (this would happen even if the interest rates remain unchanged).

4. Lastly, concerns from creditors about their risk exposure might lead them to reduce new loans and demand repayment of existing loans, aggravating the debt situation.

1.4 Other crises

In the previous sections, we defined three primary types of financial crises—banking, currency, and debt—which are essential to our empirical research focus. However, it's imperative to acknowledge the existence of numerous other financial crises that may not be within our immediate scope. In the following segment, we'll briefly approach additional categories.

The first type of crisis we find important to acknowledge is the balance of payment one, which is defined by Krugman and Obstfeld (1997) as an extreme variation in the foreign reserves sparked by a difference in the expectation for the anticipated exchange rates. However Kaminsky and Reinhart (1999) state that the currency pegs are abandoned when a BoP crisis happens.

Furthermore, it is worth noting that crises which come from outside the economic field can have a serious impact on national economies and financial markets. For example, the COVID-19 pandemic, is, initially, defined as a public health crisis. But it has had clear and severe impacts on the global economy in general, which highlights the importance of a comprehensive understanding of crises dynamics.

2 Definition Early Warning Systems (EWS)

Kovalevski (2024) defines an early warning system as *"The set of capacities needed to generate and disseminate timely and meaningful warning information to enable individuals, communities and organizations threatened by a hazard to prepare and to act appropriately and in sufficient time to reduce the possibility of harm or loss"*.

As outlined by Christofides et al. (2016), it is feasible to categorize early warning signals into four distinct groups, each with its own advantages and drawbacks. The first one employs the logit/probit approaches, where certain crisis indicators must reach a specific probability threshold to be considered in a 'crisis' (e.g., Eichengreen et al., 1995). Other non-parametric signaling approaches are used to identify crises through threshold values (e.g., Kaminsky et al., 1998). The third strategy entails segmenting the sample into countries experiencing crises and those not in crises, as determined by researchers' selection (e.g., Kamin, 1988). Recent approaches have employed alternative statistical methods to determine thresholds for early warning signals using regression trees (Ghosh and Ghosh, 2003).

2.1 Signal approach

Over the past few years, numerous researchers have documented their success in systematically predicting which countries are at an elevated risk of facing monetary crises. A particularly distinguished model, developed before 1997, aimed at predicting monetary crises is the indicators approach. Developed by Kaminsky et al. in 1998, this approach is known as the KLR model. The model employs an extensive array of monthly indicators, issuing a warning signal for a potential crisis whenever these indicators surpass a certain predetermined level (Karmarkar and Vani, 2014).

The fundamental concept behind this method is based on the idea that the economy exhibits distinct behavior as it approaches financial crises compared to more 'normal' periods. The indicators selected in the model are of a macroeconomic nature and are directly impacted by the crises. This signal-based approach uses these indicators to proactively identify crises. Since economic crises are often preceded by significant developments or imbalances, leading indicators, such as declining GDP growth rates and balance of payments issues, show exceptional values before a crisis begins. To implement the KLR approach, the percentage change in the value of each indicator is calculated to standardize them (Kaminsky et al., 1998).

Each indicator triggers a signal when it surpasses a predetermined optimal threshold level. To establish this optimal threshold for each indicator, the noise-to-signal ratio is minimized using a matrix. In this scenario, "noise" denotes random fluctuations or non-systematic variability present in economic and financial data, whereas "signal" indicates significant patterns or trends that may reflect underlying economic conditions or risks. A high noise-to-signal ratio suggests that the data is predominantly influenced by random fluctuations, rendering it challenging to identify meaningful patterns or trends. Conversely, a low noise-to-signal ratio indicates that the data contains distinct and meaningful signals, facilitating more reliable analysis and interpretation (Kaminsky et al., 1998).

The performance of each indicator is assessed based on the matrix, with cells indicating the number of months during which the indicator gave a correct signal (A), produced a false signal or 'noise' (B), failed to give a signal that would have been correct (C), and failed to give a signal that would have been incorrect (D)(Kaminsky et al.,1998).

To categorize the data into the A/B/C/D format, a binary code is assigned, considering a negative flow or a decrease as a signal and the absence of a signal otherwise. This binary encoding simplifies the subsequent classification into A/B/C/D for each indicator (Kaminsky et al.,1998).

Table 1: Confusion Matrix for Kaminsky

	Predicted Class	
	crises within 24 months	No crises within 24 months
Signal was issued	A	B
No signal was issued	C	D

Noise = B/(B+D) : Signal = A/(A+C)

To determine the optimal threshold for each indicator, KLR identifies the threshold that minimizes the noise-to-signal ratio. These thresholds are calculated based on the percentiles of distribution for each country for the respective variable.

An indicator emits a warning signal if it exceeds this critical threshold level. All calculations are performed within a 2-year crisis window.

A more advanced approach involves selecting a specific percentile from the frequency distribution, taking into account the distribution of predicted values and the number of events. The threshold level is derived using the α percentile.
α represents the percentile threshold used to identify extreme observations in a dataset calculated as 1 minus the ratio of the maximum possible number of correct signals (A+B) over the total number of observations (n).

$$\alpha = 1 - \frac{A + B}{n}$$

where
α is the threshold percentile for the indicator
$A + B$ is the maximum possible correct signals
n is the total number of observations

This α percentile, subtracted from 1, positions the threshold within the frequency distribution at higher values. Consequently, minimizing the noise-to-signal ratio results in an optimal threshold percentile for each indicator that remains consistent across all countries.

2.2 Binary model

A binary model is a type of regression where the outcome variable is binary, meaning it only takes two values, typically 0 and 1. Those values are representing the two possible choices or states. The model calculates the probability of one choice being made over another based on various explanatory variables. However the econometric challenge is to determine the conditional probability where Y = 1, considering this probability as a function of the explanatory variables. In order to do so, the most common methods are the logit and probit approaches. Where in simple words, we make the assumption that we already know the function of the dependence on the explanatory variables (Horowitz and Savin, 2001).

2.2.1 Logit vs Probit

In the field of statistics, the probit and logit (logistic) model are used as a form of regression characterized by a binary dependent variable, which is limited to two possible outcomes, such as crisis situation or no crisis. The main objective of these model is to calculate the probability that an observation with specific characteristics will be categorized into one or the other of these categories, making these models a method of binary classification (Karmarkar and Vani., 2014). The primary difference between the logit and probit models lies in the function used to link the linear combination of the predictors to the probability of the outcome (Vasisht, 2007).

Here's how these models are represented mathematically.
The logistic regression model (logit model) uses the logistic function to model the probability that a certain observation falls into one of the two categories. The logistic function is defined as follows:

$$P(Y = 1) = \frac{1}{1 + e^{-(\beta_0+\beta_1 X_1+...+\beta_k X_k)}}$$

This formula calculates the probability $P(Y = 1)$ that the dependent variable Y equals 1 using the logistic function where e is the base of the natural logarithm, and β_1 + ... + β_k, are the coefficients of the model for the independent variables X_1,...,X_k, and β_0 is the intercept.

The probit model uses the cumulative distribution function (CDF) of the standard normal distribution to model the probability. The probit model is represented as:

$$P(Y = 1) = \Phi(\beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k)$$

As above, This formula calculates the probability $P(Y = 1)$ that the dependent variable Y equals 1. Φ represents the CDF of the standard normal distribution, β_0 is the intercept, and β_1 + ... + β_k are the coefficients of the independent variables X_1,...,X_k.

2.3 Binary recursive tree

It exists more structured approaches at our disposal compared to the previous one. One such method is the Binary Recursive Tree (BRT). This statistical technique, devoid of parameters, excels in discerning meaningful patterns among indicator variables to forecast binary outcomes.

Through exhaustive examination, the BRT evaluates all potential variables across various threshold values. It then identifies the indicator, along with its optimal threshold, that effectively segregates the dataset into purer sub-samples or more homogeneous child nodes. These subdivisions exhibit a notable shift in crisis probabilities, either escalating or diminishing significantly compared to the sample average (Duttagupta and Cashin, 2011).

Formally, it is a set of rules used to predict a binary outcome, y, based on a group of explanatory variables, x_j, where j ranges from 1 to J. In each part of the tree, the data is divided using a certain value, $\hat{x}_j$, from one of the explanatory variables, into two smaller groups. This division process repeats for each new group until a final group is reached (Ghosh and Ghosh, 2003).

To illustrate, let y represent the occurrence of a crisis, where $y = 1$ if there is a crisis, and $y = 0$ otherwise. The sample is randomly divided into a main sample and a smaller test sample, which is reserved for out-of-sample robustness checks. Within the main sample, the algorithm seeks sequential splits based on explanatory variables and their threshold values that best differentiate between groups. For example, consider a scenario where a large current account deficit is often associated with currency crises and thus may serve as a useful discriminator. However, there will be instances where countries with small deficits experience crises (type I error), and others with large deficits do not (type II error). The algorithm evaluates all observed deficit values in the sample to determine the threshold value x_j^* that optimally distinguishes crisis and non-crisis countries, aiming to minimize the combined sum of type I and type II errors (Ghosh and Ghosh, 2003).

3 Dynamic models

Apart from the signaling approach, in order to implement and calculate an Early Warning System, there exist multiple mathematical models.

Candelon et al. (2014) explain that the models used to predict financial crises should be dynamic. Before looking into why the models should be dynamic, we will have a look at what is a dynamic model.

3.1 Definition

A dynamic model includes real-time data, and expects the values to evolve over time. In other words, the dynamic model describes how a whole system and its properties change with time. This is helpful to analyze relationships between variables that cannot be seen with steady models. This method contrasts with the static model which is based on historical data and fixed parameter (Ellner and Guckenheimer, 2006).

Migon et al. (2005) add a specificity and state that dynamic linear models are parametric models that describe the variation of each parameters and the availability of the data in probabilistic terms. The authors see the dynamic linear models as a generalization of the linear regression models which, throughout time, allows changes in the values of the parameters.

Different types of dynamic models exist. The first one being a model where we include the lagged binary variables (y_{t-1}). The second one includes lagged index (α_{t-1}). In the second approach, every time there is an increase in the index, a linear transmission to the next period happens, which means that the probability of a crisis to occur becomes higher. Whereas, for the first method, the index has to surpass a certain threshold to trigger a crisis in the prior period. Finally, a combination of both approaches can also be used, but it is a more complex method (Candelon et al., 2014).

3.2 Why an EWS model should be dynamic ?

We have now understood the concepts behind dynamic models, so lets look into why when using EWS, the models should be dynamic ?

Candelon et al. (2014) highlight the need for an EWS to be dynamic due to the fact that it has better forecasting abilities. Indeed, the dynamic EWS performs better or at least has the same performance in-sample but also out-of-sample. It is also the case when comparing the forecast horizon. The dynamic model performs better looking at one period ahead, but when looking a bit further, six months ahead, the dynamic one out-performs the static one as well.

Empirical research

In this section, we undertake a quantitative analysis to explore the dynamics of past financial crises across a diverse set of countries. Our empirical research will replicate and expand upon existing studies to identify and evaluate the impact of key variables across different types of financial crises (currency, debt or banking).

4 Methodology

First, we will define the geographic areas we are going to study in our research. Our sample is focused on 12 different countries chosen for their geographic diversity and the different degrees to which they have suffered or been protected from financial crises. These countries include Argentina, Australia, Brazil, Finland, Greece, Mexico, Poland, Portugal, Spain, South Africa, Turkey, and the USA.
Given that Australia has not experienced significant banking, currency, or debt crises, it has been excluded from this particular analysis.

Regarding the time-frame, we will use in our Early Warning System, it spreads from 1980 to 2019, covering approximately 37 years of financial data. Gathering consistent data across all countries for this duration was challenging, and in some cases, impossible. When data were unavailable, we decided to substitute these non-existing values with zeros. This approach not only simplified data handling but also resolved some coding complications we faced.

OOnce we have identified and described all our variables, detailed in the subsequent section, we will proceed to test the relationships between each variable. We will examine the correlations and multicollinearity among the variables. To fully understand the relationship between each variable, we will perform a bivariate regression. Additionally, we will use the Pearson correlation coefficient, which results in a correlation matrix, to gauge how strongly our variables are correlated.

Regarding multicollinearity, we will initially perform a simple regression that features an independent variable against all other variables concurrently and then run a collinearity test. This approach will help us determine the presence of multicollinearity among the variables.

Subsequently, we will implement a logistic estimation model to estimate the probabilities of financial crises to occur. This method choice has been inspired by one of the methodologies reviewed in Frankel and Saravelos' (2012) work. Our implementation will involve constructing a binary dependent variable, which indicates the presence or absence of a financial crisis within a given country-year observation.

In the final stage of our empirical study, we are going to forecast the probabilities of financial crisis to take place in each country included in our research. Then, we will evaluate the accuracy and consistency of our forecast by implementing evaluation metrics as MAE, MSE and RMSE.

All statistical analyses and model implementations will be conducted using RStudio, which provides the necessary tools for data manipulation, statistical modeling, and graphical representations.

5 Dataset

Our dataset comprises 16 financial and macroeconomic variables, collected from 1980 to 2019 with data points recorded on quarterly basis. These variables are sourced from multiple well-known databases. Indeed, a significant portion of our data comes from the Federal Reserve Bank of St. Louis (FRED)[1], while additional data are extracted from the Organisation for Economic Co-operation and Development (OECD)[2] and the International Monetary Fund (IMF)[3].

Given the diverse data availability across different countries, we encountered challenges with missing values. To address this and enable consistent model implementation, we substituted missing data points with zeros. We acknowledge that this approach may introduce bias into our analysis, which will be carefully considered when interpreting the results.

[1]FRED website: https://fred.stlouisfed.org/
[2]OECD database: https://data.oecd.org/
[3]IMF database: https://data.imf.org/

6 Variables

6.1 Consumer price index

The Consumer Price Index (CPI) serves as a fundamental economic measure, reflecting changes in the price level of a standard basket of goods and services purchased by households over time. Specifically, CPI energy focuses on tracking variations in energy prices, such as those of gasoline, electricity, and natural gas (OECD, 2024).

CPI serves as a key measure of inflation, reflecting changes in the cost of living. When CPI rises, it indicates that consumers are paying more for the same basket of goods and services, which can erode purchasing power and potentially lead to reduced consumer spending (OECD, 2024).

Central banks closely monitor CPI to inform their monetary policy decisions. It serves as a benchmark for adjusting various financial elements tied to the cost of living. This includes labor contracts, pension payments, and government benefits, which often incorporate CPI-based adjustments. When CPI rises, these payments may increase to keep pace with the rising cost of living (OECD, 2024).

6.2 Interest Rates: Long-Term Government Bond Yields

Long-term interest rates, typically referring to the yields on government bonds with maturities of ten years or more, play a critical role in the financial landscape. They represent the cost of borrowing over extended periods, typically referring to yields on government bonds with maturities of ten years or more. They are influenced by factors such as lender pricing, borrower risk, and bond market fluctuations. These rates impact investment decisions and serve as benchmarks for setting interest rates across the economy (OECD, 2024).

The yield on the 10-year Treasury bond is particularly significant, serving as a proxy for mortgage rates and reflecting investor confidence levels. When confidence is high, bond prices drop, leading to higher yields, while low confidence prompts bond prices to rise and yields to fall. Overall, long-term interest rates play a crucial role in shaping economic activity and investor sentiment (OECD, 2024).

6.3 Interest Rates: 3-Month or 90-Day Rates and Yields

Short-term interest rates denote the rates at which short-term loans are transacted among financial institutions or the rates at which short-term government securities are issued or traded in the market. These rates, usually expressed as percentages, are calculated as daily averages. They are often derived from three-month money market rates and are commonly referred to as "money market rates" or "treasury bill rates" (OECD, 2024).

6.4 Real gross domestic product (GDP)

Gross Domestic Product (GDP) is a measure of the total monetary value of all final goods and services produced within the borders of a country during a specific period, typically a quarter or a year. It encompasses all economic activities conducted within a nation's territory, including goods and services produced for sale in the market, as well as some non-market production, such as government-provided defense or education services. GDP serves as a crucial economic indicator, reflecting the overall health, performance of an economy and plays a significant role in shaping policy responses and influencing outcomes during times of crises (IMF Glossary, 2021).

We are using the variation of GDP in our dataset so that we can incorporate this fundamental economic measure into our computational model, enabling more comprehensive analysis and prediction of economic trends and outcomes.

6.5 M2/Reserve

M2 is a measure of the U.S. money stock that includes M1 (currency and coins held by the non-bank public, checkable deposits, and travelers' checks) plus savings deposits (including money market deposit accounts), small time deposits under 100,000$ and shares in retail money market mutual funds (Stlouisfed, s.d.).

The money multiplier, also known as the M2/Reserve Ratio, measures the relationship between the money supply (specifically M2) and the reserves held by banks. It quantifies how many more dollars are in circulation compared to the reserves. For instance, a money multiplier of 10 signifies that there are ten times more dollars in the economy than in reserves. This concept illustrates how an initial deposit into a bank leads to a significant increase in the money supply beyond the original deposit amount (Vedantu, s.d).

A higher money multiplier indicates a greater potential for banks to create additional money through lending. Central banks use changes in reserve requirements and open market operations to influence the money multiplier and, consequently, the money supply. By adjusting reserve requirements or conducting open market operations (Vedantu, s.d).

6.6 The Balance of Payments (BOP)

The Balance of Payments (BOP) serves as the mechanism through which countries monitor all international financial transactions within a specific timeframe, typically on a quarterly and annual basis. It accounts for all transactions conducted by both the private and public sectors to ascertain the flow of money into and out of a country. Transactions resulting in money inflows are recorded as credits, while those involving outflows are categorized as debits (Kenton, 2024).

The BOP influences for example exchange rates by reflecting the supply and demand for a country's currency in international markets. A surplus in the BOP, indicating strong demand for a country's exports, may lead to an appreciation of its currency (Kenton, 2024).

6.7 Exchange rate

An exchange rate is the rate at which one currency can be exchanged for another currency. It plays a critical role in facilitating international trade and financial transactions by determining the relative value of different currencies. Exchange rates are influenced by various factors, including supply and demand dynamics, interest rates, inflation rates, economic performance, geopolitical events, and government intervention in currency markets (OECD, 2024).

Changes in exchange rates can impact trade flows, as a stronger domestic currency makes exports more expensive for foreign buyers and imports cheaper for domestic consumers. Conversely, a weaker currency can boost exports by making them more competitive in international markets but may also increase the cost of imported goods (Chen, 2024).

6.8 Industrial production

Industrial production refers to the total output generated by industrial establishments within a specified geographical area, typically a country or region. It encompasses various sectors such as mining, manufacturing, electricity generation, gas production, steam, and air-conditioning (OECD, 2024).

This economic indicator quantifies the volume of production output and is often measured using an index relative to a reference period. The index serves to express changes in the level of industrial production over time, providing insights into the growth or contraction of industrial activity within the economy (OECD, 2024).

6.9 Reserve

Total reserves excluding gold refers to the sum of a country's foreign exchange reserves held in assets other than gold. These reserves typically consist of foreign currencies, such as U.S. dollars, euros, yen, or other major currencies, as well as certain reserve assets held with international financial institutions like the International Monetary Fund (IMF) or other central banks (OECD, 2024).

These reserves serve as a crucial component of a country's overall reserves and play a vital role in supporting its currency and managing its external financial obligations. Central banks hold these reserves to ensure stability in the foreign exchange market, provide liquidity in times of crises, and maintain confidence in the domestic currency (OECD, 2024).

We are using the variation of reserve in our dataset so that we can incorporate this measure into our model.

6.10 3-Month Treasury Bill Secondary Market Rate

The 3-Month Treasury Bill Secondary Market Rate refers to the interest rate at which 3-month Treasury bills are traded on the secondary market. Treasury bills, also known as T-bills, are short-term debt securities issued by the United States government to finance its operations and manage its cash flow. The secondary market for Treasury bills allows investors to buy and sell these securities before their maturity date. The 3-month Treasury Bill secondary market rate reflects the prevailing market interest rate for these securities at any given time (Dupont et al., 1999).

This rate is determined by supply and demand dynamics in the market and is influenced by factors such as changes in monetary policy, economic conditions, investor sentiment, and the overall level of interest rates in the economy (Loo, 2023).

The 3-Month Treasury Bill Secondary Market Rate serves as a benchmark for short-term interest rates in the broader economy. Changes in this rate can affect borrowing costs for businesses, consumers, and governments. Changes in the 3-Month Treasury Bill Secondary Market Rate can signal shifts in market sentiment and investor confidence (OECD, 2024).

6.11 Market Yield of 10-Year U.S Treasury Securities

The 10-Year Constant Maturity yield represents the yield on Treasury securities with a maturity of exactly 10 years, as determined by the U.S. Treasury Department. It reflects the annualized return that investors would receive if they purchased and held a 10-Year Treasury Security until maturity, with interest payments made semi-annually (U.S. Department of the Treasury, 2022).

The Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity is an important benchmark for long-term interest rates in the financial markets. It is widely used by investors, economists, and policymakers to assess the cost of borrowing for the U.S. government and to gauge broader trends in interest rates and economic conditions (Zucchi, 2023).

Changes in the 10-Year Treasury yield can reflect broader trends in global economic conditions. For example, a decline in the yield may indicate expectations of weaker economic growth or deflationary pressures, which could have spillover effects on other countries, particularly those with close economic ties to the United States (CBRE, 2023).

6.12 Import goods and services

Import of goods and services, as an economic variable, refers to the total value of products and services purchased from foreign sources by residents of a country within a specific period (The World Bank, s.d.).

This variable encompasses all types of goods and services brought into the country, including raw materials, finished goods, and various services such as transportation, tourism, and intellectual property rights. It serves as a crucial component of a nation's balance of payments and reflects the level of international trade and economic integration (The World Bank, s.d.).

6.13 Export goods and services

Export of goods and services refers to the commercial activity of selling products and services produced within a country to customers located in other countries. Exporting goods and services is an essential component of international trade and contributes significantly to a country's economic growth, employment opportunities, and overall prosperity (The World Bank, s.d.).

6.14 Money Supply

In summary, M1 represents the most liquid assets, M2 includes additional less liquid assets, and M3 is the broadest measure of money supply, encompassing all forms of money and liquid assets. For each money supply variable, we are utilizing the variation in their values to better align them with our mathematical model.

6.14.1 M1

M1 refers to the narrowest measure of money supply, encompassing the most liquid forms of money. It includes physical currency (such as coins and paper money) in circulation, demand deposits (checking accounts), and other liquid assets that can be quickly converted into cash (The investopedia team, 2023).

6.14.2 M2

M2 is a broader measure of money supply than M1. It includes all components of M1, as well as savings deposits, time deposits (such as certificates of deposit or CDs) with a value of less than \$100,000, and money market mutual funds held by individuals (The investopedia team, 2024).

6.14.3 M3

M3 is the broadest measure of money supply and includes all components of M2, plus large time deposits (those with a value of \$100,000 or more), institutional money market funds, and other large liquid assets (Chen, 2023).

7 Relationship between variables

7.1 Bivariate regression

Bivariate regression serves as a useful method in assessing the significance of variables in crisis measure. In our research, we draw upon methodologies advocated by Frankel and Saravelos (2012), whose framework hinges on identifying key indicators such as the nominal local currency percentage change against the US dollar, equity market returns, GDP, industrial production, and recourse to IMF financing. These indicators serve as barometers for measuring crises.

Our statistical approach entails conducting bivariate regressions utilizing these key indicators as dependent variables and various independent variables, predominantly macroeconomic in nature, that are closely associated with financial crises.

We proceeded to perform bivariate regressions utilizing four key indicators: CPI, GDP, the nominal local currency percentage change against the US dollar, and industrial production. These selections were made in alignment with the indicators utilized by Frankel and Saravelos (2012).

The detailed bivariate regression tables for each country are available in the appendices (see Appendix B.2).

7.1.1 Dependant variables

- CPI (Consumer Price Index)
- GDP (Gross Domestic Product)
- Nominal local currency percentage change against the US dollar (Ex rate)
- Industrial production (IP)

7.1.2 Independent variables

- Long-Term Interest Rate (IR LT)
- Short-Term Interest Rate (IR CT)
- M1
- M2

- M3
- Balance of Payments: Current Account (BoP)
- Reserves (Res)
- 3-Months U.S Treasury Bill (3M)
- 10-Year U.S Treasury Securities (10Y)
- M2/Reserve (Multi)
- Import (Imp)
- Export (Exp)

7.2 Bivariate regression results

Three dimensions need to be considered. The first dimension concerns the statistical significance of the test, indicated by the t-statistic. The t-statistic measures the size of the regression coefficient relative to the standard error of the estimate. For a 95% confidence level, the absolute value of the t-statistic must exceed 1.96 for the test to be considered significant and for the null hypothesis, which states there is no significant relationship between the variables, to be rejected. Below this threshold, the null hypothesis cannot be rejected, and while the coefficient may not necessarily be poor, it cannot be considered significant.

Therefore, to confirm significance, attention should be directed to the p-value of the independent variable.

For each country, a comprehensive table has been constructed, detailing the regression results for the four dependent variables. These tables include the coefficients of the estimated independent variables alongside their respective t- values. To aid in interpretation, a color-coding system has been employed to signify the significance level based on the p- value.

If no color is indicated, it means that the variable is not deemed significant. Green highlighting denotes significance at an alpha level of less than 0.05, while a combination of green and yellow signifies significance at an alpha level of less than 0.01, indicating high significance.

Notably, a significant portion of the independent variables demonstrate significance at the 0.01 level. This observation instills confidence in the reliability and usability of our dataset, suggesting its robustness in capturing meaningful relationships within the analyzed context.

The second dimension entails examining the signs of the coefficients. It is evident that while many coefficients vary inconsistently between countries. However, we notice that the most significant variables (alpha <0.01) tend to have positive coefficients. In other words, as the independent variable increases, the dependent variable also tends to increase. This positive association suggests that changes in the independent variable are associated with corresponding changes in the dependent variable in the same direction.

The final dimension pertains to regression coefficients, which indicate the strength of the relationship between two variables. The regression coefficient measures the proportion of volatility in the dependent variable explained by the independent variable. For instance, the regression coefficient of CPI as a function of Long-term Interest Rate for Brazil is 0.1717, indicating that in our sample, an increase of 1% in the Long-term Interest Rate results (all else being equal) in a 0.1717% increase of the CPI.

Below is a table representing regression results for Brazil, highlighting the significance of independent variables:

Column1	CPI	Column2	GDP	Column3	EXCHANGE RATE	Column4	Industrial prod	Column5
	Estimate	*t value*	*Estimate*	*t value*	*Estimate*	*t value*	*Estimate*	*t value*
(Intercept)	18.52559	2.503788444	8681.236	0.591429121	0.827752836	2.628038685	-12.86120977	-2.107119208
`INTREST RATE LT`	0.171792	0.335275973	9312.446	9.161326521	0.025270631	1.158565619	0.157661892	0.372998852
`IR CT`	-0.023784	-0.134631478	1030.383	2.940060082	0.006567637	0.873326747	-0.078109756	-0.535980678
M1	2.18E-11	0.516597994	8.37E-07	9.989268521	-6.75291E-12	-3.756932711	1.02753E-10	2.949935231
M2	3.03E-12	0.145329511	-2.94E-07	-7.099742013	-2.52745E-12	-2.843729657	-4.28425E-11	-2.487458983
M3	-1.2E-12	-0.154401432	6.2E-08	4.018776859	1.16287E-12	3.510204424	1.10671E-11	1.723889419
`BOP : CURRRENT ACCOUNT`	0.72007	1.30270241	676.0232	0.616491741	0.100932403	4.289495849	-0.604808326	-1.32638502
Reserve	-3.79E-11	-2.050880276	7.61E-07	20.73782183	8.33961E-12	10.58772571	2.72878E-11	1.787727964
`10Y CONSTANT MATURITY`	-5.188207	-2.874063327	-1187.714	-0.331654798	-0.19893677	-2.588806044	2.78345565	1.869153485
`3Y CONSTANT MATURITY`	-2.091705	-2.628635794	-1938.625	-1.228058882	-0.102612891	-3.029264463	1.881605318	2.866421185
Multi	-1.097676	-1.911912611	5459.849	4.793687627	0.247389561	10.12232903	0.705814532	1.490273176
`export (Variation previous peri	0.066637	0.638090162	-105.997	-0.511631791	0.008484453	1.908524334	-0.066898256	-0.776541801
import	-0.023807	-0.215415013	-734.3014	-3.349173803	-0.012929595	-2.748262645	0.241420024	2.648029366

Figure 2: Results of bivariate analysis for Brazil

Upon reviewing all the regressions and analyzing their results, our initial conclusion is that we encountered a data issue. In order to maintain a consistent sample size, we had to input zeros for missing data, which in turn introduced bias into our coefficients. Taking the example of Finland, Greece or Japan, we found insufficient information regarding variables CPI Energy, M3, and short term interest rate. It is evident from the results (where green cells indicate significance with a p-value <0.05) that variables with incomplete information are not significant.

Column1	CPI	Column2	GDP	Column3	EXCHANGI	Column4	Industrial p	Column5
	Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value
(Intercept)	0.321245707	3.018402044	43670.55117	11.864092	1.25919709	1.5239904	2.48986284	0.934656141
`CPI energy`	0.089865153	6.676216399	276.2464091	0.59339217	-0.1417259	-1.356242	0.08335627	0.247408164
`INTREST RATE LT`	0.008044679	0.787608192	113.4310622	0.32109947	0.10872355	1.371115	-0.15477162	-0.605382006
`IR CT`	0.004269032	0.505511155	-559.153852	-1.91442658	0.01588963	0.2423616	-0.01564811	-0.074028659
`BOP : CURRRENT ACCOUNT`	-0.013176021	-2.05160627	1036.267699	4.66538818	0.21308542	4.2737808	0.39199436	2.438519595
Reserve	-3.89944E-05	-3.75445971	1.843584705	5.13232303	-0.0002201	-2.730032	-0.00016583	-0.637906303
`10Y CONSTANT MATURITY`	0.046809834	1.791248694	-8833.919216	-9.77413401	0.37082765	1.8278463	0.07066322	0.10803112
`3Y CONSTANT MATURITY`	0.041042329	3.491268602	-5907.239962	-14.5292084	0.61448716	6.7330655	0.14449064	0.491052208
`export (Variation previous period)`	-0.001579018	-0.50401154	-35.27360424	-0.32554373	-0.0152798	-0.628232	0.15058802	1.920350589
import	0.000847503	0.280328418	-79.1031033	-0.75652875	0.00061749	0.0263091	0.14421474	1.905777391

Figure 3: Results of bivariate analysis for Finland

Column1	CPI	Column2	GDP	Column3	EXCHANGE RATE	Column4	Industrial production	Column5
	Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value
(Intercept)	-0.127533296	-0.625472964	40376.37631	9.111217496	0.393770695	1.15716869	-0.319209972	-0.536800555
`CPI energy`	0.062919804	2.959681476	-679.8856607	-1.471490998	-0.041083553	-1.157960987	-0.020443247	-0.329730434
`INTREST RATE LT`	-0.022536711	-1.849768404	1136.337148	4.291391557	0.021538194	1.059264548	0.038606181	1.086513701
`IR CT`	-0.000463084	-0.054901877	-175.2605334	-0.95603961	-0.009250666	-0.657156762	0.021105499	0.857975356
`BOP : CURRRENT ACCOUNT`	0.030576791	2.6850407	-3369.847101	-13.61549037	0.022335766	1.175244272	-0.005995496	-0.180524292
Reserve	-2.26418E-05	-2.125311498	1.538991923	6.646779566	-6.31047E-05	-3.54928557	-1.04986E-05	-0.337902935
`10Y CONSTANT MATURITY`	0.272434811	3.937043934	-9208.721129	-6.123096445	0.223704507	1.937094104	0.041285473	0.204576844
`3Y CONSTANT MATURITY`	0.183236039	7.886166852	-4604.30207	-9.117651579	0.359568751	9.272681271	0.047952544	0.707649606
`export (Variation previous period)`	-0.006366625	-1.86044924	-36.74434119	-0.494041137	0.001860172	0.325709228	0.034797257	3.486623816
import	0.005325735	1.994734012	4.708032743	0.081135147	-0.002473347	-0.555084083	-0.0171647	-2.204414183

Figure 4: Results of bivariate analysis for Greece

Column1	CPI	Column2	GDP	Column3	EXCHANGE RA	Column4	Industrial produ	Column5
	Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value
(Intercept)	0.019268603	0.084812129	3483.031104	0.396893922	84.65485375	5.77031311	-14.38083932	-1.873175556
`CPI energy`	0.135069415	8.58085223	37569.06854	2.29227714	0.643128219	0.632718801	0.139950794	0.263108739
`INTREST RATE LT`	-0.017500271	-0.595302584	44946.08938	0.8739567	2.693324638	1.418800974	-2.083399368	-2.097258843
`IR CT`	-0.039108382	-0.4239593	1.0483E-11	0.022851006	-8.596534548	-1.443170012	-13.1451899	-4.217039604
M1	1.68083E-16	0.204266845	2.48692E-10	0.914562427	4.15656E-13	7.822560768	2.71142E-15	0.097511921
M2	-9.96225E-17	-0.204251828	-1.20192E-10	-1.643826971	-2.21657E-13	-7.037690848	6.04709E-16	0.036689474
M3	-2.12569E-17	-0.162083207	29442.48995	2.864199416	-5.50319E-14	-6.498181663	1.10695E-15	0.249776865
`BOP : CURRRENT ACCOUNT`	-0.034678738	-1.880824655	1.47162E-07	1.901317655	4.87992929	4.098626312	0.999692356	1.604493264
Reserve	6.56021E-14	0.472532607	-45363.20634	-2.118510022	-2.95496E-12	-0.329613604	4.89597E-12	1.04361273
`10Y CONSTANT MATURITY`	0.008238791	0.214509531	-25281.74977	-2.409839561	7.243638185	2.920650612	3.161499637	2.435918344
`3Y CONSTANT MATURITY`	0.024729435	1.314169856	-35.55080173	-5.428386394	5.059775339	4.163976917	2.50010578	3.931716506
Multi	3.79865E-06	0.323375736	-40.44203054	-0.019044029	0.010572304	13.93757022	0.000237099	0.597302922
`export (Variation previous perio	0.012390898	3.253006948	452.4442306	0.219817428	-0.557264586	-2.265600899	-0.115430513	-0.896787034
import	-0.014561775	-3.944279469	0	0	-0.228852839	-0.959951852	0.426332429	3.417340444

Figure 5: Results of bivariate analysis for Japan

What is important to grasp initially is that the data are biased. This leads us to make a decision regarding the significance of the data. The question becomes: which variables should we consider, given that they are significant for some countries but not for others ? We have chosen to retain the data if it is significant for more than 40% of the countries. Additionally, we will adapt our logistic estimation model based on how the model reacts to biased variables.

We noticed that most of the variables showed significant regression results . Firstly, because we managed to gather data for these variables, and more importantly, they are reliable. We had the intuition that these variables would have an impact given their importance in the overall macroeconomy.

In our analysis, we observed that one independent variable was not consistently significant. Therefore, we decided to remove it from our crises indicators. This variable is imports.

We will consider the remaining variables significant for our model. It is important to note that the sample size is relatively small, and a larger sample would likely lead to better coefficient significance.

7.3 Correlation Analysis

We are now going to analyse the correlation matrices of the variables for each country included in our empirical research. It is important to have an initial understanding of the strength and direction of the relationships between variables for the future of our study. Indeed, the Pearson correlation quantifies the degree to which different variables are linearly related. Each coefficient ranges from -1, implying a perfect negative correlation, to +1, meaning a perfect positive correlation. A coefficient equal to 0 implies no linear correlation (Turney, 2022).

To visually interpret these relationships, we will utilize heatmaps. These diagrams are particularly effective in highlighting the degrees of correlation among variables. The detailed correlation matrices for each country are available in the appendices (see Appendix B.2).

It is important to note that some entries in the matrices might be marked as 'NA', represented by grey sections in the heatmaps. These indicate missing data for variables that are not available for certain countries.

Figure 6: Heatmap for Argentina

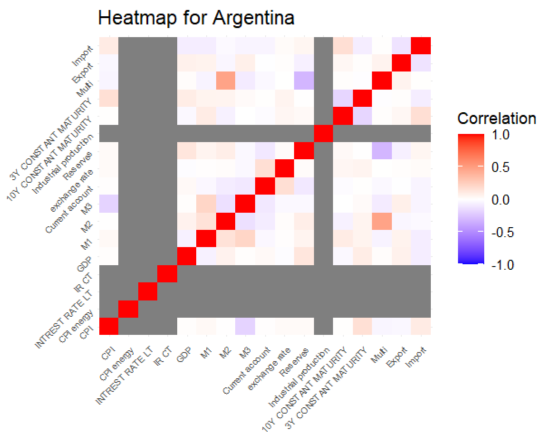
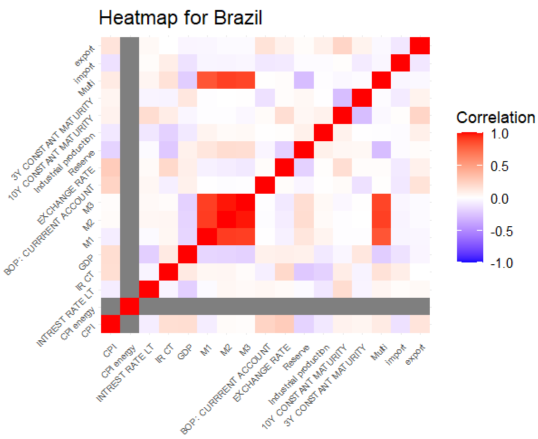


Figure 7: Heatmap for Brazil



Argentina does not show very strong correlations between any of its variables. However, we can notice some moderate positive correlations between M2/reserves and the money supply

(M2) and a negative moderate correlation between M2/reserves and the reserves. Brazil shows a robust positive correlation between all types of money supply (M1, M2, M3) and M2/reserves.

Figure 8: Heatmap for Finland

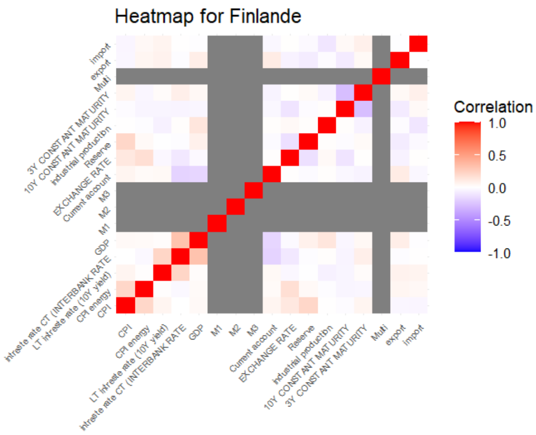
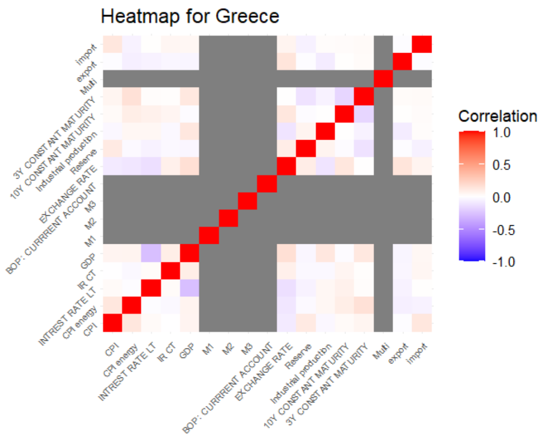


Figure 9: Heatmap for Greece



Finland does not show any strong correlations between its variables. However, we can see a moderate negative relationship between the 3-Month Treasury Bill and the 10- Year Constant Maturity. Additionally, we notice a moderate positive correlation between the CPI and reserves, and the CPI energy with the exchange rate. Greece shows that GDP and the long-term interest rate are negatively correlated. GDP is also moderately positively correlated with industrial production, the exchange rate, and the 3-Month Treasury Bill.

Figure 10: Heatmap for Japan

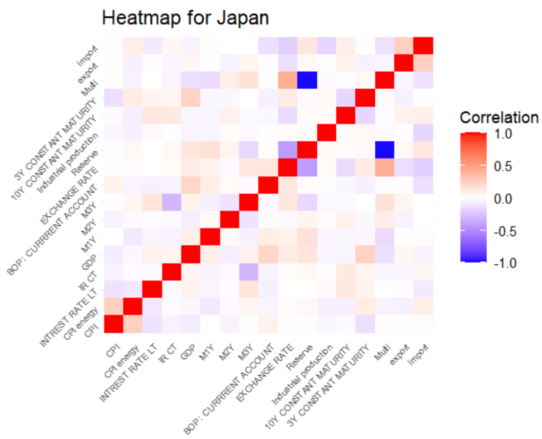
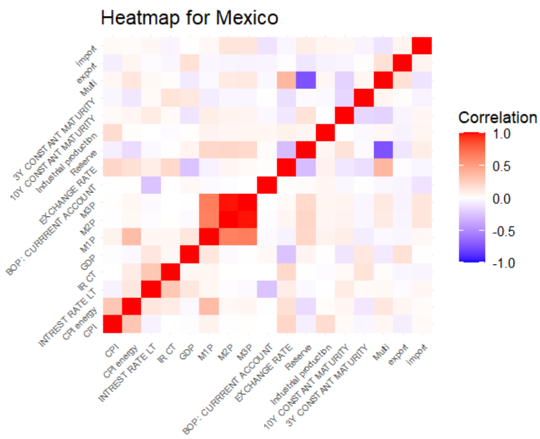


Figure 11: Heatmap for Mexico



Japan shows strong relationships between M2/reserves and the reserves and the exchange rate. There also is a negative correlation between the reserves and M2/reserves and the exchange rate, and a positive correlation between M2/reserves and the exchange rate. Mexico shows a negative correlation between M2/reserves and reserves, similar to Japan. Additionally, we observe robust positive correlations between all the money supplies (M1, M2, M3).

Figure 12: Heatmap for Poland

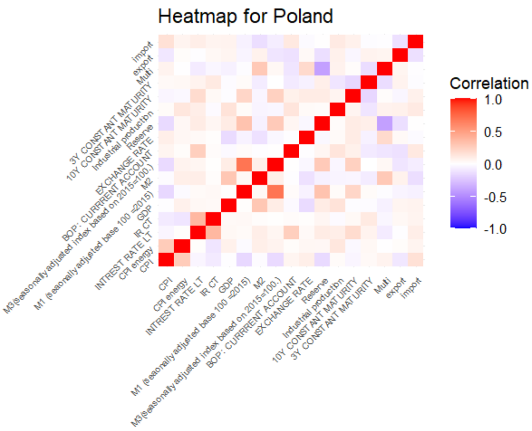
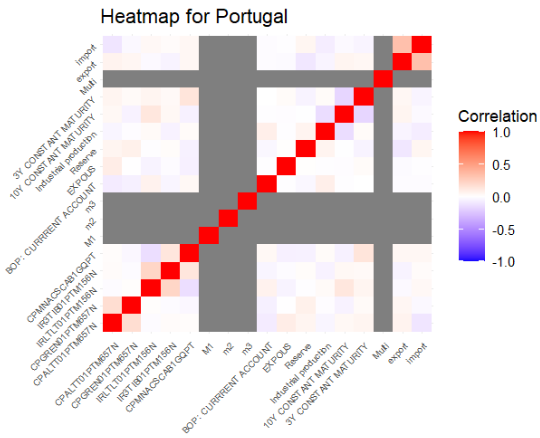


Figure 13: Heatmap for Portugal



Poland shows a positive correlation between the narrow (M1) and broad money supply (M3), and a negative correlation between the reserves and M2/reserves. Portugal does not show any strong correlation between its variables.

Figure 14: Heatmap for South Africa

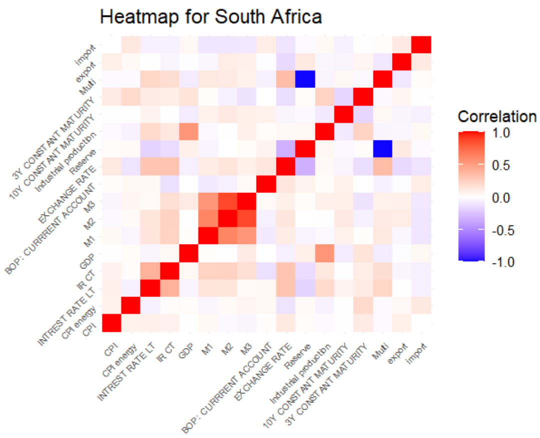
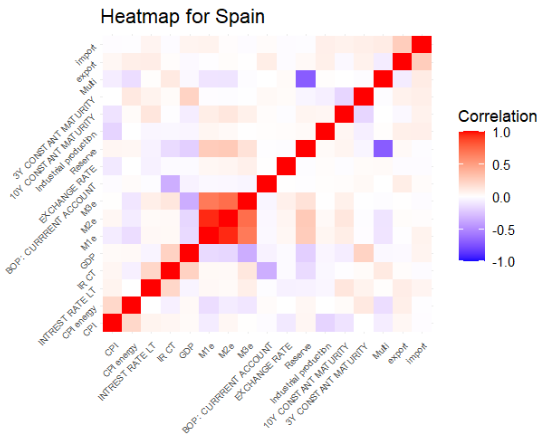


Figure 15: Heatmapfor Spain



South Africa and Spain show strong negative correlation between the reserves and the M2/reserves, and positive correlations occur between M1, M2, M3.

Figure 16: Heatmap for Turkey

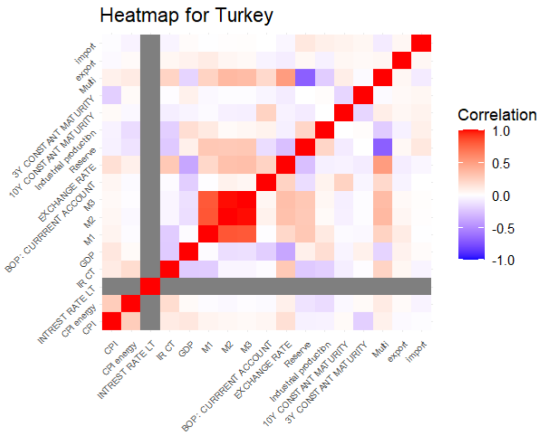
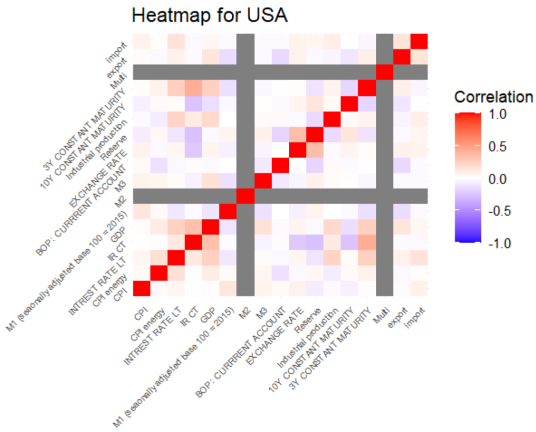


Figure 17: Heatmap for USA



For the United States, no strong or robust correlation have been detected. However, Turkey follows a pattern similar to Mexico and Japan with a negative correlation between M2/reserves and reserves, and positive correlations across money supplies.

7.4 Multicollinearity

In the following section, we assess the presence of multicollinearity among variables. Multicollinearity occurs when there is a significant correlation between two or multiple independent variables. In other words, it allows one variable to be linearly predicted from the others. This condition complicates the analysis by hiding the individual impacts of independent variables on the dependent variable (Bhandari, 2024).

To detect the presence of multicollinearity, we will use the Variance Inflation Factor (VIF) method. The VIF measures how much the variance of an estimated regression coefficient is increased due to correlations among variables. It is calculated as:

$$VIF = \frac{1}{1 - R^2}$$

where R^2 is the coefficient of determination from regressing the CPI variable on all the other variables. A VIF exceeding the threshold, which is set at 10, indicates significant multicollinearity. This suggests a potential need to reconsider the inclusion of the affected variables (Shrestha, 2020).

We examined the results of the VIF tests conducted on all variables across each country. Below, you will find graphs describing the levels of correlation. For countries where no significant correlations were detected, the corresponding graphs are included in Appendix B.3.

Figure 18: Multicollinearity for Japan

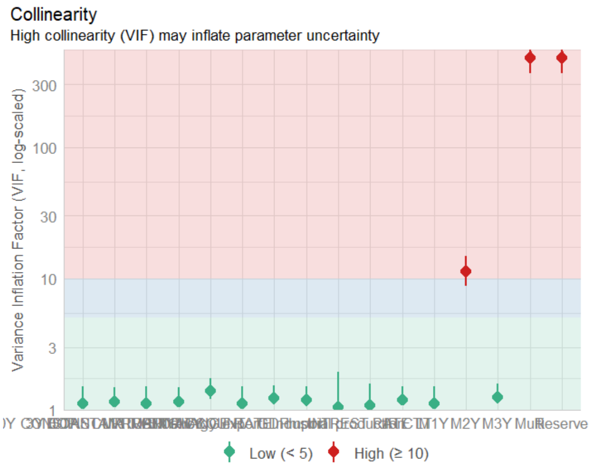


Figure 19: Multicollinearity for Mexico

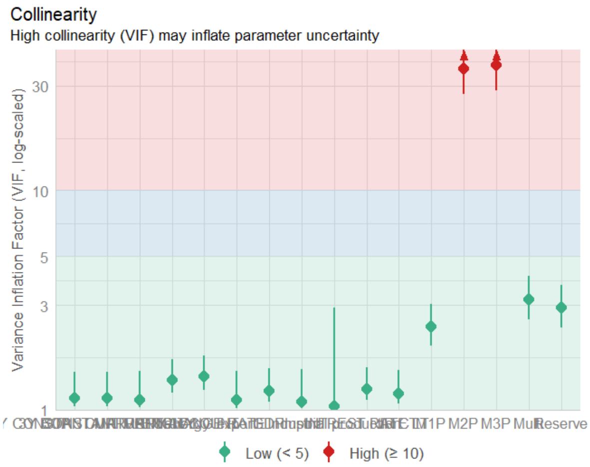


Figure 20: Multicollinearity for Brazil

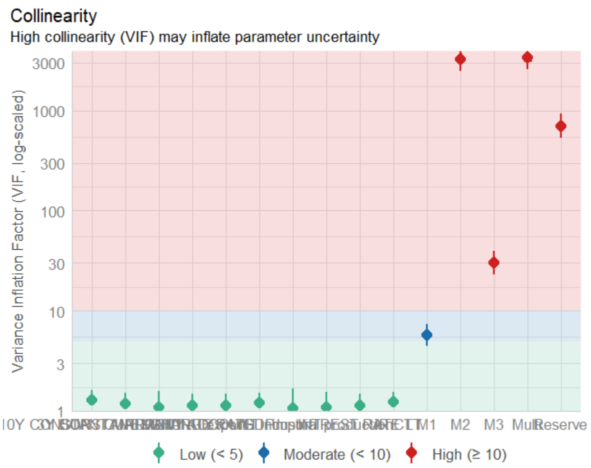


Figure 21: Multicollinearity for Spain

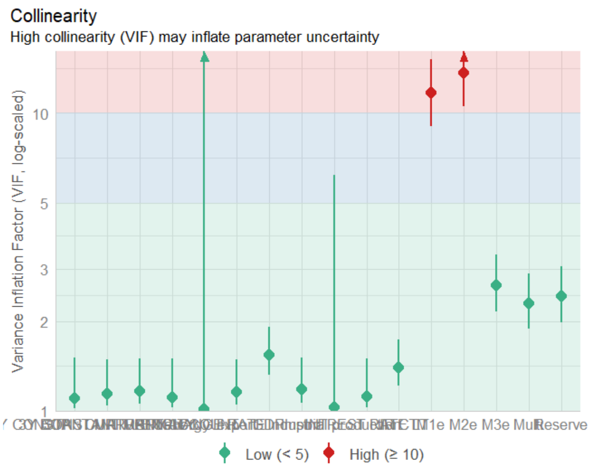


Figure 22: Collinearity for South Africa

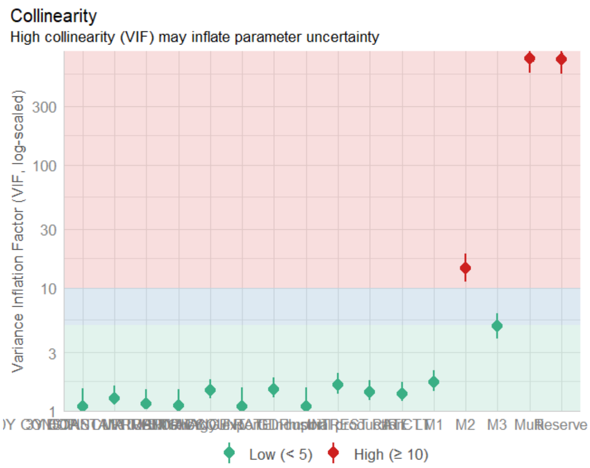
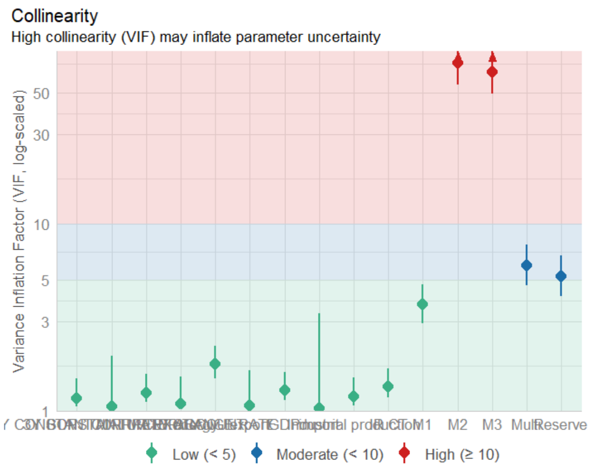


Figure 23: Multicollinearity for Turkey



From the results obtained, it is evident that most variables do not show any multicollinearity. However, some exceptions have been identified in variables within six out of twelve countries: Brazil, Japan, Spain, Mexico, South Africa and Turkey. In each of these countries, Money Supply (M2) consistently shows signs of multicollinearity.

Additionally, we notice that the multicollinearity for each country remains more or less the same. Indeed, the broadest money supply (M3) appears highly correlated for Brazil, Mexico, and Turkey. The reserves are multicollinear in Japan, Brazil, and South Africa. Finally, the M2/Reserves shows multicollinearity in South Africa, Japan and Brazil. Spain stands out with M1 as the only significantly correlated variable unique to it.

Our findings suggest that the presence of multicollinearity is highly prevalent in variables that are related to money supply. This is likely due to their inter-correlated nature of the variables.

Despite these findings, we have decided to maintain the variables that showed multicollinearity for two reasons. Firstly, multicollinearity is not prevalent in most of the countries, which means removing these variables could unnecessarily bias the model for other countries. Secondly, we have seen in the bivariate regression that they are strongly significant. Detailed VIF values can be found in Appendix B.4.

8 EWS dynamic model

In this next section, we have modeled the probability of occurrence of a financial crisis. After having done the modeling, then we proceeded with a specialization model that helped in identifying the most relevant variables for each type of financial crises.

8.1 Dichotomous Variable

We needed to first construct a dichotomous variable, that is, a binary variable which takes value 1 if a crisis is taking place, and 0 if otherwise. That binary variable is, now, our dependent variable in the logistic estimation model.

We will use the database of Nguyen et al.(2022) to create our binary variable Y (the database can be found in the appendix C.1). We have the data for every year in which a crisis of a given type occurred for the whole panel of countries from his database. Of course, we will focus on the countries we have chosen.

That said, to simplify our database and transform our dichotomous variable into the same frequency as our other variables, we are making the hypothesis that if a crisis had taken place in some year, it was within each quarter of that year, so that we had quarterly data instead of annual data. In other words, our binary variable equals 1 for all four periods for each year that a crisis occurred for a given country, and 0 otherwise. We have created a dichotomous variable for debt, currency, and banking crises for each country.

8.2 The logit model

In our study, once we had defined a binary response variable, we used a logistic estimation model to estimate the probability of the dependent variable being equal to 1, based on the independent variables (X), which are included in our model. Remember that, as it has been indicated above, the logistic estimation model is estimated as:

$$P(Y = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k)}}$$

This equation models an underlying latent tendency Y^*, which determines the binary out-

come.
While Y^* itself is not directly observed, it conceptually represents the linear combination of predictors and a logistic error component that affects the probability of occurrence of the event (Bartolucci, and Farcomeni, 2009). The logistic function transforms this linear combination into a probability that lies between 0 and 1.

8.3 Specification model

Previously, we have defined all our dependent and independent variables and implemented our logistic estimation model. In this particular section, our aim is to look for the key and most effective variables to help us know and predict if a crisis is taking place or not.

For this purpose, we decided to use the model's specification or the stepwise regression method. The basic idea is pretty simple: we have proceeded in a backward elimination, meaning we have started with the logistic estimation model containing all of our variables, then removed the least significant one at a time until all the included variables are statistically significant.

Different criteria exist to check the significance, such as ROC, P-value, or AUC. However, we have decided to use the P-value criterion, as it is the one we are most familiar with. Hence, at each step, we remove the variable with the highest P-value until all remaining variables have a P-value of less than or equal to 0.05, at which point they are considered statistically significant.

We should, however, be aware that some variables were not available for certain countries, so our results may be slightly biased. Moreover, there were some cases where our model performed better, meaning a higher R^2 score and graphically better outcomes, if we considered some non-significant variables.

Once we have identified, for each country, the most significant variable depending on the crisis, we calculated how many times that variable is significant overall. We can then make a generalization, from there, actually stating which is the most effective variable, based on the crisis.

8.4 Results

The basis of our work is to determine which variables are the most significant and, therefore, should be included in our Early Warning System (EWS) model, depending on the type of crisis. Before conducting our tests, we hypothesized that the significant variables would vary according to each type of crisis. Our objective was to identify patterns where one or more variables consistently recurred.

As previously mentioned, the primary criterion for variable significance is the P-value. Our methodology involves progressively removing variables that do not demonstrate statistical significance. During this process for each country and type of crisis, we constructed three distinct matrices—one for each type of crisis. These matrices include the countries and variables, alongside a binary indicator that specifies whether a particular variable X for country Y is significant in our model for that type of crisis.

From this data, we were then able to ascertain how frequently each variable was significant across the different scenarios.

8.4.1 Currency crises

We are now going to analyze the results for the currency crisis. The significance matrix can be found below.

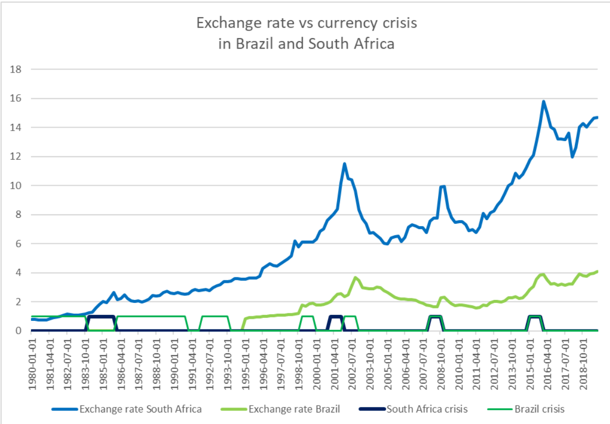
Table 2: Significance matrix

Currency	**CPI**	**CPIE**	**LT**	**CT**	**GDP**	**M1**	**M2**	**M3**	**BOP**	**EX R**	**RES**	**IP**	**10Y**	**3M**	**Multi**	**EXP**
Argentina	0	0	0	0	0	1	0	0	0	0	1	0	0	1	1	0
Brazil	0	0	1	0	0	0	1	0	0	0	1	1	1	0	0	1
Greece	0	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0
Mexico	0	1	1	1	0	0	0	0	0	0	0	0	1	1	0	0
Poland	0	1	0	1	0	0	0	0	0	1	0	0	0	1	0	1
Portugal	1	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0
South Africa	1	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1
Spain	0	0	0	1	0	0	0	0	0	0	0	1	0	1	0	0
Turkey	1	1	0	1	0	0	0	0	1	1	0	0	0	0	1	0
Sum	3	4	3	4	0	1	1	0	1	4	2	4	2	5	2	3

If we look at the results, we can notice that the variable which seems to have been the most significant across all the different countries is the 3-Month Treasury Bill. We also notice that the broadest money supply (M3) has never been significant. This is no big surprise as M3 was rarely significant in the bivariate regressions, while the 3M Treasury Bill was significant 26 times over 39.

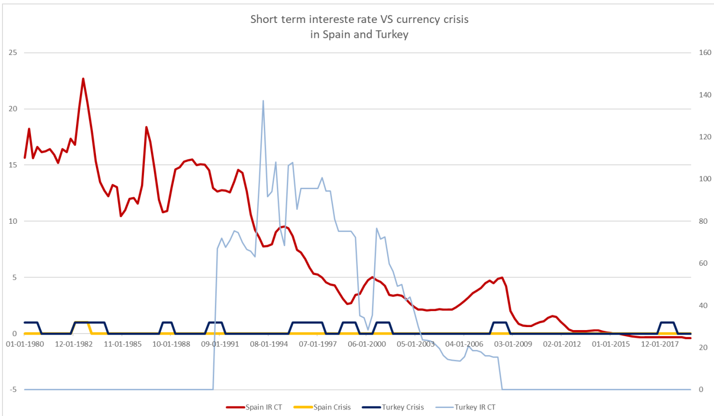
We can also notice that the industrial production, the exchange rate, the CPI energy, and the short-term interest rate were the variables where the significance was just below the highest. In order to better understand if there is a real link between the occurrence of crises and the variables we will plot the dichotomous variable against a few significant variable to better visualize the link.

Figure 24: Exchange rate vs Currency crises for South Africa and Brazil



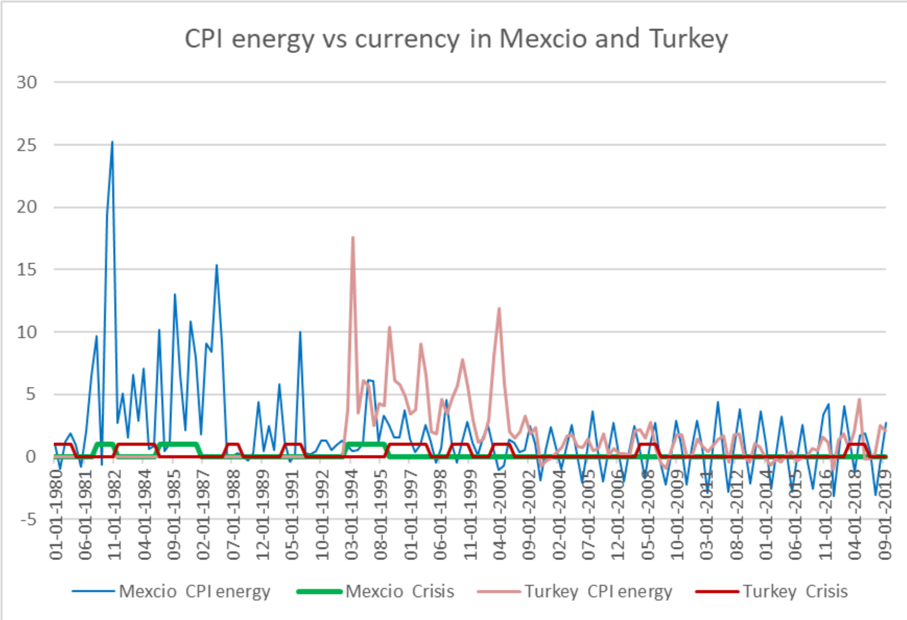
By looking at the dates where a crisis had happened and the exchange rate, we can clearly see a pattern. There is a peaking trend when a crisis had happened in the exchange rate. For example, during the 2015 crisis, we can observe the highest peak for the South African exchange rate and a slight increase for Brazil.

Figure 25: Short term interest rate vs Currency crises for Turkey and Spain



For this graph, we set Turkey's interest rate on the secondary axis for better visualization and interpretation. For Spain, in 1982, the short-term interest rate was at its highest, and a currency crisis occurred at that moment. For Turkey, between 1992 and 2002, the dichotomous variable follows a similar trend as the interest rate. When the interest rate peaked or was relatively high, a currency crisis occurred.

Figure 26: CPI Energy vs Currency crises for Mexico and Turkey



Compared to the previous graph, it is a little harder to identify any pattern between crisis occurrence and the CPI Energy variable. Let us be aware that before 1994, CPI Energy data was not available for Turkey, so it does not appear on the graph. We notice, however, that CPI energy indicates a peak for most of the crises that had taken place. For the multiple crises occurring in Turkey between 1995 and 2002, we find that CPI Energy follows the same pattern, meaning that it goes up and down, and each time the level of the CPI is high, a crisis took place.

Below are the dynamic EWS models for Poland and Greece, here we can see that the model has a better accuracy for Poland that for Greece. The graphs and the results of the logistic estimation model for the remaining countries can be found in Appendix D.1.

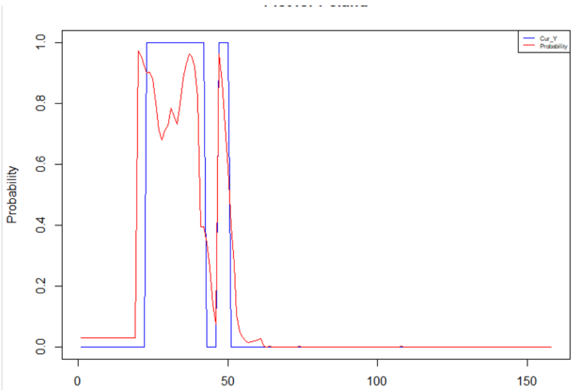


Figure 27: Logit Estimation for Poland

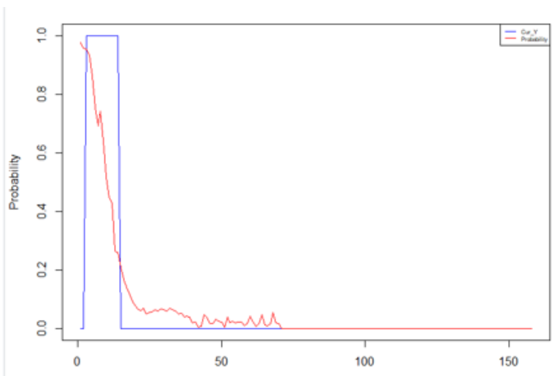


Figure 28: Logit Estimation for Greece

8.4.2 Banking crises

Below is the matrix we created using our logistic estimation model for the banking crises. Our tables show that the 10 Year U.S Constant Maturity variable outperforms the other variables. This variable was significant 9 times our of 11.

Table 3: Significative matrice

Currency	**CPI**	**CPIE**	**LT**	**CT**	**GDP**	**M1**	**M2**	**M3**	**BOP**	**EX R**	**RES**	**IP**	**10Y**	**3M**	**Multi**	**EXP**
Argentine	1	0	0	0	0	1	0	0	1	0	0	0	1	1	0	1
Brazil	1	0	0	1	1	0	0	0	1	1	0	0	1	1	1	0
Finland	1	1	1	1	1	0	0	0	1	0	1	1	1	1	0	1
Greece	0	0	1	1	0	0	0	0	0	1	0	0	1	0	0	0
Japan	0	0	0	1	0	0	0	0	1	1	0	1	1	0	0	0
Mexico	1	0	0	0	0	1	1	1	0	0	0	0	0	0	1	0
Portugal	0	0	1	1	1	0	0	0	1	0	0	0	1	1	0	0
Poland	1	1	0	0	0	0	0	0	0	1	0	0	1	0	1	1
Spain	0	0	1	0	1	1	0	0	0	1	1	0	1	0	1	0
Turkey	1	1	0	0	1	0	0	0	0	1	0	1	0	1	1	1
USA	0	1	0	1	0	0	0	0	0	0	1	0	1	1	0	0
Sum	6	4	4	6	5	3	1	1	5	6	3	3	9	6	5	4

We will concentrate on the latter. Below you will find a graph with 10 Year U.S Constant Maturity and banking crises for 3 countries (Greece, Portugal and Brazil).

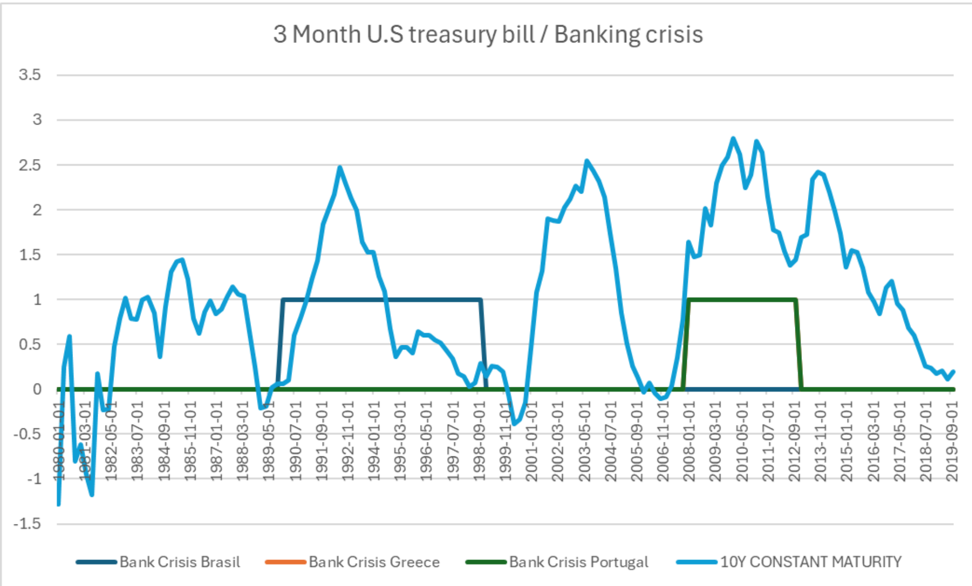


Figure 29: Banking crises (Greece, Portugal and Brazil) with 10 Year constant maturity

We can clearly see a pattern emerging. As far as the 2008 crises is concerned, the period of low yields on 10-Year Constant Maturity prior to 2008 contributed to a credit boom and an underestimation of financial risks. Rising yields highlighted the weaknesses of banks and financial institutions with high exposure to the property market. Higher mortgage rates led to an increase in defaults and foreclosures, which reduced the value of mortgage-backed securities (MBS) held by many banks. The loss in value of these assets led to a liquidity and solvency crisis. The effect of this was so great that it had an impact on European countries during this period. We can also see that we have the same pattern with Brazil. A fall in the rate before the crisis and a rise during it.

In 1989, inflation in Brazil was extremely high, prompting the government to adopt economic stabilisation measures. These measures included the liberalisation of prices and exchange rates, as well as a series of monetary stabilisation plans. However, these actions initially failed to control inflation, leading to a loss of confidence in the banking system.

As the economic situation worsened, investors demanded higher yields to compensate for the increased risk, leading to a rise in long-term interest rates, including those on 10-Year. This rise in rates exacerbated the banking crisis because it increased the cost of financing for banks and businesses, leading to a spiral of defaults and bankruptcies.

In the matrix we note that 3 other variables stand out for their number of times they were significant. In fact, the variables are short term interest rate, Exchange rate and 3 Month U.S Treasury Bill.

We will be focusing on the short term interest rate and the 3-year U.S. Treasury bill. For the following 3 countries: Portugal, Greece and USA (the short term interest rate is the same for Greece and Portugal as they are both in the euro zone). The curves of both variables are clearly similar. The short term interest rate follows the same pattern but with a lag of around 1 year. This lag can also be seen in relation to the recession period.

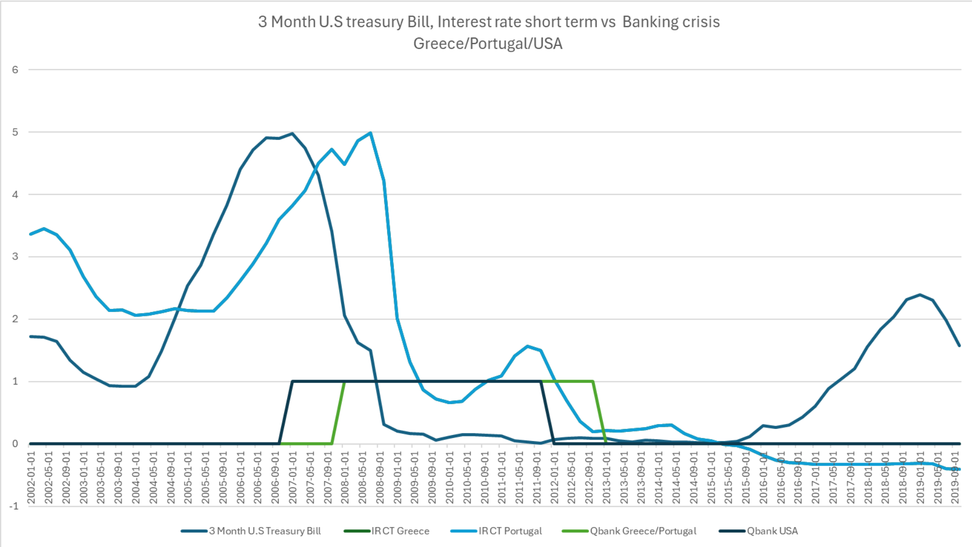


Figure 30: Banking crises (Greece, Portugal and USA) with 3 Year U.S treasury bill and Euro short term interest rate

A low rate for 3-month Treasury bills or short term rate reflects strong demand for safe assets. This means that investors are fleeing risky assets, which can exacerbate the liquidity and solvency problems of financial institutions, thereby increasing the risk of banking crises.

Banks often rely on a rising yield curve to borrow at short-term rates and lend at long-term rates, taking advantage of the spread between the two. When short-term rates are very low and long-term rates do not follow, banks' interest margins fall, which affects their profitability. A fall in profitability can lead to a fall in confidence and perceived solvency, contributing to the risk of a banking crisis.

Below are the dynamic EWS models for Greece, Portugal, Brazil, and the USA. As we can observe, for these four countries, the probability of occurrence is high when a crisis happened and remains low when no crisis occurred, except for the USA, where some peaks appear randomly. The results and graphs for the other countries can be found in the Appendix, referenced as D.2.

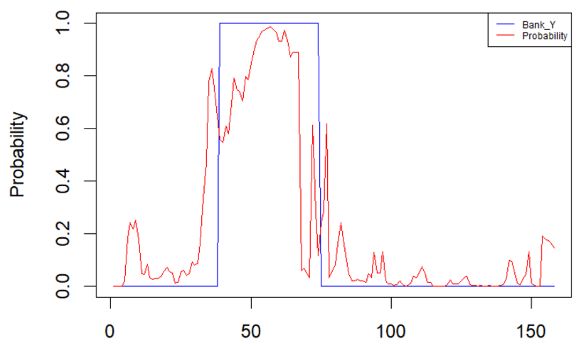


Figure 31: Logit Estimation for Brasil

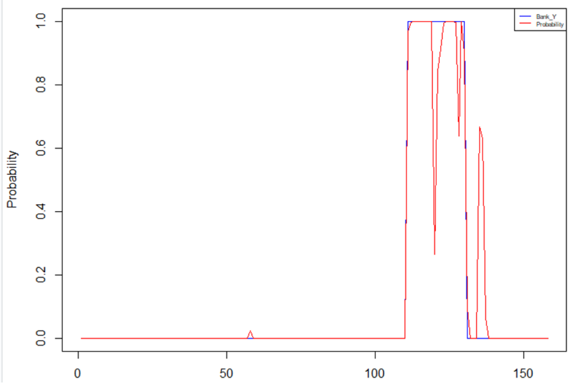


Figure 32: Logit Estimation for Greece

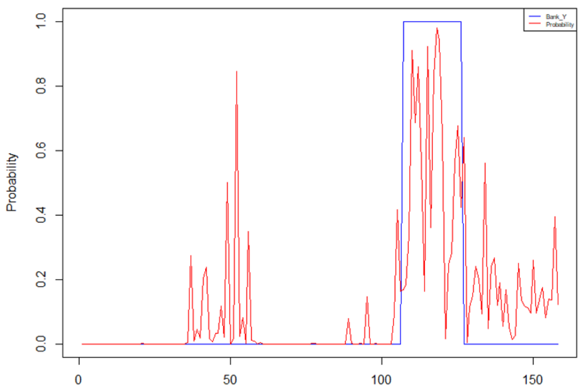


Figure 33: Logit Estimation for USA

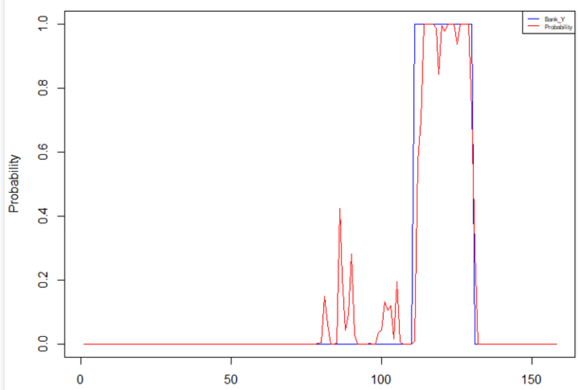


Figure 34: Logit Estimation for Portugal

8.4.3 Debt crises

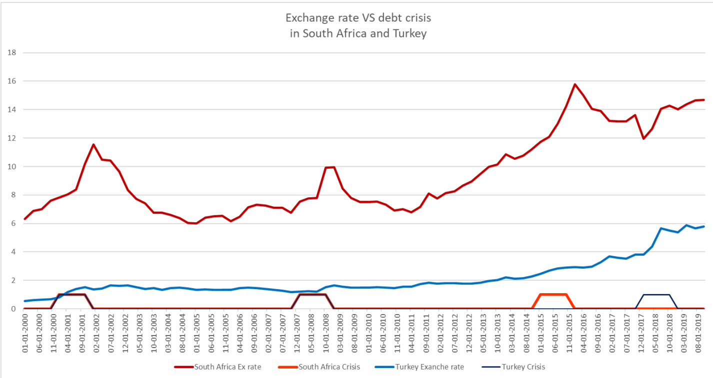
Below is the matrix we created using our logistic estimation model for the debt crises. Our tables show that the exchange rate outperforms the other variables. This variable was significant for 7 countries over a total of 8. We can also observe that the CPI, 10-YearConstant Maturity, 3-Month Treasury Bill and the exports was significant in more than half the countries.

Table 4: Significative matrice

Currency	**CPI**	**CPIE**	**LT**	**CT**	**GDP**	**M1**	**M2**	**M3**	**BOP**	**EX R**	**RES**	**IP**	**10Y**	**3M**	**Multi**	**EXP**
Argentine	1	0	0	0	1	1	0	1	1	1	0	0	1	1	0	1
Brazil	1	0	0	0	0	1	0	1	1	1	0	0	0	0	1	0
Greece	0	0	1	0	0	0	0	0	0	1	0	0	1	1	0	0
Mexico	1	1	1	0	1	0	0	0	0	1	0	0	1	1	1	1
Portugal	0	1	1	1	1	0	0	0	0	1	0	1	1	0	0	1
Poland	1	1	0	0	0	0	0	0	0	1	0	1	1	1	0	1
South Africa	0	0	1	0	0	0	0	0	0	1	0	1	0	1	1	0
Turkey	1	0	0	0	1	0	0	0	1	0	0	1	0	0	0	1
Sum	5	3	4	1	4	2	0	2	3	7	0	4	5	5	3	5

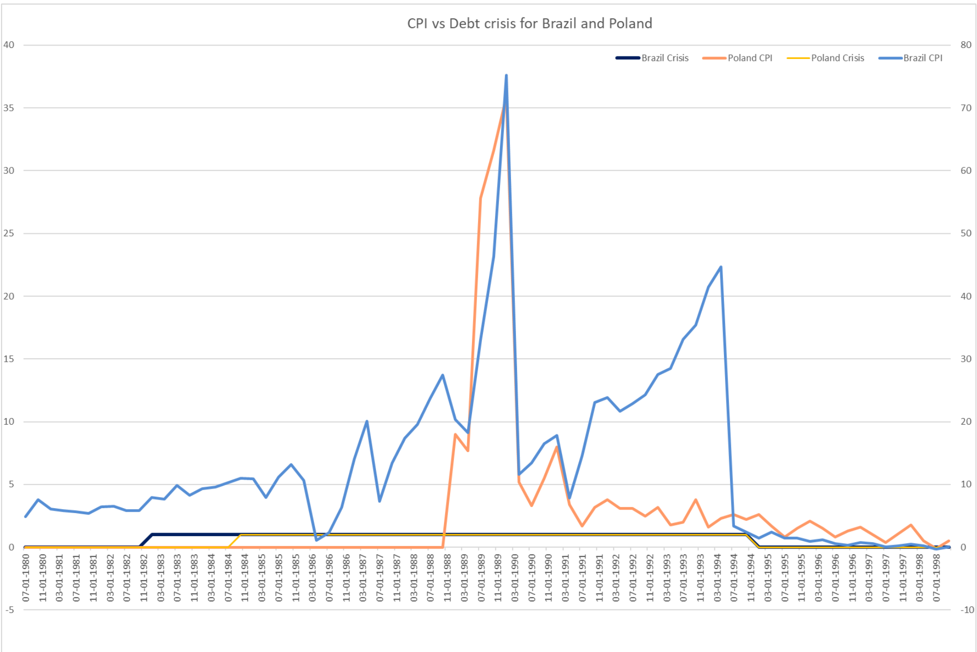
To better visualize the link between crisis occurrences and significant variables, we will plot some of the significant variables against the binary dichotomous variable.

Figure 35: Exchange rate vs debt crises in South Africa, and Turkey



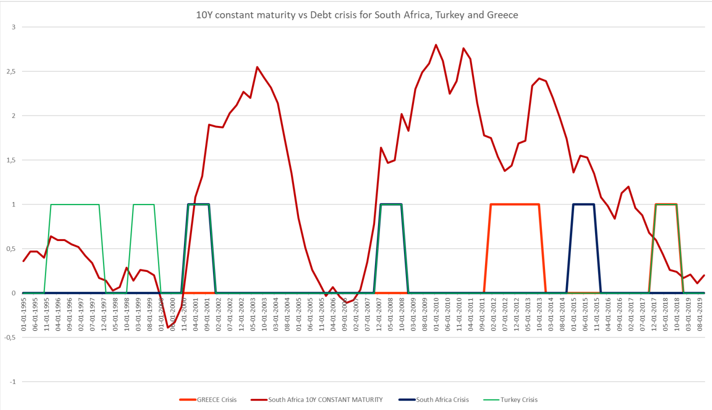
In the graph on the left, we can notice that, in South Africa, a debt crisis happened when the exchange rate was increasing, and about to reach a peak. Turkey follow a similar pattern but with a smaller amplitude of movement.

Figure 36: CPI vs Debt crises in Brazil and Poland



From the graph on the above, we can understand that there is a link between the debt crisis and the country's CPI. Indeed, we observe that the Brazilian crisis started concurrently with an upward trend in the CPI. The crisis nearly ended when the CPI returned to its initial value. In the case of Poland, further verification is needed due to the absence of recorded CPI data before 1989. However, it is evident that the highest peak in CPI occurred during the debt crisis, and by the time the crisis had ended, the CPI had already decreased significantly.

Figure 37: 10-year constant maturity for Greece, South Africa and Turkey



Here, we can state that most of the time, a debt crisis happened right before the 10Y Constant Maturity peaked. Indeed, this was the case for Turkey and South Africa in 2001 and 2008, and for Greece in 2011. However, we can also observe some crises that occurred during the downward trend in 2015 and 2018.

Below are the dynamic EWS models for Brazil and South Africa. We can observe that the probability results from our model align accurately with the occurrence of crises. The results and plots for the remaining countries can be found in Appendix D.3.

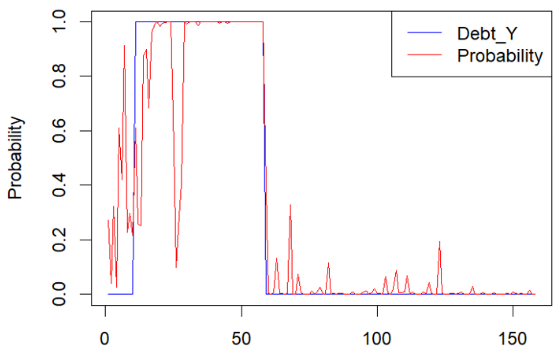


Figure 38: Logit Estimation for Brazil

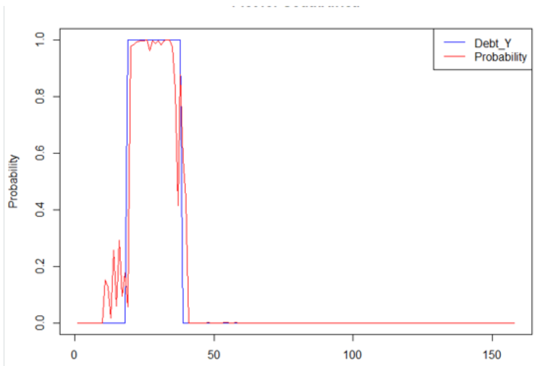


Figure 39: Logit Estimation for South Africa

9 Forecast financial crises

Once we have analysed all the probabilities of occurrence for each type of crisis, we thought that it would be interesting to forecast that probability and have a look into the future.

However, since our variables data stops in 2019, we have decided to forecast up until 2029. As we are already in 2024, this will allow us to see if our model can accurately predict the recent years. It is important to be aware that the recent years have been unusual due to the COVID-19 crisis which, initially, is a health crisis that had important impacts on the economy. Therefore, it would not be surprising if our model fails to predict any crises for that period.

To forecast the probabilities, we decided to linearly predict the variables that were significant previously. We began by performing a linear regression of the probabilities we obtained with the logistic estimation model against the latest values of all significant variables. Once we had the linear model, we predicted the variables independently using the predict function in RStudio. We set our confidence interval at 95% and decided to forecast 40 values. In order to determine whether a currency crisis would occur, we had to set a threshold. Although there are methods such as the Accuracy Measure (AM) or the Credit-Scoring Approach (CSA) for choosing the optimal threshold, we encountered difficulties in implementing these methods. Therefore, we decided to set a threshold for each country based on the probability level of previous crises that occurred in those countries.

9.1 Currency crises forecast

To forecast the probability of a currency crisis occurring, we included the five most significant variables from the previous section in our forecasting model: CPI Energy, Short-term Interest Rate, Industrial Production, Exchange Rate, and the 3-Month U.S. Treasury Bill. These variables were available for most of the countries we analyzed, except for Argentina, Brazil, and Mexico. For Argentina, we could only use two variables: the Exchange Rate and the 3-Month Treasury Bill. For Mexico and Brazil, we excluded CPI Energy from the analysis.

Below, you can find the plot representing the forecasts of the probability for a currency crisis to occur in South Africa and Brazil. The graphs for the other countries are available in Appendix

E.1.

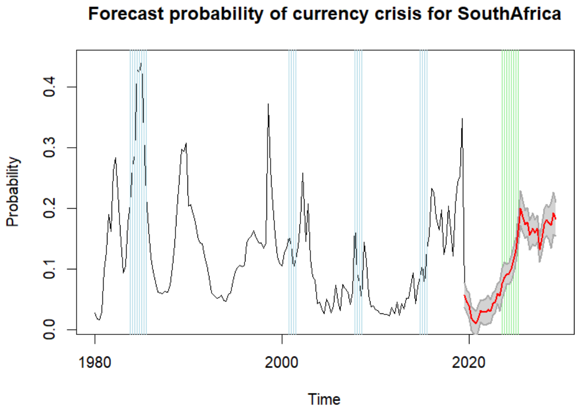


Figure 40: Currency crises Probability for South Africa

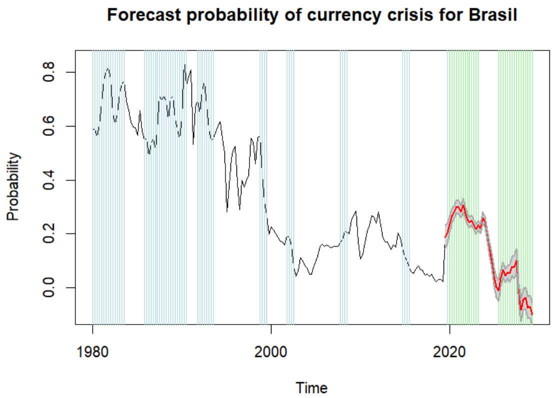


Figure 41: Currency crises Probability for Brazil

Looking at the graphs, we can observe that our model forecasts currency crises for South Africa and Brazil. The results for South Africa are somewhat unusual, as the predicted currency crisis stops just before the peak. However, we can see that the probability of our model for earlier crises also peaks right after the crisis. For Brazil, our model forecasts a currency crisis from 2020 to 2023 and another from 2026 to 2029. We will conduct a deeper analysis of the results for Brazil in the following section.

9.2 Banking crises forecast

We have forecast the probability of a banking crisis to take place. To do so, we have followed the same process as for the currency crises. We included the most significant variables we found previously, being CPI, Short-Term Interest Rate, Exchange Rate, 10Y Constant Maturity and 3- M Treasury Bill. Nevertheless, for Argentina we had to exclude the short-term interest rate as it is not available.

The graph showing our forecast is below for Portugal and Brazil, the other countries' graphs can be found in the appendix E.2.

Figure 42: Banking crises Probability for Portugal

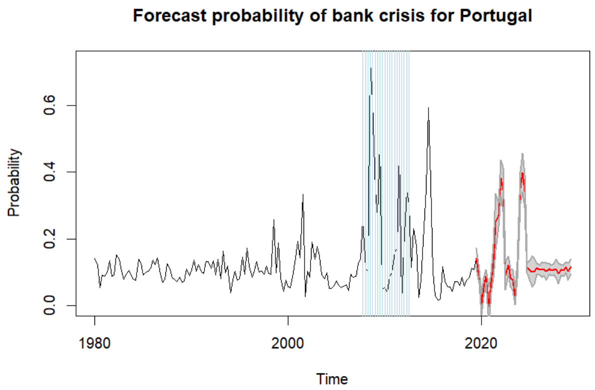
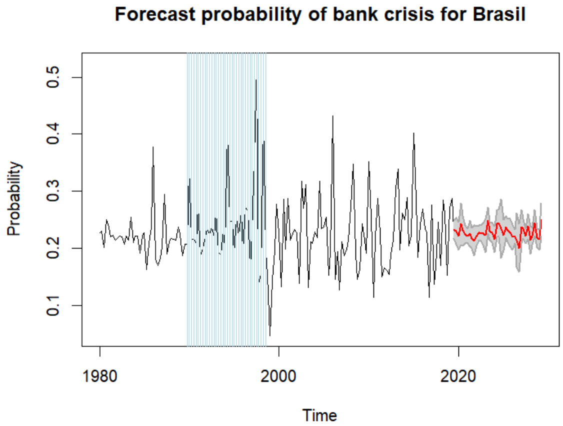


Figure 43: Banking crises Probability for Brazil



Our forecasting model does not predict any banking crises for either Portugal or Brazil. In Brazil, the trend remains relatively low and constant, with minimal variation. Therefore, according to our forecasting model, no banking crises are expected in the future. However, we can see some alarming spikes in Portugal. It is surprising that our model does not predict a crisis during these spikes. Thus, it could be beneficial for the country to be aware that the probability of a crisis is increasing around 2025, even though our model does not currently predict any banking crises.

9.3 Debt crises forecast

For the Debt crises occurrence probability, we have included in our forecasting model the Exchange Rate, CPI, 3-Month Treasury Bill, 10-Year Constant Maturity and the Export.

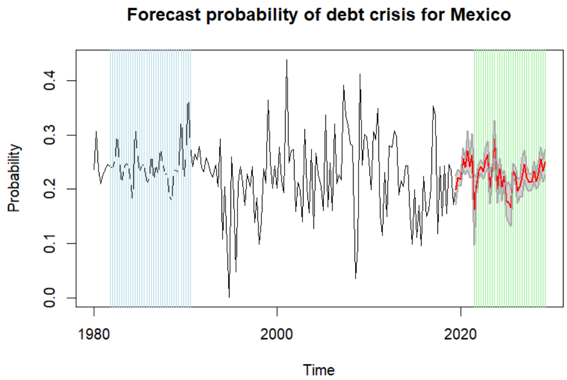


Figure 44: Debt crises Probability for Mexico

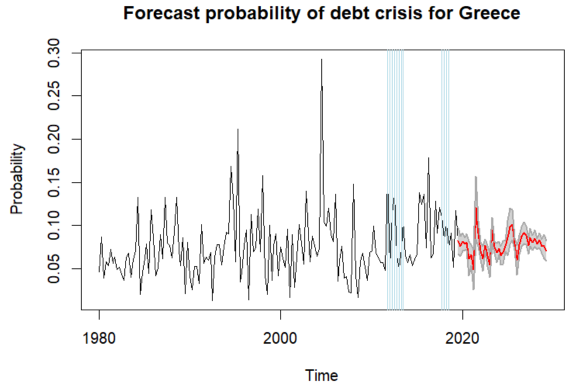


Figure 45: Debt crises Probability for Greece

rom the graphs, we observe that our model predicts a debt crisis in Mexico starting in 2024 and continuing until 2029. However, we find these results surprising, as Mexico has not experienced a debt crisis since 1990, and the probability levels remain relatively low, but similar to those during the 1982 crisis. For Greece, despite experiencing a couple of debt crises quite recently, our model does not predict any debt crises in the future

9.4 Forecast model evaluation

In this section we will evaluate our forecast model, in order to have an idea on whether or not it is reliable. To do so we will use the 3 most common methods : MAE, MSE, RMSE. The **MAE** calculates the mean of the differences between the predicted values and the actual values. The **MSE** calculates the average of the square differences between the actual and predicted values. The **RMSE**, is the square root of the MSE. The results for the banking and currency crises forecast are below, the ones for the debt crises forecast can be found in the appendix E.4.

Table 5: Evaluation metrics for banking crises forecasts

Bank	**MAE**	**MSE**	**RMSE**
Brazil	0.049	0.004	0.062
Finland	0.008	0.000	0.010
Greece	0.084	0.015	0.124
Japan	0.023	0.001	0.028
Mexico	0.035	0.002	0.044
Poland	0.012	0.000	0.019
Portugal	0.083	0.015	0.121
Spain	0.083	0.013	0.113
Turkey	0.032	0.001	0.037
USA	0.104	0.028	0.167
Argentine	0.041	0.003	0.052
Average	0.050	0.007	0.071

Table 6: Evaluation metrics for currency crises forecasts

Currency	**MAE**	**MSE**	**RMSE**
Greece	0.023	0.001	0.028
Poland	0.069	0.006	0.081
Portugal	0.022	0.001	0.027
South Africa	0.030	0.002	0.043
Turkey	0.030	0.001	0.038
Spain	0.012	0.000	0.013
Brazil	0.064	0.006	0.074
Mexico	0.026	0.0008	0.028
Argentine	0.031	0.001	0.037
Average	0.046	0.005	0.058

For the banking crises forecast, we notice that our model show an reasonable level of accuracy with the MAE and RMSE, on average, being around 5% and 7%. For the currency crises, the results are, overall, slightly better, with the MAE and RMSE being both around 5%. hese results are surprising, as we observed that the forecasts for the currency crises were sometimes strange.

However, we notice a strong variability across different countries, which can be explained by the lack of data for certain countries or the quality of the data as well. For example, the MAE, for the banking crises, ranges from 0.008 (Finland) to 0.104 (USA) and from 0.010 (Finland) to 0.167 (USA) for the RMSE. This variability gives us an indication that the model performs well for some countries but less well for others, which is an indicator of unreliability.

10 Brazil analysis

We have decided to conduct a more thorough analysis of Brazil for two reasons. First, Brazil has experienced each type of crisis we are analyzing in this research. Additionally, we have access to almost all the necessary variables for Brazil (except for CPI Energy), although some were not usable for logistic estimation (e.g., M2).

For a bit of history, Brazil has endured oil shocks and severe inflation, leading to financial crises. Particularly during the 1980s and 1990s, Brazil faced several currency, debt, and banking crises. In 1993, Brazil implemented the 'Real Plan' to achieve stability and growth. While this plan did not prevent other crises from occurring, no further debt crises have occurred since the year following its introduction (Rigolon and Giambiagi, 1999).

We will now have a look at the results we found when we conducted our logistic estimation and forecast on the occurrence of a currency, debt, or banking crisis.

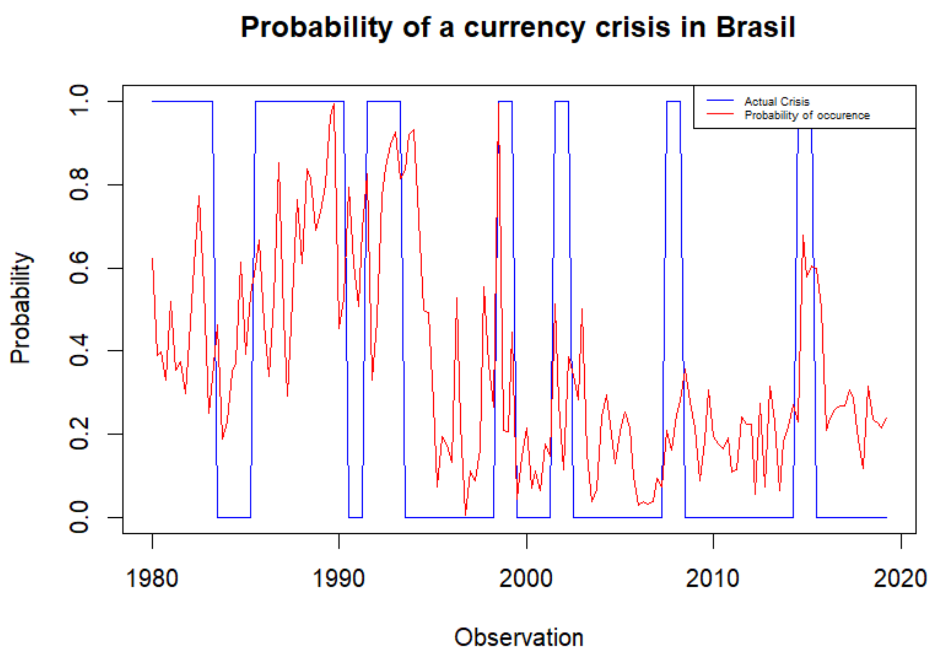


Figure 46: Probability of occurrence of a currency crisis in Brazil

From the graph, we can see that for currency crises, our model shows peaks when crises occur. However, entering the 21st century, it is clear that the accuracy of our probabilities is much lower than in previous years, and the probability peaks slightly after the beginning of the crisis.

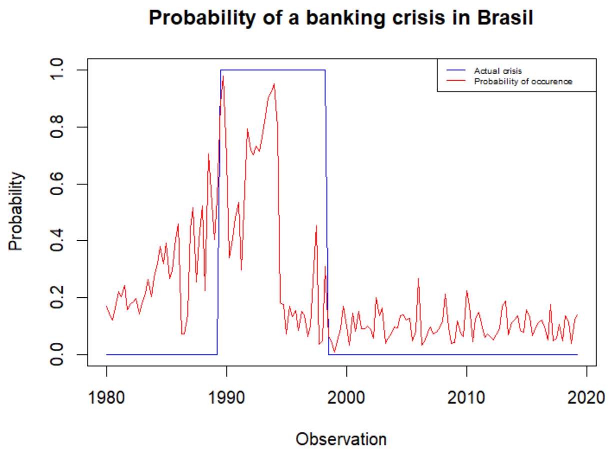


Figure 47: Probability of occurrence of a banking crisis in Brazil

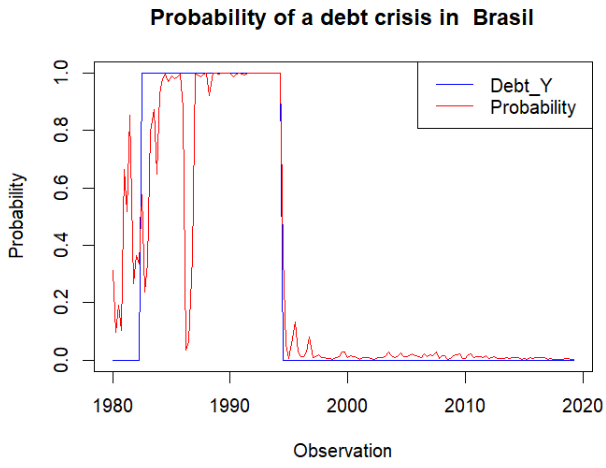


Figure 48: Probability of occurrence of a debt crisis in Brazil

Our model for both banking and debt crises performs reasonably well. Indeed, for the banking crisis that occurred between 1990 and 1998, we can see that the probability reaches almost 1 at the start of the crisis, but the probability declines as we approach the end of the crisis. Regarding the debt crisis from 1983 to 1994, we observe that the probability closely follows the occurrence of the crisis, even though it shows a strange dip around 1987.

Lets have a look at the forecast of the occurrence of a financial crisis in Brazil.

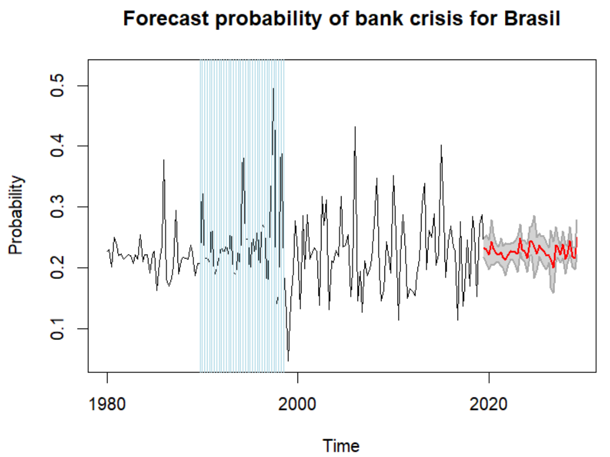


Figure 49: Probability of occurrence of a banking crisis in Brazil

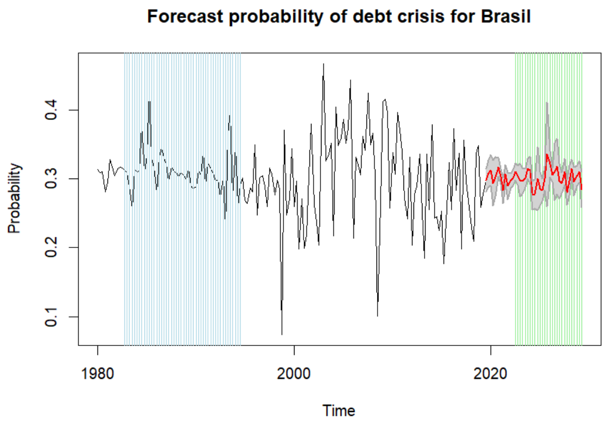


Figure 50: Probability of occurrence of a debt crisis in Brazil

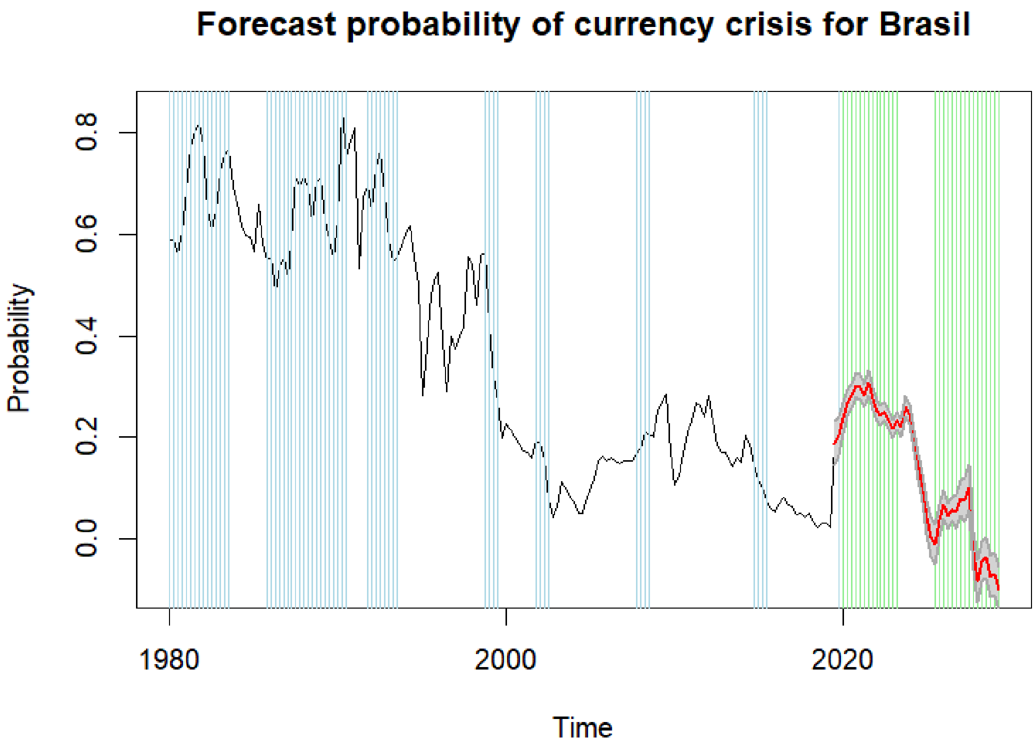


Figure 51: Probability of occurrence of a currency crisis in Brazil

We observe that our model does not predict any future banking crises; we also observe that our probability forecasts remain quite stable. We can see that our model predicts a long debt crisis starting in 2022 and continuing until 2029. This is quite surprising, as no debt crisis has taken place since 1994. However, as our model takes into account the probability of previous crises, it makes sense that it would predict one. For the currency crisis prediction, our model anticipates two crises: one starting in 2020 and ending in 2023, which could be linked to the COVID-19 crisis, but according to us, it is unlikely as that crisis originated in the health sector. Our model also predicts a crisis in 2026, but the probability is quite low. However, we note that the Brazilian currency is unstable and has suffered from several crises, therefore, it is not surprising to expect future currency crises.

11 Limitations

During our empirical research, we encountered several difficulties, and we will now discuss the limitations we faced.

One of our initial challenges was selecting variables. Since we were exploring three types of crises using the same database, deciding which variables to include was difficult. Due to limited knowledge about each variable's impact, we opted for variables most commonly referenced in the literature.

Then, to construct our dichotomous variables, we needed to find data detailing the dates of crisis occurrences in the countries of interest. Although we utilized the Nguyen et al. (2022) database, which provides annual data, we converted it to quarterly data by assuming that if a crisis occurred in a given year, it persisted throughout all four quarters. This transformation may have introduced errors in our model, as a crisis might not have affected every quarter.

Additionally, the quality of the data we used for our variables was questionable, and finding complete and appropriate data was challenging. First, some variables were unavailable for certain countries (e.g., CPI Energy for Brazil). Second, inconsistencies in data lengths and sizes presented issues. Finally, some datasets contained missing values. To resolve data issues, we standardized all datasets by replacing missing values with zeros to ensure uniformity across countries.

During the implementation of our EWS model, particularly in the general to specific phase, we realized there were many criteria we could have considered to identify the most significant variables (e.g., ROC, AUC). We chose to use P-value, as it was the most familiar and understood criterion. However, by the end of this thesis, we recognized it might not have been the most relevant or reliable criterion. For future research, we recommend using more accurate criteria.

Finally, we frequently encountered coding issues, with the determination of an optimal threshold being one of the most impactful. We had to set the threshold for each country based on previous crises.

Conclusion

The aim of our master's thesis was to identify the most significant variables to include in a dynamic Early Warning System (EWS) based on the type of financial crises, in order to create the best fitting model. Our empirical research covered 12 countries and tested 16 different variables.

The key findings of our research indicate that for currency crises, the most significant variables are CPI energy, the short-term interest rate, the exchange rate, industrial production, and the 3-Month Treasury Bill. For banking crises, the crucial variables include the exchange rate, CPI, short-term interest rate, 3-Month Treasury Bill, and, most importantly, the 10-Year Constant Maturity. For debt crises, the key variables are the exchange rate, CPI, 10-Year Constant Maturity, and the 3-Month Treasury Bill.

We observe that significant variables remain relatively similar across all three types of crises. Notably, the 3-Month Treasury Bill and the exchange rate are significantly important for all three types of crises.

Our forecasting model predicted a few debt and currency crises for the future, especially for South American countries (Brazil, Mexico, and Argentina). However, no significant banking crises have been predicted.

By incorporating the identified variables into EWS models, policymakers and financial institutions could better anticipate and mitigate the impacts of potential financial crises.

Future research should focus on enhancing data collection and including additional variables in the study. Moreover, future studies should expand the analysis to include more countries and broader economic contexts, providing a more detailed understanding of the behavior of the key drivers of financial crises.

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Appendix

A Second generation crises

A.1 Philips Curve

$$y = \bar{y} + \alpha(\varepsilon - \varepsilon^e) - u \tag{1}$$

where

$\varepsilon - \varepsilon^e$ = output gain from the unexpected devaluation

u = negative supply shock

ε^e = expectation in the change of exchange rate ε

$\bar{y}$ = natural output level

A.2 Loss function minimization

$$Min_{\varepsilon} L(.) = \frac{\partial L(.)}{\partial \varepsilon} \tag{2}$$

$$\Leftrightarrow 2\alpha[(\bar{y} - y^*) + \alpha(\varepsilon - \varepsilon^e) - u] + 2\beta\varepsilon = 0$$

$$\Leftrightarrow \alpha(\bar{y} - y^*) + \alpha^2(\varepsilon - \varepsilon^2) - \alpha u + \beta\varepsilon = 0$$

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

A.3 Equilibrium second generation crises

$$E(\varepsilon) = \underbrace{P(u<\underline{u})\ E(\varepsilon|u<\underline{u})}_{A} + \overbrace{E(\varepsilon|u>-u)\ P(u>\bar{u})}^{C} + \underbrace{P(u\in \underline{u};\bar{u})\ E(\varepsilon|\underline{u}<u<\bar{u})}_{B} \qquad (3)$$

(A1) : $P(u<\underline{u}) = \frac{\underline{u}+\mu}{2\mu}$

A(2) : $E(\varepsilon|u<\underline{u}) = \frac{\alpha(y^*-\bar{y}+\alpha^2\varepsilon^e)+\alpha E(u|u<\underline{u})}{\alpha^2+\beta}$

B = 0 because $E(\varepsilon|\underline{u}<u<\bar{u}) = 0$

C(1): $P(u>\bar{u}) = \frac{\mu-\bar{u}}{2\mu}$

C(2) : $E(\varepsilon|u>\bar{u}) = \frac{\alpha}{\alpha^2+\beta}[y^*-\bar{y}+\alpha\varepsilon^e] + \frac{\alpha}{\alpha^2+\beta}\frac{\mu+\bar{u}}{2}$

For the first equilibrium we need to sum $A(1)\times A(2) + C(1)\times C(2)$

$$E(\varepsilon) = \frac{\alpha}{\alpha^2+\beta}\Big\{[y^*-\bar{y}+\alpha\varepsilon^e][1+\frac{\bar{u}-\underline{u}}{2\mu}] + \frac{\bar{u}^2-\underline{u}^2}{4\mu}\Big\}$$

For the second equilibrium we need focus only on C(1)*C(2)

$$E(\varepsilon) = (\frac{\mu-\bar{u}}{2\mu})(\frac{\alpha}{\alpha^2+\beta})[(y^*-\bar{y}+\alpha\varepsilon^e)+\frac{\mu-\underline{u}}{2}$$

The third is dedicated to the pure float:

$$E(\varepsilon) = \frac{\alpha}{\alpha^2+\beta}(y^*-\bar{y}+\alpha\varepsilon^e) \quad E(u)=0$$

B Relationship between variables

B.1 Bivariate regression

Column1	CPI	Column2	GDP	Column3	EXCHANGE RATE	Column4
	Estimate	t value	Estimate	t value	Estimate	t value
(Intercept)	8.985990581	5.422845651	9.224228258	2.717233731	-0.607317931	2.717233731
M1	0.130116296	1.173631877	-0.032146653	-0.141537536	0.023754022	-0.141537536
M2	-5.15048E-14	-0.031116495	6.97775E-13	0.205775778	2.38427E-13	0.205775778
M3	-0.290943493	-2.721937465	-0.050726487	-0.231654081	0.00333605	-0.231654081
`BOP : CURRRENT A	0.256673062	1.780630249	0.10446957	0.353768317	-0.092174006	0.353768317
Reserve	-6.26444E-11	-2.4413635	-1.01658E-10	-1.933876366	1.26226E-11	-1.933876366
`10Y CONSTANT M	-2.082021298	-4.810522503	-1.93727611	-2.184913647	0.211987276	-2.184913647
`3Y CONSTANT MA	-0.945066208	-5.892455531	-0.146986344	-0.447349276	0.158553168	-0.447349276
Multi	-0.125845525	-1.756799051	-0.000327047	-0.002228589	-0.007965461	-0.002228589
`export (Variation	0.030933423	1.059092386	0.167665407	2.802108825	0.028118459	2.802108825
import	0.004975002	0.202898684	0.032939	0.655740525	0.004875475	0.655740525

Figure B.1: Results of bivariate analysis for Argentina

Column1	CPI	Column2	GDP	Column3	EXCHANGE RATE	Column4	Industrial product	Column5
	Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value
(Intercept)	4.324790398	3.787839741	3166891.887	5.790153082	-1.033552927	-0.967180229	0.885732777	1.347831333
`CPI energy`	0.220015703	8.095958012	-15623.84599	-1.200142442	0.011788355	0.463463903	-0.018244997	-1.166446091
`INTREST RATE LT`	-0.014365793	-0.286232257	43401.50143	1.805194534	0.104178428	2.217762002	-0.010865752	-0.37614479
`IR CT`	-0.000355179	-0.02072361	50535.324	6.155225131	0.155640368	9.70261984	-0.004473547	-0.453499622
M1	-1.38547E-12	-1.284776252	-1.27307E-07	-0.246440738	9.816E-12	9.725517697	-2.49891E-13	-0.402611943
M2	2.51537E-13	0.397338382	6.59988E-07	2.176334447	2.13262E-12	3.599319571	1.63745E-13	0.449400966
M3	2.86601E-13	0.482553241	-6.0551E-07	-2.128232428	-4.56861E-12	-8.218632942	-1.58024E-14	-0.046227084
`BOP : CURRRENT ACCOUNT`	-0.036051609	-0.180931629	-6649.668481	-0.069665878	-0.21271366	-1.140600039	0.160976972	1.403653459
Reserve	-1.94136E-11	-3.04177763	1.70685E-05	5.582728523	1.02851E-10	17.21784003	-2.32557E-12	-0.633077612
`10Y CONSTANT MATURITY`	-0.575840994	-2.257290802	-616916.2122	-5.048256266	-0.413257051	-1.730825807	-0.155727024	-1.060608779
`3Y CONSTANT MATURITY`	-0.255611565	-2.3940227	-321296.5775	-6.281800516	-0.114057621	-1.141353644	-0.043641993	-0.71016398
Multi	-0.035847507	-3.193432971	18742.25718	3.485387028	0.083027993	7.902628017	-0.008907024	-1.378598428
`export (Variation previous p	0.008566983	0.683243696	-2038.76798	-0.339426544	-0.010909201	-0.929584351	-0.003972985	-0.550517321
import	-0.014052313	-1.026911165	-2522.777807	-0.38485252	-0.001859704	-0.145203478	0.032437396	4.118483602

Figure B.2: Results of bivariate analysis for Finland

Column1	CPI	Columr	GDP	Column3	EXCHANGE RATE	Columr	Industrial production	Columr
	Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value
(Intercept)	0.001161783	0.00127	7559.194398	2.293576823	0.131165339	1.549141	0.527291843	0.395661
`CPI energy`	0.192305397	0.326741	1706.004873	0.804594947	0.022421254	0.411615	0.684556284	0.798436
`INTREST RATE LT`	0.222666077	1.01501	2025.095178	2.562402265	-0.0473716	-2.333211	-0.577360192	-1.806686
`IR CT`	-0.007538728	-0.142851	273.8789956	1.440557797	0.018572813	3.802627	-0.35550778	-4.624397
M1	-0.031029764	-0.884097	1579.019541	12.48803999	0.017811082	5.483163	0.024271083	0.474712
M2	2.46078E-12	0.79886	-3.98584E-08	-3.591722978	-1.84753E-12	-6.4805	-5.94424E-13	-0.132469
M3	-0.004159014	-0.205991	97.80150847	1.344586597	0.003315575	1.774337	0.007003367	0.238114
`BOP : CURRRENT ACCOUNT`	-16.91856885	-1.094052	-123170.5215	-2.210886977	-3.530519811	-2.466792	40.27975349	1.788054
Reserve	4.32544E-11	0.803577	1.62268E-06	8.367861715	2.85323E-12	0.572735	-3.62962E-11	-0.462889
`10Y CONSTANT MATURITY`	-1.432472613	-1.822187	28469.81391	10.05256175	0.30645617	4.21206	4.289012863	3.745273
`3Y CONSTANT MATURITY`	0.223698594	0.664526	20834.20379	17.17952481	0.202967461	6.514704	2.575260071	5.251573
Multi	-0.18128665	-0.905784	6395.363955	8.869708798	0.246225457	13.29264	-0.082749313	-0.28382
`export (Variation previous period)`	0.091852059	1.88538	164.3271963	0.936278372	0.011916307	2.642843	-0.003283391	-0.046265
import	0.053049286	1.198417	88.47601057	0.554803766	0.005690716	1.38904	0.146732091	2.27548

Figure B.3: Results of bivariate analysis for Greece

Column1	CPI	Column2	GDP	Column3	EXCHANGE RATE	Column4	Industrial product	Column5
	Estimate	t value	Estimate	t value	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)
(Intercept)	-0.141356592	-1.377545522	62634.04018	34.82208511	-57.02313912	0.001402308	1.339337334	0.302017868
`CPI energy`	0.218859892	9.967597147	433.6462591	1.12671572	-3.295126781	0.380655674	-0.123249323	0.65665985
`INTREST RATE LT`	-0.013432923	-1.467989702	-353.37073	-2.203116668	4.69126193	0.003133157	0.08650793	0.454325031
`IR CT`	0.008796768	1.635173163	-1276.519247	-13.53699956	4.862421701	4.23469E-07	0.075313116	0.268410976
`BOP : CURRENT ACCOUNT`	0.015704805	2.640843626	-760.4366151	-7.295039042	-2.503002017	0.014805032	0.160043692	0.034366735
Reserve	-6.98984E-06	-1.205058229	0.001993671	0.019608697	0.00327993	0.001160803	-2.30935E-05	0.752494356
`10Y CONSTANT MATURITY`	0.182944021	4.287919547	-10598.29767	-14.17160293	11.71049338	0.109920238	-0.958975422	0.076541831
`3Y CONSTANT MATURITY`	0.106684231	8.40085348	-5448.562096	-24.47707601	14.62810018	3.19624E-10	0.229250761	0.154108815
`export (Variation previous pe	0.001089946	0.179531418	-7.534454618	-0.070801376	-0.008641526	0.993356768	0.106500912	0.165999488
import	-0.005807574	-1.123717044	30.54424834	0.337167818	-0.988443294	0.264263088	0.015897481	0.80749398

Figure B.4: Results of bivariate analysis for Japan

Column1	CPI	Column2	GDP	Column3	EXCHANGE RATE	Column4	Industrial production	Column5
	Estimate	t value	Estimate	t value	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)
(Intercept)	0.001161783	0.001269922	-0.51902126	-1.243120089	7.629802807	2.60181E-07	73.57168939	4.39302E-08
`CPI energy`	0.192305397	0.326740526	-0.006488266	-0.269435196	0.048164289	0.554931137	0.820150336	0.265567811
`INTREST RATE LT`	0.222666077	1.015010246	0.040034412	1.595305141	-0.018576608	0.82694594	2.912358028	0.000206381
`IR CT`	-0.007538728	-0.142851406	0.004034141	0.327945441	0.028339288	0.4965733	0.094256281	0.801822523
M1	-0.031029764	-0.884096645	5.07494E-13	0.572277552	2.67027E-11	2.05796E-15	-1.40045E-10	7.26671E-07
M2	2.46078E-12	0.798860459	-1.93289E-12	-1.08196191	1.25761E-11	0.039034369	3.39598E-10	4.65158E-09
M3	-0.004159014	-0.205990922	1.39959E-12	1.07501603	-2.3084E-11	5.44892E-07	-2.07432E-10	5.89766E-07
`BOP : CURRRENT ACCOUNT`	-16.91856885	-1.094051795	0.007220543	0.43708368	0.044976396	0.421840656	0.020231377	0.967997476
Reserve	4.32544E-11	0.803577297	5.60421E-12	0.941144413	1.57795E-10	9.14683E-13	5.19934E-10	0.004789001
`10Y CONSTANT MATURITY`	-1.432472613	-1.822187015	0.120397003	1.926233527	-0.679358187	0.001606059	-15.63823847	1.1388E-13
`3Y CONSTANT MATURITY`	0.223698594	0.664526021	0.090378311	3.553500524	-0.58434052	2.61786E-10	-9.405671226	8.68034E-24
Multi	-0.18128665	-0.90578353	0.000396119	0.642551281	-0.001384271	0.507518545	0.038996041	0.039684806
`export (Variation previous period)	0.091852059	1.885380203	0.006191228	1.457030956	-0.019019589	0.187491055	0.100963743	0.43682015
import	0.053049286	1.198416855	-0.000459708	-0.152435491	-0.010619714	0.299209896	0.108634698	0.239098812

Figure B.5: Results of bivariate analysis for Mexico

Column1	CPI	Column2	GDP	Column3	EXCHANGE RATE	Column4	Industrial produc	Column5
	Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value
(Intercept)	4.927064648	6.323408826	47716.07433	2.418946134	0.075910077	0.281890425	8.785240399	2.190711101
`CPI energy`	0.280580107	5.401612896	-946.5434546	-0.7197897	0.017594039	0.980054058	0.003382547	0.012652574
`IR CT`	0.007722578	1.827823538	-383.2639751	-3.583178717	-0.009215062	-6.310853773	-0.022287595	-1.0249523
M1	-4.7735E-11	-2.444214165	3.29933E-06	6.673083289	4.50339E-11	6.672057554	2.49889E-10	2.486101244
M2	7.7368E-11	1.817887863	2.27358E-06	2.110153815	5.69197E-11	3.869779222	-3.43575E-11	-0.156854062
M3	-5.38212E-11	-1.423377211	-3.54729E-06	-3.705634177	-7.18552E-11	-5.498488099	-1.77134E-11	-0.091020341
`BOP : CURRRENT ACCOUNT`	-0.000869494	-0.015847135	5534.064736	3.984070644	0.179140333	9.447036124	-2.092985964	-7.411721282
Reserve	-5.05614E-11	-5.823199564	5.73198E-06	26.07628145	6.14938E-11	20.49232588	-8.77745E-11	-1.96416995
`10Y CONSTANT MATURITY`	-0.403913288	-1.984933587	-10319.94853	-2.003244053	0.054606247	0.776458165	0.809095333	0.772548929
`3Y CONSTANT MATURITY`	-0.167123713	-2.038209275	-6910.721557	-3.329144024	-0.020238354	-0.714173571	-0.290273017	-0.687837459
Multi	-0.772651238	-5.848550081	39333.8324	11.76059953	0.343599489	7.525495688	-1.501374658	-2.208117847
`export (Variation previous peri	0.018763969	1.534422274	434.1666578	1.402410492	0.005297934	1.25355849	0.030395369	0.482943217
import	0.013384178	1.331056151	-868.3329063	-3.411060496	-0.002269081	-0.652938813	0.041291105	0.797865407

Figure B.6: Results of bivariate analysis for Portugal

Column1	CPI	Column2	GDP	Column3	EXCHANGE RATE	Column4	Industrial production	Column5
	Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value
(Intercept)	-0.185223817	-0.872845073	291764.1531	12.59552209	-141.8886976	-4.516857418	0.898541184	1.607260818
`CPI energy`	0.100047121	6.058514066	-184.1643551	-0.102167086	-2.928812293	-1.198122729	0.109610728	2.519547907
`INTREST RATE LT`	0.027782527	1.135228208	-8160.24285	-3.054628577	8.28143505	2.285942303	0.010161743	0.15761142
`IR CT`	-0.013995128	-0.827934448	-8644.485684	-4.684919647	-5.799819112	-2.317831035	-0.117849334	-2.646392438
M1	-2.82951E-13	-1.387650776	1.109E-07	4.982462814	-9.85829E-11	-3.266014799	-1.1638E-12	-2.166487467
M2	2.2199E-13	1.595697639	-9.17046E-08	-6.038812263	5.53343E-11	2.686950023	8.46198E-13	2.308855053
M3	-2.55041E-14	-1.707584001	9.58107E-09	5.876647547	1.78735E-12	0.808405798	-3.15675E-14	-0.802269669
`BOP : CURRRENT ACCOUNT`	-0.015712642	-0.979157454	-4665.449091	-2.663426268	-11.74025567	-4.942300145	0.108363401	2.563267784
Reserve	3.2059E-12	0.779028851	4.31457E-07	0.960472596	3.0122E-09	4.944651028	-2.52466E-11	-2.328701431
`10Y CONSTANT MATURITY`	0.038967227	0.672219489	-15555.5743	-2.458337782	10.95955008	1.277181354	0.107634662	0.704809562
`3Y CONSTANT MATURITY`	0.040196215	1.523139393	-1316.224349	-0.456907529	9.023871542	2.309913067	0.148760959	2.139693128
Multi	0.000218844	0.894027134	79.73374019	2.984024349	0.078667675	2.171005263	-0.002114958	-3.279639726
`export (Variation previous period)`	-0.005618414	-1.128433541	620.8110515	1.142261545	-0.271381362	-0.36820567	0.016298118	1.242532325
import	0.000294311	0.057553392	-451.7921252	-0.809370872	-0.315949545	-0.417379376	0.007470171	0.554502594

Figure B.7: Results of bivariate analysis for Brasil

Column1	CPI	Column2	GDP	Column3	EXCHANGE RATE	Column4	Industrial product	Column5
	Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value
(Intercept)	0.11967521	0.739164705	2019662.759	10.58257356	-1.299097479	-4.800999808	-6.133594675	-1.632917549
`CPI energy`	0.100209058	19.03126832	11921.17356	1.920680738	0.025276881	2.872348663	-0.200933717	-1.644847856
`INTREST RATE LT`	-0.104790894	-4.302101259	-120018.5919	-4.180045688	-0.120331465	-2.955896438	1.770736379	3.133452791
`IR CT`	0.065398881	1.831111501	93167.90075	2.213024377	0.215392979	3.608518539	-1.385370398	-1.671947113
M1	0.00083388	0.823746269	20564.92193	17.23425608	0.010377992	6.134177151	-0.053378581	-2.272842008
M3	-3.20208E-15	-0.495419522	2.76615E-08	3.630707874	1.54501E-14	1.430288825	2.18593E-15	0.014577719
`BOP : CURRRENT ACC	0.017122362	1.51979485	-150842.7291	-11.35850293	-0.217128275	-11.53162752	-0.789895367	-3.022059596
Reserve	-1.02232E-12	-1.101386358	4.0378E-06	3.69040569	5.73849E-12	3.69917608	9.7826E-11	4.542769405
`10Y CONSTANT MATU	0.179906721	4.161730828	5759.099949	0.113020346	0.303578815	4.201951057	-3.048361938	-3.039522011
`3Y CONSTANT MATUI	0.078897576	1.76933617	-37690.83788	-0.717063978	-0.04738841	-0.635875015	0.090400722	0.087383766
`export (Variation pre	0.001645508	0.390817577	-8052.243662	-1.622431695	-0.013618697	-1.935363664	0.216305621	2.214389759
import	0.000863747	0.220322478	-1132.235015	-0.245010258	-0.00125377	-0.191356389	0.236604372	2.601400359

Figure B.8: Results of bivariate analysis for Turkey

B.2 Correlation matrices

Table 7: Correlation Matrix For Argentina

	CPI	CPI Energy	IR LT	IR CT	GDP	M1	M2	M3	BoP	Ex R	Res	IP	10Y	3Y	Multi	Exp	Imp
CPI	1.00																
CPI Energy	NA	1.00															
IR LT	NA	NA	1.00														
IR CT	NA	NA	NA	1.00													
GDP	0.01	NA	NA	NA	1.00												
M1	0.03	NA	NA	NA	-0.06	1.00											
M2	0.00	NA	NA	NA	0.07	0.15	1.00										
M3	-0.19	NA	NA	NA	0.01	0.22	-0.13	1.00									
BoP	0.01	NA	NA	NA	0.03	-0.03	-0.08	-0.10	1.00								
Ex R	0.03	NA	NA	NA	-0.01	0.01	0.02	-0.03	0.17	1.00							
Res	0.02	NA	NA	NA	0.13	0.06	0.09	-0.03	-0.10	0.02	1.00						
IP	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.00					
10Y	0.01	NA	NA	NA	-0.03	0.10	-0.06	-0.00	-0.02	0.05	0.03	NA	1.00				
3Y	0.16	NA	NA	NA	0.09	0.06	0.06	0.02	0.01	0.06	0.01	NA	-0.17	1.00			
Multi	-0.04	NA	NA	NA	0.01	-0.05	0.48	-0.09	-0.03	0.00	-0.31	NA	0.01	-0.01	1.00		
Exp	-0.04	NA	NA	NA	0.07	0.07	-0.04	0.08	-0.01	0.01	-0.06	NA	0.04	0.01	0.06	1.00	
Imp	0.10	NA	NA	NA	-0.08	-0.08	-0.03	-0.05	-0.05	0.02	0.05	NA	0.17	-0.08	0.01	-0.12	1.00

Table 8: Correlation Matrix for Brazil

	CPI	CPI Energy	IR LT	IR CT	GDP	M1	M2	M3	BOP	Ex R	Res	IP	10Y	3M	Multi	Imp	Exp
CPI	1.00																
CPI Energy	NA	1.00															
IR LT	-0.08	NA	1.00														
IR CT	0.17	NA	-0.04	1.00													
GDP	0.17	NA	-0.20	0.11	1.00												
M1	-0.08	NA	-0.02	0.04	-0.17	1.00											
M2	0.02	NA	0.04	0.05	-0.19	0.90	1.00										
M3	0.02	NA	0.03	0.02	-0.20	0.90	0.98	1.00									
BOP	0.22	NA	0.04	-0.07	0.07	-0.00	-0.01	-0.01	1.00								
Ex R	0.26	NA	0.03	0.20	0.08	-0.06	-0.08	-0.09	0.02	1.00							
Res	-0.19	NA	-0.02	-0.23	0.07	0.13	0.18	0.17	-0.04	-0.20	1.00						
IP	-0.10	NA	-0.10	-0.20	-0.09	0.06	0.03	0.03	0.00	0.01	0.07	1.00					
10Y	0.07	NA	0.18	0.09	-0.04	-0.01	-0.01	-0.03	0.02	0.17	0.04	0.07	1.00				
3Y	0.05	NA	-0.04	-0.05	0.12	-0.01	0.00	0.00	-0.13	0.01	0.04	-0.00	-0.28	1.00			
Multi	0.10	NA	0.05	0.15	-0.21	0.82	0.89	0.88	0.01	0.02	-0.28	-0.01	-0.03	-0.01	1.00		
Imp	-0.13	NA	0.02	0.09	-0.12	-0.04	-0.05	-0.04	-0.10	-0.09	-0.02	-0.02	0.01	-0.09	-0.04	1.00	
Exp	0.14	NA	0.03	0.00	-0.04	-0.04	-0.02	-0.02	0.15	0.07	0.02	0.08	0.22	0.07	-0.03	-0.10	1.00

Table 9: Correlation Matrix for Spain

	CPI	CPI Energy	IR LT	IR CT	GDP	M1e	M2e	M3e	BoP	Ex R	Res	IP	10Y	3M	Multi	Exp	Imp
CPI	1.00																
CPI Energy	0.20	1.00															
IR LT	0.06	0.00	1.00														
IR CT	0.05	-0.06	0.21	1.00													
GDP	0.03	0.03	-0.05	0.23	1.00												
M1e	-0.08	-0.14	0.04	0.03	-0.16	1.00											
M2e	0.04	-0.08	0.03	0.03	-0.17	0.95	1.00										
M3e	0.01	-0.11	0.08	0.13	-0.35	0.67	0.72	1.00									
BoP	-0.02	0.02	-0.01	-0.35	-0.05	-0.03	-0.03	-0.04	1.00								
Ex R	-0.09	-0.00	-0.06	-0.02	-0.02	0.04	0.05	0.08	0.00	1.00							
Res	0.05	0.04	-0.06	-0.15	-0.21	0.26	0.28	0.15	-0.01	-0.01	1.00						
IP	-0.18	-0.00	-0.04	-0.04	-0.04	0.05	0.03	0.00	0.01	0.01	0.03	1.00					
10Y	-0.12	0.02	0.13	-0.01	-0.08	0.09	0.13	0.08	0.02	-0.01	0.05	0.05	1.00				
3Y	0.00	0.11	0.07	0.02	0.23	-0.01	-0.01	-0.01	0.03	0.02	-0.04	-0.07	-0.17	1.00			
Multi	-0.08	-0.14	0.01	0.11	-0.03	-0.11	-0.12	-0.01	-0.00	0.03	-0.70	0.01	0.00	-0.01	1.00		
Exp	0.04	0.09	0.09	0.01	-0.03	-0.01	0.02	0.01	0.09	-0.02	0.03	0.08	-0.03	0.07	-0.08	1.00	
Imp	-0.01	-0.01	0.06	-0.02	0.06	0.06	0.01	-0.02	0.02	-0.02	-0.01	0.08	0.07	0.08	0.10	0.26	1.00

Table 10: Correlation Matrix for Finland

	CPI	CPI Energy	LT IR (10Y)	IR CT	GDP	M1	M2	M3	CA	Ex R	Res	IP	10Y	3M	Multi	Exp	Imp
CPI	1.00																
CPI Energy	0.21	1.00															
LT IR (10Y)	0.05	0.01	1.00														
IR CT	0.00	-0.03	0.22	1.00													
GDP	0.03	0.02	0.01	0.32	1.00												
M1	NA	NA	NA	NA	NA	1.00											
M2	NA	NA	NA	NA	NA	NA	1.00										
M3	NA	NA	NA	NA	NA	NA	NA	1.00									
CA	0.05	0.03	0.03	-0.19	-0.18	NA	NA	NA	1.00								
Ex R	0.12	0.17	-0.03	-0.10	-0.03	NA	NA	NA	0.01	1.00							
Res	0.21	0.03	-0.01	-0.01	0.07	NA	NA	NA	-0.02	-0.13	1.00						
IP	0.00	-0.01	-0.06	0.01	0.13	NA	NA	NA	0.01	0.03	0.01	1.00					
10Y	-0.02	-0.04	-0.04	-0.05	-0.04	NA	NA	NA	-0.04	-0.11	-0.02	0.01	1.00				
3Y	0.05	-0.04	0.02	0.08	0.04	NA	NA	NA	-0.05	0.01	0.03	-0.05	-0.28	1.00			
Multi	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.00		
Exp	-0.04	0.05	0.07	-0.01	0.09	NA	NA	NA	0.10	-0.05	-0.08	-0.02	-0.08	0.03	NA	1.00	
Imp	-0.04	0.03	0.06	0.01	-0.01	NA	NA	NA	-0.03	0.01	-0.02	-0.10	0.03	0.08	NA	-0.00	1.00

Table 11: Correlation Matrix for Greece

	CPI	CPI Energy	IR LT	IR CT	GDP	M1	M2	M3	BoP	Ex R	Res	IP	10Y	3M	Multi	Exp	Imp
CPI	1.00																
CPI Energy	0.13	1.00															
IR LT	0.03	-0.01	1.00														
IR CT	-0.00	-0.03	0.02	1.00													
GDP	0.06	0.06	-0.27	0.09	1.00												
M1	NA	NA	NA	NA	NA	1.00											
M2	NA	NA	NA	NA	NA	NA	1.00										
M3	NA	NA	NA	NA	NA	NA	NA	1.00									
BoP	NA	NA	NA	NA	NA	NA	NA	NA	1.00								
Ex R	-0.09	-0.10	-0.13	0.08	0.16	NA	NA	NA	NA	1.00							
Res	0.11	-0.02	-0.06	-0.03	-0.04	NA	NA	NA	NA	0.09	1.00						
IP	-0.03	0.04	0.04	-0.03	0.12	NA	NA	NA	NA	-0.11	0.06	1.00					
10Y	0.03	0.09	0.07	0.05	-0.02	NA	NA	NA	NA	0.13	-0.02	0.00	1.00				
3Y	0.05	0.16	0.01	0.01	0.12	NA	NA	NA	NA	0.00	-0.12	-0.06	-0.17	1.00			
Multi	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.00		
Exp	-0.01	-0.07	-0.05	-0.04	-0.04	NA	NA	NA	NA	0.14	-0.01	-0.08	0.01	0.02	NA	1.00	
Imp	0.13	-0.06	0.01	0.05	0.04	NA	NA	NA	NA	0.06	-0.06	0.02	0.02	0.03	NA	-0.01	1.00

Table 12: Correlation Matrix for Japan

	CPI	CPI Energy	IR LT	IR CT	GDP	M1Y	M2Y	M3Y	BoP	Ex R	Res	IP	10Y	3M	Multi	Exp	Imp
CPI	1.00																
CPI Energy	0.25	1.00															
IR LT	-0.12	-0.10	1.00														
IR CT	-0.05	-0.02	-0.02	1.00													
GDP	-0.08	-0.04	0.07	0.06	1.00												
M1Y	0.00	-0.09	-0.05	-0.05	0.09	1.00											
M2Y	-0.05	-0.02	-0.02	-0.02	-0.07	0.04	1.00										
M3Y	0.01	0.05	0.14	-0.31	0.07	-0.06	-0.12	1.00									
BoP	0.07	-0.05	-0.06	-0.05	0.21	0.09	0.02	-0.02	1.00								
Ex R	-0.00	0.02	0.00	0.02	0.10	0.07	-0.02	0.13	0.12	1.00							
Res	-0.01	0.04	-0.00	0.04	0.13	0.16	0.06	-0.17	0.02	-0.43	1.00						
IP	-0.04	-0.06	0.02	-0.01	-0.05	-0.05	0.02	-0.03	0.01	0.02	0.03	1.00					
10Y	-0.02	-0.07	0.12	0.11	-0.04	-0.04	0.08	-0.02	-0.04	-0.15	0.02	0.02	1.00				
3Y	-0.13	0.10	0.06	0.05	0.24	-0.03	-0.03	-0.00	-0.06	0.10	-0.03	0.04	-0.17	1.00			
Multi	0.01	-0.05	-0.00	-0.05	-0.14	-0.15	0.09	0.15	-0.01	0.42	-0.99	-0.02	-0.01	0.02	1.00		
Exp	-0.00	-0.07	-0.00	-0.04	0.04	-0.00	-0.06	0.05	0.01	-0.14	0.03	-0.01	0.07	-0.06	-0.04	1.00	
Imp	-0.01	0.09	-0.09	0.04	-0.05	0.01	0.00	-0.00	-0.13	-0.20	0.12	-0.17	0.08	-0.00	-0.12	0.25	1.00

Table 13: Correlation Matrix for Mexico

	CPI	CPI Energy	IR LT	IR CT	GDP	M1P	M2P	M3P	BoP	Ex R	Res	IP	10Y	3M	Multi	Exp	Imp
CPI	1.00																
CPI Energy	0.30	1.00															
IR LT	-0.05	0.12	1.00														
IR CT	0.00	0.10	0.29	1.00													
GDP	-0.01	-0.03	0.12	0.04	1.00												
M1P	0.06	0.35	0.04	0.04	0.13	1.00											
M2P	-0.01	0.04	-0.01	0.00	-0.02	0.64	1.00										
M3P	0.01	0.04	-0.02	0.00	-0.00	0.65	0.99	1.00									
BoP	0.00	-0.01	-0.26	0.00	0.04	-0.02	-0.01	-0.00	1.00								
Ex R	0.21	0.16	0.09	0.20	-0.26	-0.05	0.05	0.03	0.01	1.00							
Res	-0.07	-0.15	-0.03	0.00	0.06	0.20	0.21	0.19	0.02	-0.28	1.00						
IP	0.18	0.02	-0.00	-0.02	0.01	0.06	0.05	0.05	0.04	0.07	0.05	1.00					
10Y	0.03	0.05	0.10	0.03	-0.11	0.09	0.06	0.06	-0.03	-0.10	0.15	-0.01	1.00				
3Y	-0.04	-0.10	0.03	0.14	0.12	-0.08	-0.04	-0.04	0.00	-0.14	-0.02	-0.03	-0.17	1.00			
Multi	0.04	0.13	0.03	0.02	-0.09	-0.03	0.10	0.12	-0.03	0.37	-0.75	0.04	-0.19	0.05	1.00		
Exp	-0.07	0.05	-0.02	-0.04	0.16	-0.04	-0.04	-0.05	-0.05	-0.01	-0.11	-0.05	-0.05	0.01	0.16	1.00	
Imp	0.03	0.02	0.04	-0.05	-0.00	0.04	0.13	0.13	-0.12	-0.04	0.09	0.05	0.04	-0.05	-0.12	0.06	1.00

Table 14: Correlation Matrix for Poland

	CPI	CPI Energy	IR LT	IR CT	GDP	M1	M2	M3	BoP	Ex R	Res	IP	10Y	3M	Multi	Exp	Imp
CPI	1.00																
CPI Energy	0.27	1.00															
IR LT	-0.04	0.01	1.00														
IR CT	-0.09	-0.11	0.37	1.00													
GDP	-0.01	0.07	0.04	0.03	1.00												
M1	-0.16	-0.02	0.03	0.04	0.01	1.00											
M2	-0.02	0.08	0.09	0.02	0.29	0.04	1.00										
M3	-0.16	0.06	0.05	0.01	0.10	0.69	0.08	1.00									
BoP	0.05	0.02	0.25	0.02	-0.03	0.02	-0.01	0.00	1.00								
Ex R	0.09	0.04	0.03	0.01	-0.15	-0.06	-0.13	-0.03	-0.01	1.00							
Res	-0.16	0.04	0.10	0.05	0.10	0.31	-0.06	0.27	0.05	-0.04	1.00						
IP	0.02	0.13	0.09	-0.02	0.15	0.02	-0.05	-0.04	0.13	0.03	0.02	1.00					
10Y	-0.04	-0.03	0.18	0.03	-0.01	0.21	-0.04	0.24	0.07	0.10	0.10	0.06	1.00				
3Y	0.03	0.04	0.06	0.11	-0.02	0.02	-0.08	-0.00	-0.09	-0.06	0.08	-0.11	-0.17	1.00			
Multi	0.06	-0.00	-0.09	-0.04	-0.06	-0.01	0.28	0.04	-0.11	0.19	-0.41	0.07	0.01	-0.14	1.00		
Exp	-0.10	0.02	-0.01	0.04	0.05	-0.05	0.07	-0.11	-0.13	0.03	-0.14	0.07	-0.04	0.06	0.05	1.00	
Imp	0.16	0.06	0.09	0.06	0.06	-0.06	-0.14	-0.08	0.11	-0.02	0.00	0.11	0.07	-0.01	-0.01	-0.13	1.00

Table 15: Correlation Matrix for Portugal

	CPI	CPI Energy	IR LT	IR CT	GDP	M1	M2	M3	BoP	Ex R	Res	IP	10Y	3M	Multi	Exp	Imp
CPI	1.00																
CPI Energy	0.17	1.00															
IR LT	-0.02	0.01	1.00														
IR CT	0.02	-0.02	0.22	1.00													
GDP	0.02	-0.03	-0.14	0.13	1.00												
M1	NA	NA	NA	NA	NA	1.00											
M2	NA	NA	NA	NA	NA	NA	1.00										
M3	NA	NA	NA	NA	NA	NA	NA	1.00									
BoP	-0.08	-0.06	0.07	-0.04	0.04	NA	NA	NA	1.00								
Ex R	0.09	-0.00	-0.05	-0.02	-0.06	NA	NA	NA	-0.01	1.00							
Res	0.05	0.08	-0.01	0.02	-0.06	NA	NA	NA	-0.03	0.01	1.00						
IP	-0.04	-0.01	0.03	-0.05	0.02	NA	NA	NA	0.08	-0.01	0.06	1.00					
10Y	0.04	-0.05	0.13	0.04	-0.06	NA	NA	NA	-0.01	-0.01	-0.00	-0.15	1.00				
3Y	0.05	0.03	0.05	0.03	0.14	NA	NA	NA	-0.00	0.02	-0.05	0.02	-0.17	1.00			
Multi	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.00		
Exp	0.06	0.05	-0.02	-0.05	0.04	NA	NA	NA	-0.02	-0.02	-0.10	-0.05	0.05	0.04	NA	1.00	
Imp	-0.11	-0.03	0.03	0.02	0.04	NA	NA	NA	-0.02	-0.01	0.05	-0.07	-0.03	-0.05	NA	0.33	1.00

Table 16: Correlation Matrix for South Africa

	CPI	CPI Energy	IR LT	IR CT	GDP	M1	M2	M3	BoP	Ex R	Res	IP	10Y	3M	Multi	Exp	Imp
CPI	1.00																
CPI Energy	0.07	1.00															
IR LT	0.08	-0.06	1.00														
IR CT	0.07	0.02	0.40	1.00													
GDP	-0.00	0.02	-0.05	0.04	1.00												
M1	0.03	-0.04	0.14	0.23	0.01	1.00											
M2	-0.03	0.03	0.13	0.23	-0.01	0.62	1.00										
M3	-0.05	0.05	0.03	0.17	0.11	0.54	0.87	1.00									
BoP	0.01	0.04	0.04	-0.13	-0.00	-0.09	-0.06	0.03	1.00								
Ex R	0.12	-0.12	0.30	0.30	-0.07	0.10	0.13	0.08	0.12	1.00							
Res	0.02	0.03	-0.19	-0.15	0.08	-0.05	0.00	0.02	0.06	-0.34	1.00						
IP	-0.02	-0.06	0.19	0.12	0.54	-0.03	-0.01	0.08	0.02	0.03	0.04	1.00					
10Y	-0.01	-0.00	0.06	-0.01	-0.08	0.08	0.11	0.08	0.07	-0.05	-0.03	-0.09	1.00				
3Y	0.11	0.19	0.10	0.10	0.14	0.01	-0.06	-0.13	-0.00	-0.14	0.02	0.23	-0.17	1.00			
Multi	-0.02	-0.03	0.21	0.17	-0.08	0.11	0.11	0.07	-0.07	0.35	-0.99	-0.05	0.04	-0.03	1.00		
Exp	0.09	0.03	0.00	-0.04	-0.01	-0.04	0.09	0.08	-0.01	-0.16	0.11	-0.04	-0.04	0.05	-0.10	1.00	
Imp	0.00	0.12	-0.06	-0.06	0.04	-0.11	-0.10	-0.10	0.09	-0.12	-0.02	0.03	-0.06	-0.00	0.01	0.11	1.00

Table 17: Correlation Matrix for Turkey

	CPI	CPI Energy	IR LT	IR CT	GDP	M1	M2	M3	BoP	Ex R	Res	IP	10Y	3M	Multi	Exp	Imp
CPI	1.00																
CPI Energy	0.26	1.00															
IR LT	NA	NA	1.00														
IR CT	0.10	0.18	NA	1.00													
GDP	0.12	0.03	NA	-0.22	1.00												
M1	0.06	-0.02	NA	-0.22	-0.02	1.00											
M2	0.04	-0.03	NA	-0.04	-0.14	0.82	1.00										
M3	0.03	-0.01	NA	-0.04	-0.13	0.81	0.99	1.00									
BoP	0.05	-0.02	NA	-0.02	-0.21	-0.01	0.07	0.05	1.00								
Ex R	0.16	0.08	NA	0.28	-0.38	0.21	0.33	0.33	0.23	1.00							
Res	-0.06	-0.12	NA	-0.23	0.08	0.29	0.28	0.29	-0.15	-0.27	1.00						
IP	-0.05	-0.15	NA	-0.20	0.17	0.11	0.03	0.04	0.06	-0.06	0.21	1.00					
10Y	0.03	-0.03	NA	-0.07	-0.05	-0.02	-0.06	-0.07	0.23	-0.05	-0.08	-0.00	1.00				
3Y	-0.20	0.03	NA	-0.01	0.07	-0.03	-0.01	-0.01	-0.04	-0.08	-0.00	0.01	-0.17	1.00			
Multi	0.07	0.10	NA	0.22	-0.18	0.23	0.36	0.35	0.20	0.51	-0.69	-0.22	0.09	-0.02	1.00		
Exp	-0.03	0.02	NA	0.04	0.07	0.10	0.05	0.03	-0.05	-0.08	0.04	-0.06	0.04	0.03	0.04	1.00	
Imp	-0.01	-0.05	NA	-0.05	0.02	-0.01	0.01	0.01	-0.00	-0.04	0.12	0.08	0.07	0.04	-0.08	0.04	1.00

Table 18: Correlation Matrix for USA

	CPI	CPI Energy	IR LT	IR CT	GDP	M1	M2	M3	BoP	Ex R	Res	IP	10Y	3M	Multi	Exp	Imp
CPI	1.00																
CPI Energy	0.03	1.00															
IR LT	0.05	0.16	1.00														
IR CT	-0.00	-0.01	0.12	1.00													
GDP	0.02	0.10	0.24	0.32	1.00												
M1	0.12	0.03	-0.10	-0.02	-0.11	1.00											
M2	NA	NA	NA	NA	NA	NA	1.00										
M3	0.06	0.05	0.02	-0.06	0.16	-0.13	NA	1.00									
BoP	0.03	-0.13	-0.03	0.02	-0.02	-0.00	NA	-0.09	1.00								
Ex R	0.07	-0.03	0.05	-0.23	0.06	-0.06	NA	-0.04	-0.00	1.00							
Res	-0.08	0.04	-0.11	-0.27	-0.03	0.06	NA	0.07	-0.18	0.34	1.00						
IP	-0.03	-0.08	0.22	0.11	0.20	-0.00	NA	0.02	0.02	-0.03	-0.16	1.00					
10Y	-0.06	0.02	0.02	-0.26	-0.14	-0.03	NA	0.01	-0.02	0.06	0.14	0.03	1.00				
3Y	0.01	0.08	0.25	0.42	0.24	-0.14	NA	-0.03	0.00	0.02	-0.12	0.06	-0.17	1.00			
Multi	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.00		
Exp	0.02	-0.03	0.07	-0.02	0.13	-0.14	NA	-0.02	-0.16	0.07	-0.03	-0.04	-0.11	0.09	NA	1.00	
Imp	0.07	0.01	0.14	-0.03	0.04	-0.02	NA	-0.02	-0.02	0.06	0.05	0.09	-0.01	-0.04	NA	0.14	1.00

B.3 Multicollinearity graphs

Figure B.9: Multicollinearity for Portugal

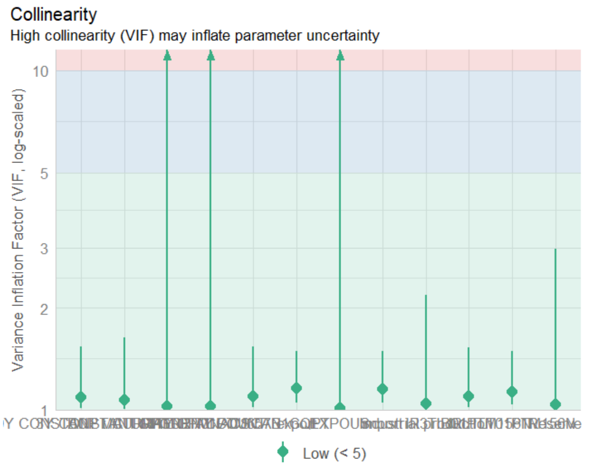


Figure B.10: Multicollinearity for USA

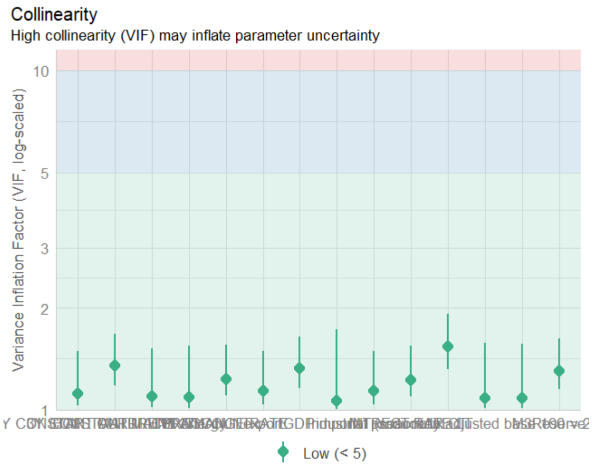


Figure B.11: Collinearity for Argentina

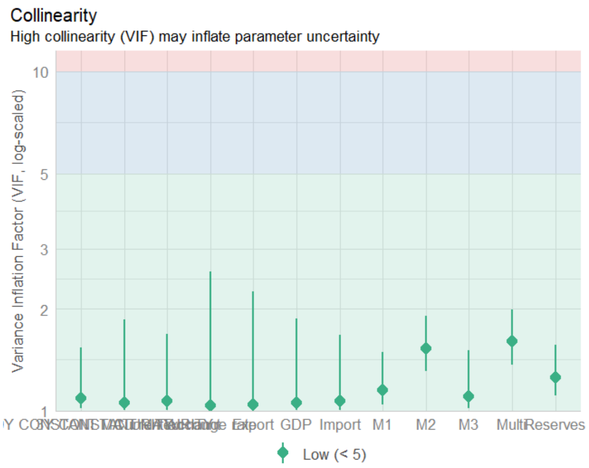


Figure B.12: Multicollinearity for Poland

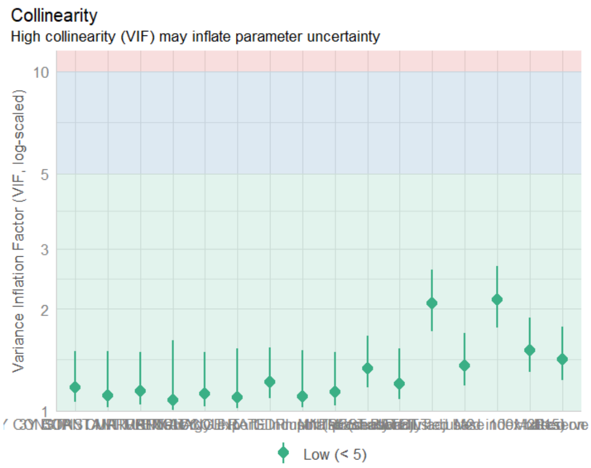


Figure B.13: Multicollinearity for Finland

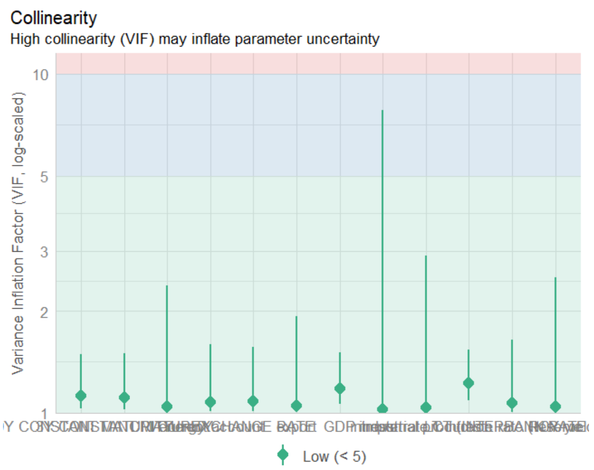
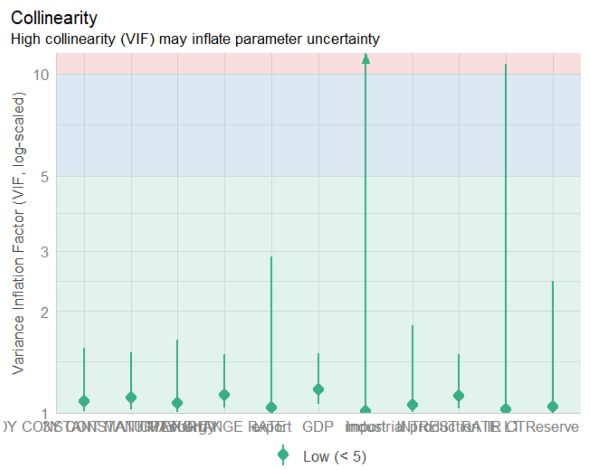


Figure B.14: Multicollinearity for Greece



B.4 VIF values

Figure B.15: VIF for Argentina

```
> col_arg
# Check for Multicollinearity

Low Correlation

                 Term  VIF   VIF 95% CI Increased SE Tolerance Tolerance 95% CI
                  GDP 1.05 [1.00, 1.87]         1.03      0.95     [0.53, 1.00]
                   M1 1.15 [1.05, 1.49]         1.07      0.87     [0.67, 0.96]
                   M2 1.53 [1.31, 1.90]         1.24      0.65     [0.53, 0.76]
                   M3 1.10 [1.02, 1.51]         1.05      0.91     [0.66, 0.98]
      Current account 1.07 [1.01, 1.69]         1.03      0.94     [0.59, 0.99]
        exchange rate 1.04 [1.00, 2.58]         1.02      0.96     [0.39, 1.00]
             Reserves 1.25 [1.11, 1.57]         1.12      0.80     [0.64, 0.90]
 10Y CONSTANT MATURITY 1.09 [1.02, 1.53]        1.04      0.92     [0.65, 0.98]
  3Y CONSTANT MATURITY 1.06 [1.00, 1.86]        1.03      0.95     [0.54, 1.00]
                Multi 1.60 [1.36, 1.99]         1.27      0.62     [0.50, 0.73]
               Export 1.04 [1.00, 2.25]         1.02      0.96     [0.44, 1.00]
               Import 1.07 [1.01, 1.67]         1.03      0.94     [0.60, 0.99]
```

Figure B.16: VIF for Brazil

```
> col_br
# Check for Multicollinearity

Low Correlation

                  Term  VIF        VIF 95% CI Increased SE Tolerance Tolerance 95% CI
      INTREST RATE LT 1.13 [    1.04,     1.49]         1.06      0.88     [0.67, 0.97]
                 IR CT 1.22 [    1.09,     1.54]         1.11      0.82     [0.65, 0.92]
                   GDP 1.20 [    1.08,     1.52]         1.10      0.83     [0.66, 0.93]
 BOP : CURRRENT ACCOUNT 1.08 [   1.01,     1.57]         1.04      0.92     [0.64, 0.99]
         EXCHANGE RATE 1.14 [    1.04,     1.49]         1.07      0.88     [0.67, 0.96]
 Industrial production 1.09 [    1.02,     1.53]         1.04      0.92     [0.65, 0.98]
 10Y CONSTANT MATURITY 1.28 [    1.13,     1.59]         1.13      0.78     [0.63, 0.89]
  3Y CONSTANT MATURITY 1.18 [    1.07,     1.51]         1.09      0.85     [0.66, 0.94]
                import 1.07 [    1.01,     1.67]         1.03      0.94     [0.60, 0.99]
                export 1.13 [    1.04,     1.49]         1.06      0.88     [0.67, 0.97]

Moderate Correlation

 Term  VIF        VIF 95% CI Increased SE Tolerance Tolerance 95% CI
   M1 5.70 [   4.47,     7.36]         2.39      0.18     [0.14, 0.22]

High Correlation

    Term     VIF          VIF 95% CI Increased SE Tolerance Tolerance 95% CI
      M2 3261.13 [2481.86, 4285.17]        57.11  3.07e-04     [0.00, 0.00]
      M3   30.01 [  22.98,   39.31]         5.48      0.03     [0.03, 0.04]
 Reserve  705.09 [ 536.71,  926.39]        26.55  1.42e-03     [0.00, 0.00]
   Multi 3403.78 [2590.42, 4472.63]        58.34  2.94e-04     [0.00, 0.00]
```

Figure B.17: VIF for Finland

```
> col_fin
# Check for Multicollinearity

Low Correlation

                                   Term  VIF   VIF 95% CI Increased SE Tolerance Tolerance 95% CI
                             CPI energy 1.04 [1.00, 2.38]         1.02      0.96     [0.42, 1.00]
         LT intreste rate (10Y yield) 1.07 [1.01, 1.64]         1.03      0.93     [0.61, 0.99]
  intreste rate CT (INTERBANK RATE 1.22 [1.09, 1.54]         1.11      0.82     [0.65, 0.92]
                                    GDP 1.18 [1.06, 1.50]         1.09      0.85     [0.67, 0.94]
                        Current account 1.08 [1.01, 1.59]         1.04      0.93     [0.63, 0.99]
                          EXCHANGE RATE 1.08 [1.01, 1.57]         1.04      0.92     [0.64, 0.99]
                                Reserve 1.04 [1.00, 2.51]         1.02      0.96     [0.40, 1.00]
                  industrial production 1.04 [1.00, 2.91]         1.02      0.96     [0.34, 1.00]
                  10Y CONSTANT MATURITY 1.12 [1.03, 1.49]         1.06      0.89     [0.67, 0.97]
                   3Y CONSTANT MATURITY 1.11 [1.02, 1.50]         1.05      0.90     [0.67, 0.98]
                                 export 1.05 [1.00, 1.93]         1.03      0.95     [0.52, 1.00]
                                 import 1.03 [1.00, 7.83]         1.01      0.97     [0.13, 1.00]
```

Figure B.18: VIF for Greece

```
> col_grec
# Check for Multicollinearity

Low Correlation

                  Term  VIF     VIF 95% CI Increased SE Tolerance Tolerance 95% CI
            CPI energy 1.07 [1.01,   1.64]         1.03      0.93     [0.61, 0.99]
      INTREST RATE LT 1.12 [1.03,   1.49]         1.06      0.89     [0.67, 0.97]
                 IR CT 1.02 [1.00,  10.70]         1.01      0.98     [0.09, 1.00]
                   GDP 1.18 [1.06,   1.50]         1.08      0.85     [0.67, 0.94]
         EXCHANGE RATE 1.13 [1.04,   1.49]         1.06      0.88     [0.67, 0.96]
               Reserve 1.04 [1.00,   2.44]         1.02      0.96     [0.41, 1.00]
 Industrial production 1.06 [1.00,   1.82]         1.03      0.95     [0.55, 1.00]
 10Y CONSTANT MATURITY 1.09 [1.01,   1.56]         1.04      0.92     [0.64, 0.99]
  3Y CONSTANT MATURITY 1.11 [1.02,   1.50]         1.05      0.90     [0.66, 0.98]
                export 1.04 [1.00,   2.90]         1.02      0.96     [0.34, 1.00]
                import 1.01 [1.00, 191.48]         1.01      0.99     [0.01, 1.00]
```

Figure B.19: VIF for Japan

```
> col_jap
# Check for Multicollinearity

Low Correlation

                   Term  VIF      VIF 95% CI Increased SE Tolerance Tolerance 95% CI
             CPI energy 1.15 [ 1.04,  1.49]         1.07      0.87     [0.67, 0.96]
       INTREST RATE LT 1.08 [ 1.01,  1.59]         1.04      0.93     [0.63, 0.99]
                  IR CT 1.20 [ 1.07,  1.52]         1.09      0.84     [0.66, 0.93]
                    GDP 1.22 [ 1.09,  1.54]         1.10      0.82     [0.65, 0.92]
                    M1Y 1.11 [ 1.02,  1.50]         1.05      0.90     [0.67, 0.98]
                    M3Y 1.26 [ 1.11,  1.57]         1.12      0.80     [0.64, 0.90]
 BOP : CURRRENT ACCOUNT 1.11 [ 1.03,  1.50]         1.05      0.90     [0.67, 0.98]
          EXCHANGE RATE 1.40 [ 1.22,  1.74]         1.18      0.71     [0.57, 0.82]
  Industrial production 1.05 [ 1.00,  1.94]         1.03      0.95     [0.52, 1.00]
  10Y CONSTANT MATURITY 1.11 [ 1.02,  1.50]         1.05      0.90     [0.67, 0.98]
   3Y CONSTANT MATURITY 1.15 [ 1.05,  1.49]         1.07      0.87     [0.67, 0.96]
                 export 1.11 [ 1.02,  1.50]         1.05      0.90     [0.67, 0.98]
                 import 1.19 [ 1.07,  1.51]         1.09      0.84     [0.66, 0.93]

High Correlation

    Term    VIF         VIF 95% CI Increased SE Tolerance Tolerance 95% CI
     M2Y  11.37 [  8.79,  14.81]         3.37      0.09     [0.07, 0.11]
 Reserve 475.89 [362.29, 625.21]        21.81  2.10e-03     [0.00, 0.00]
   Multi 477.42 [363.45, 627.22]        21.85  2.09e-03     [0.00, 0.00]
```

Figure B.20: VIF for Mexico

```
> col_mex
# Check for Multicollinearity

Low Correlation

                   Term  VIF     VIF 95% CI Increased SE Tolerance Tolerance 95% CI
             CPI energy 1.37 [ 1.20,  1.70]         1.17      0.73     [0.59, 0.84]
       INTREST RATE LT 1.25 [ 1.11,  1.56]         1.12      0.80     [0.64, 0.90]
                  IR CT 1.19 [ 1.07,  1.51]         1.09      0.84     [0.66, 0.93]
                    GDP 1.22 [ 1.09,  1.54]         1.11      0.82     [0.65, 0.91]
                    M1P 2.40 [ 1.97,  3.03]         1.55      0.42     [0.33, 0.51]
 BOP : CURRRENT ACCOUNT 1.11 [ 1.02,  1.50]         1.05      0.90     [0.67, 0.98]
          EXCHANGE RATE 1.42 [ 1.23,  1.76]         1.19      0.71     [0.57, 0.81]
                Reserve 2.93 [ 2.37,  3.72]         1.71      0.34     [0.27, 0.42]
  Industrial production 1.04 [ 1.00,  2.92]         1.02      0.96     [0.34, 1.00]
  10Y CONSTANT MATURITY 1.13 [ 1.03,  1.49]         1.06      0.89     [0.67, 0.97]
   3Y CONSTANT MATURITY 1.13 [ 1.03,  1.49]         1.06      0.89     [0.67, 0.97]
                  Multi 3.20 [ 2.57,  4.07]         1.79      0.31     [0.25, 0.39]
                 export 1.10 [ 1.02,  1.51]         1.05      0.91     [0.66, 0.98]
                 import 1.09 [ 1.02,  1.53]         1.05      0.91     [0.65, 0.98]

High Correlation

 Term   VIF     VIF 95% CI Increased SE Tolerance Tolerance 95% CI
  M2P 35.87 [27.43, 47.00]         5.99      0.03     [0.02, 0.04]
  M3P 37.32 [28.54, 48.91]         6.11      0.03     [0.02, 0.04]
```

Figure B.21: VIF for Poland

```
Low Correlation

                                         Term  VIF   VIF 95% CI Increased SE Tolerance Tolerance 95% CI
                                   CPI energy 1.07 [1.01, 1.62]         1.04      0.93     [0.62, 0.99]
                               INTREST RATE LT 1.34 [1.17, 1.67]         1.16      0.75     [0.60, 0.85]
                                        IR CT 1.20 [1.08, 1.52]         1.10      0.83     [0.66, 0.93]
                                          GDP 1.22 [1.09, 1.54]         1.10      0.82     [0.65, 0.92]
           M1 (seaonally adjusted base 100 =2015) 2.07 [1.72, 2.60]         1.44      0.48     [0.38, 0.58]
                                           M2 1.36 [1.19, 1.69]         1.17      0.73     [0.59, 0.84]
 M3(seasonally adjusted index based on 2015=100.) 2.13 [1.76, 2.67]         1.46      0.47     [0.37, 0.57]
                         BOP : CURRRENT ACCOUNT 1.14 [1.04, 1.49]         1.07      0.87     [0.67, 0.96]
                                EXCHANGE RATE 1.13 [1.03, 1.49]         1.06      0.89     [0.67, 0.97]
                                      Reserve 1.42 [1.23, 1.77]         1.19      0.70     [0.57, 0.81]
                        Industrial production 1.14 [1.04, 1.49]         1.07      0.88     [0.67, 0.96]
                        10Y CONSTANT MATURITY 1.17 [1.06, 1.50]         1.08      0.85     [0.67, 0.94]
                         3Y CONSTANT MATURITY 1.11 [1.03, 1.50]         1.05      0.90     [0.67, 0.98]
                                        Multi 1.51 [1.30, 1.88]         1.23      0.66     [0.53, 0.77]
                                       export 1.09 [1.02, 1.53]         1.05      0.91     [0.65, 0.98]
                                       import 1.11 [1.02, 1.51]         1.05      0.90     [0.66, 0.98]
> plot(col_pol) #PERFECT
```

Figure B.22: VIF for Portugal

```
> col_port
# Check for Multicollinearity

Low Correlation

                   Term  VIF        VIF 95% CI Increased SE Tolerance Tolerance 95% CI
       CPGREN01PTM657N 1.02 [1.00,     16.77]         1.01      0.98     [0.06, 1.00]
       IRLTLT01PTM156N 1.13 [1.03,      1.49]         1.06      0.89     [0.67, 0.97]
       IR3TIB01PTM156N 1.09 [1.02,      1.53]         1.05      0.91     [0.65, 0.98]
       CPMNACSCAB1GQPT 1.09 [1.02,      1.53]         1.05      0.92     [0.65, 0.98]
 BOP : CURRRENT ACCOUNT 1.02 [1.00,     12.52]         1.01      0.98     [0.08, 1.00]
                EXPOUS 1.01 [1.00, 17434.73]         1.00      0.99     [0.00, 1.00]
               Reserve 1.04 [1.00,      2.98]         1.02      0.96     [0.34, 1.00]
  Industrial production 1.05 [1.00,      2.18]         1.02      0.96     [0.46, 1.00]
  10Y CONSTANT MATURITY 1.09 [1.01,      1.54]         1.04      0.92     [0.65, 0.99]
   3Y CONSTANT MATURITY 1.07 [1.01,      1.63]         1.04      0.93     [0.61, 0.99]
                export 1.16 [1.05,      1.49]         1.08      0.86     [0.67, 0.95]
                import 1.15 [1.05,      1.49]         1.07      0.87     [0.67, 0.95]
```

Figure B.23: VIF for South Africa

```
> col_sa
# Check for Multicollinearity

Low Correlation

                    Term  VIF       VIF 95% CI Increased SE Tolerance Tolerance 95% CI
              CPI energy 1.10 [ 1.02,    1.51]         1.05      0.91     [0.66, 0.98]
         INTREST RATE LT 1.42 [ 1.23,    1.77]         1.19      0.70     [0.57, 0.81]
                   IR CT 1.38 [ 1.20,    1.71]         1.17      0.73     [0.58, 0.83]
                     GDP 1.50 [ 1.29,    1.87]         1.23      0.66     [0.53, 0.77]
                      M1 1.71 [ 1.45,    2.14]         1.31      0.58     [0.47, 0.69]
                      M3 4.87 [ 3.84,    6.27]         2.21      0.21     [0.16, 0.26]
  BOP : CURRRENT ACCOUNT 1.15 [ 1.05,    1.49]         1.07      0.87     [0.67, 0.95]
           EXCHANGE RATE 1.46 [ 1.26,    1.82]         1.21      0.68     [0.55, 0.79]
   Industrial production 1.63 [ 1.39,    2.03]         1.28      0.61     [0.49, 0.72]
   10Y CONSTANT MATURITY 1.09 [ 1.02,    1.53]         1.05      0.91     [0.66, 0.98]
    3Y CONSTANT MATURITY 1.28 [ 1.13,    1.59]         1.13      0.78     [0.63, 0.89]
                  export 1.08 [ 1.01,    1.56]         1.04      0.92     [0.64, 0.99]
                  import 1.09 [ 1.01,    1.55]         1.04      0.92     [0.65, 0.99]

High Correlation

    Term    VIF         VIF 95% CI Increased SE Tolerance Tolerance 95% CI
      M2  14.58 [ 11.23,   19.03]          3.82      0.07     [0.05, 0.09]
 Reserve 721.32 [549.06,  947.72]         26.86  1.39e-03     [0.00, 0.00]
   Multi 730.68 [556.18,  960.01]         27.03  1.37e-03     [0.00, 0.00]
```

Figure B.24: VIF for Spain

```
> col_Esp
# Check for Multicollinearity

Low Correlation

                    Term  VIF       VIF 95% CI Increased SE Tolerance Tolerance 95% CI
              CPI energy 1.11 [ 1.03,    1.50]         1.06      0.90     [0.67, 0.97]
         INTREST RATE LT 1.12 [ 1.03,    1.49]         1.06      0.90     [0.67, 0.97]
                   IR CT 1.40 [ 1.22,    1.74]         1.18      0.72     [0.58, 0.82]
                     GDP 1.54 [ 1.32,    1.91]         1.24      0.65     [0.52, 0.76]
                     M3e 2.65 [ 2.15,    3.35]         1.63      0.38     [0.30, 0.46]
  BOP : CURRRENT ACCOUNT 1.17 [ 1.06,    1.50]         1.08      0.86     [0.67, 0.95]
           EXCHANGE RATE 1.01 [ 1.00,  445.77]         1.01      0.99     [0.00, 1.00]
                 Reserve 2.43 [ 1.99,    3.06]         1.56      0.41     [0.33, 0.50]
   Industrial production 1.03 [ 1.00,    6.17]         1.01      0.97     [0.16, 1.00]
   10Y CONSTANT MATURITY 1.10 [ 1.02,    1.51]         1.05      0.91     [0.66, 0.98]
    3Y CONSTANT MATURITY 1.14 [ 1.04,    1.49]         1.07      0.87     [0.67, 0.96]
                   Multi 2.29 [ 1.88,    2.89]         1.51      0.44     [0.35, 0.53]
                  export 1.16 [ 1.05,    1.49]         1.07      0.87     [0.67, 0.95]
                  import 1.18 [ 1.07,    1.51]         1.09      0.84     [0.66, 0.94]

High Correlation

 Term   VIF       VIF 95% CI Increased SE Tolerance Tolerance 95% CI
  M1e 11.65 [ 9.00,   15.17]         3.41      0.09     [0.07, 0.11]
  M2e 13.62 [10.50,   17.76]         3.69      0.07     [0.06, 0.10]
```

Figure B.25: VIF for Turkey

Low Correlation

Term	VIF	VIF 95% CI	Increased SE	Tolerance	Tolerance 95% CI
CPI energy	1.09	[1.02, 1.53]	1.05	0.91	[0.66, 0.98]
IR CT	1.35	[1.18, 1.68]	1.16	0.74	[0.60, 0.85]
GDP	1.29	[1.14, 1.61]	1.14	0.77	[0.62, 0.88]
M1	3.69	[2.94, 4.71]	1.92	0.27	[0.21, 0.34]
BOP : CURRRENT ACCOUNT	1.25	[1.11, 1.57]	1.12	0.80	[0.64, 0.90]
EXCHANGE RATE	1.77	[1.49, 2.21]	1.33	0.56	[0.45, 0.67]
Industrial production	1.19	[1.07, 1.51]	1.09	0.84	[0.66, 0.93]
10Y CONSTANT MATURITY	1.16	[1.05, 1.49]	1.08	0.86	[0.67, 0.95]
3Y CONSTANT MATURITY	1.05	[1.00, 1.97]	1.03	0.95	[0.51, 1.00]
export	1.07	[1.01, 1.65]	1.03	0.93	[0.61, 0.99]
import	1.03	[1.00, 3.31]	1.02	0.97	[0.30, 1.00]

Moderate Correlation

Term	VIF	VIF 95% CI	Increased SE	Tolerance	Tolerance 95% CI
Reserve	5.22	[4.11, 6.73]	2.28	0.19	[0.15, 0.24]
Multi	5.99	[4.69, 7.74]	2.45	0.17	[0.13, 0.21]

High Correlation

Term	VIF	VIF 95% CI	Increased SE	Tolerance	Tolerance 95% CI
M2	71.90	[54.85, 94.34]	8.48	0.01	[0.01, 0.02]
M3	64.48	[49.20, 84.59]	8.03	0.02	[0.01, 0.02]

Figure B.26: VIF for USA

```
> col_USA
# Check for Multicollinearity
```

Low Correlation

Term	VIF	VIF 95% CI	Increased SE	Tolerance	Tolerance 95% CI
CPI energy	1.09	[1.01, 1.55]	1.04	0.92	[0.65, 0.99]
INTREST RATE LT	1.23	[1.09, 1.54]	1.11	0.82	[0.65, 0.91]
IR CT	1.54	[1.32, 1.91]	1.24	0.65	[0.52, 0.76]
GDP	1.32	[1.16, 1.65]	1.15	0.76	[0.61, 0.86]
M1 (seaonally adjusted base 100 = 2015)	1.08	[1.01, 1.57]	1.04	0.92	[0.64, 0.99]
M3	1.08	[1.01, 1.57]	1.04	0.92	[0.64, 0.99]
BOP : CURRRENT ACCOUNT	1.10	[1.02, 1.52]	1.05	0.91	[0.66, 0.98]
EXCHANGE RATE	1.23	[1.10, 1.55]	1.11	0.81	[0.64, 0.91]
Reserve	1.30	[1.15, 1.63]	1.14	0.77	[0.61, 0.87]
Industrial production	1.14	[1.04, 1.49]	1.07	0.88	[0.67, 0.96]
10Y CONSTANT MATURITY	1.12	[1.03, 1.49]	1.06	0.90	[0.67, 0.97]
3Y CONSTANT MATURITY	1.35	[1.18, 1.68]	1.16	0.74	[0.60, 0.85]
export	1.13	[1.04, 1.49]	1.07	0.88	[0.67, 0.96]
import	1.06	[1.01, 1.73]	1.03	0.94	[0.58, 0.99]

C EWS Model

C.1 Dichotomous Variable

Figure C.1: crises occurrence (Nguyen and al., 2022)

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Table A2
Crises dates by country and type

Country	Banking crises	Debt crises	Currency crises	Twin crises	Triple crises
	(1970–2019)	(1960–2019)	(1950–2019)	(1970–2019)	(1970–2019)
Afghanistan		1964–1966; 1976; 2000–2008; 2010–2012; 2014–2019	1963		
Albania	1994	1991–2002	1997		
Algeria	1990–1994	1991–1998	1988; 1990–1991; 1994		1990–1991
Angola		1989–2006; 2018–2019	1991–1999; 2015–2016; 2018	2018	
Anguilla					
Antigua and Barbuda		1985–1986; 1996–2011; 2014–2016			
Argentina	1980–1982; 1989–1991; 1995; 2001–2003	1982–1993; 2001–2016	1955; 1958; 1962; 1967; 1975; 1981–1982; 1984; 1987–1989; 2002; 2013–2016; 2018		1980–1982; 2001–2002
Armenia	1994	1993–1998		1993–1994	
Aruba					
Australia					
Austria	2008–2012				
Azerbaijan	1995		1994; 2015–2016	1994–1995	
Bahamas					
Bahrain					
Bangladesh	1987		1975		
Barbados		2018–2019			
Belarus	1995	1994–1996	1996–2000; 2009; 2011; 2015		1994–1996
Belgium	2008–2012				
Belize		2006–2007; 2012–2013; 2017			
Benin	1988–1992	1965–1981; 1983–2000; 2003	1994		
Bermuda					
Bhutan		1991–1993	1966; 1991	1991	
Bolivia	1986; 1994	1960–1969; 1980–1998; 2001	1953; 1956; 1958; 1972–1973; 1982–1985		
Bosnia and Herzegovina	1992–1996	1994–2000			
Botswana			1984–1985; 2001		
Brazil	1990–1993; 1994–1998	1983–1994	1953; 1957–1958; 1961; 1964; 1968; 1976; 1979–1983; 1987–1990; 1992–1993; 1999; 2002; 2008; 2015		
Brunei Darussalam					
Bulgaria	1996–1997	1990–1999	1990–1991; 1993–1994; 1996–1997	1991–1992; 1996–1997	
Burkina Faso	1990–1994	1986–2006	1994		
Burundi	1994–1998	1996–2009	1983; 1988		
Cabo Verde	1993	1985–2003			
Cambodia		1971–2019	1969; 1971–1972; 1992–1993		
Cameroon	1987–1991; 1995–1997	1985–2007	1994	1994–1995	
Canada					
Cayman Islands			1972		
Central African Republic	1976; 1995–1996	1972–1985; 1987–2019	1994	1994–1995	
Chad	1983; 1992–1996	1974–2004; 2014–2015; 2018–2019	1994		
Channel Islands					
Chile	1976; 1981–1985	1972–1975; 1983–1990	1951; 1955–1956; 1962–1963; 1967; 1971–1975; 1982–1983; 1985	1971–1975	1981–1983

Country	Banking crises	Debt crises	Currency crises	Twin crises	Triple crises
Czech Republic	1996–2000				
Denmark	2008–2009				
Djibouti	1991–1995	1992–2010; 2017–2019		1991–1995	
Dominica		2002–2018			
Dominican Republic	2003–2004	1961–1964; 1966–1969; 1982–1999	1985; 1987–1988; 1990–1991; 2003	2003	
Ecuador	1982–1986; 1998–2002	1982–1995; 1999–2000; 2008–2009	1970; 1982–1983; 1985–1986; 1988; 1992; 1998–1999		1982–1983; 1998–1999
Egypt	1980	1964–1970; 1977; 1979–1994	1979; 1989–1991; 2003; 2016–2017		1979–1980
El Salvador	1989–1990	1981–1993; 2017	1986; 1990	1989–1990	
Equatorial Guinea	1983	1981–2002; 2017	1994		
Eritrea	1993	2002–2018	1992–1993; 2001	1992–1993; 2001–2002	
Estonia	1992–1994				
Ethiopia		1990–2011	1992–1993		
Faroe Islands					
Fiji			1998		
Finland	1991–1995		1957; 1967		
France	2008–2009				
French Polynesia					
Gabon		1986–2007	1994		
Gambia, The		1982–1989; 2001–2014; 2019	1957; 1984; 1986; 2002–2003	2001–2003	
Georgia	1991–1995	1994–2006	1998–1999		
Germany	2008–2009				
Ghana	1982–1983	1965–1977; 1979; 1982; 1987–1996; 1998–2004; 2015–2018	1967; 1971; 1978; 1983–1984; 1986–1987; 1992–1993; 1996; 1999–2000; 2009; 2014	1970–1971; 1978–1979; 1986–1987; 1998–2000; 2014–2015	1982–1983
Gibraltar			2008		
Greece	2008–2012	1960–1965; 2012–2013; 2018	1953; 1981; 1983		
Grenada		1984–2018			
Guatemala		1986–2006	1986; 1990	1986	
Guinea	1985; 1993	1986–2018	1999; 2005		1985–1986
Guinea-Bissau	1995–1998; 2014–2017	1979–2018	1994	1994–1995	
Guyana	1993	1976–2018	1984; 1987; 1989; 1991		
Haiti	1994–1998	1963–1965; 1968–1972; 1985–1995	1991–1992; 2002–2003; 2019		
Honduras		1982–2007	1990		
Hungary	1991–1995; 2008–2012				
Iceland	2008–2012		1960; 1967–1968; 1974–1975; 1978; 1980–1983; 1989; 2008	2008	
India	1993		1966; 1991		
Indonesia	1997–2001	1966–1970; 1998–2002	1978–1979; 1983; 1986; 1997–1998; 2000		1997–1998
Iran		1987–1991	1955; 1957; 1993; 2013		
Iraq		1988–2019			
Ireland	2008–2012	2013			
Israel	1983–1986		1953; 1962; 1974–1975; 1977–1981; 1983–1984	1983–1984	
Italy	2008–2009		1981		
Jamaica	1996–1998	1978–2013	1978; 1983–1984; 1991–1994	1978	
Japan	1997–2001				
Jordan	1989–1991	1988–2008	1988–1989		1988–1989
Kazakhstan	2008		1999; 2015–2016		
Kenya	1985; 1992–1994	1989–1994; 1998–2002; 2004–2007	1981; 1993	1992–1993	

Luxembourg	2008–2012				
Macedonia, FYR	1993–1995	1992–1997	1997		
Madagascar	1988	1981–2016	1984; 1987; 1994; 2004	1987–1988	
Malawi		1982–1983; 1987–1990; 1998–2006	1992; 1994; 1997–1998; 2000; 2012; 2015–2016	1997–1998	
Malaysia	1997–1999		1997–1998	1997–1998	
Maldives			1975		
Mali	1987–1991	1964; 1970–1980; 1983–2006; 2015–2017	1994		
Malta					
Marshall Islands					
Mauritania	1984	1978–2019	1992–1993		
Mauritius			1981		
Mexico	1981–1985; 1994–1996	1982–1990	1954; 1976–1977; 1982; 1985–1986; 1994–1995	1994–1995	1981–1982
Micronesia					
Moldova	2014–2018	1996; 1998–2018	1988–1999; 2015	1998–1999; 2014–2015	
Monaco					
Mongolia	2008–2009	1997–2004	1993; 1996–1997	1996–1997	
Montenegro					
Montserrat					
Morocco	1980–1984	1983–1992; 1999–2002	1981	1980–1981	
Mozambique	1987–1991	1980; 1984–2018	1987; 1991–1993; 1995; 2001; 2015–2016	1987	
Myanmar		2000–2018	1975; 2012		
Namibia			1984–1985; 2001; 2008; 2015		
Nauru		1994–2019			
Nepal	1988		1967; 1991		
Netherlands	2008–2009				
Netherlands Antilles					
New Caledonia			1958–1959		
New Zealand			1984; 2008		
Nicaragua	1990–1993; 2000–2001	1978–2018	1979; 1985; 1988; 1990	1978–1979; 1990	
Niger	1983–1985	1983–2014; 2016–2018	1994	1983–1985	
Nigeria	1991–1995; 2009–2012	1982–2006	1986–1987; 1989; 1992; 1999; 2016	1991–1992	
Norway	1991–1993				
Oman					
Pakistan		1972–1978; 1998–2002	1955; 1972	1972	
Palau					
Panama	1988–1989	1983–2003			
Papua New Guinea		2016–2018	1997–1998		
Paraguay	1995	1985–1994	1952–1953; 1955–1956; 1984; 1986–1987; 1989; 2001–2002	1984–1985; 1985–1987	
Peru	1983	1968–1970; 1978–1980; 1983–1998	1967; 1976–1978; 1981–1985; 1987–1990	1983	
Philippines	1983–1986; 1997–2001	1983–1992	1962; 1970; 1983–1984; 1997–1998	1997–1998	1983–1984
Poland	1992–1994	1981–1994	1978–1980; 1982; 1986–1990; 1992	1981–1982; 1992	
Portugal	2008–2012	2013	1982–1983		
Puerto Rico		2016–2019			
Qatar					
Romania	1998–1999		1973; 1990–1993; 1996–1997; 1999	1996–1997	
Russian Federation	1998; 2008–2009	1991–2004	1998–1999; 2014–2015	1998	
Rwanda		1992–2007	1966; 1990–1991; 1995		
Samoa		1982–1985	1983	1982–1983	
San Marino			1981		
Sao Tome and Principe	1992	1985–2019	1987–1988; 1991; 1994–1997	1991–1992	

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Table A2 (*continued*)

Country	Banking crises	Debt crises	Currency crises	Twin crises	Triple crises
South Africa		1985–1987; 1989	1984–1985; 2001; 2008; 2015	1984–1985	
South Sudan		2014–2019	2015–2016	2014–2016	
Spain	1977–1981; 2008–2012		1983		
Sri Lanka	1989–1991	1996–2002	1977–1978		
St. Kitts and Nevis		2011–2012			
St. Lucia					
St. Vincent and the Grenadines		2002–2005			
Sudan		1977–2019	1981–1982; 1985; 1987–1988; 1991–1992; 1994–1996; 1998; 2012; 2018		
Suriname		1998–2010	1994; 1999; 2016	1998–1999	
Eswatini	1995–1999		1984–1985; 2001; 2008; 2015		
Sweden	1991–1995; 2008–2009		1993		
Switzerland	2008–2009				
Syrian Arab Republic		1990–2001; 2005	1954; 1988; 2011; 2013; 2015–2016		
Tajikistan		1994–2006	1995; 1997; 1999; 2015	1994–1995	
Tanzania	1987–1988	1978–2018	1983–1984; 1986; 1992	1986–1987	
Thailand	1983; 1997–2000		1997	1997	
Timor-Leste					
Togo	1993–1994	1977–2011	1994	1993–1994	
Tonga		2002–2004; 2013–2014; 2018			
Trinidad and Tobago		1988–1990	1985–1986; 1993		
Tunisia	1991				
Turkey	1982–1984; 2000–2001	1978–1980; 1999	1958–1959; 1970; 1978–1980; 1983–1984; 1988; 1991; 1994; 1996–1997; 1999; 2001; 2008; 2018	1978–1980; 1982–1984	1999–2001
Turkmenistan		1994–2002	1995–1996	1994–1996	
Tuvalu					
Uganda	1994	1978–2006	1981; 1983–1987; 1991		
Ukraine	1998–1999; 2008–2010; 2014–2018	1998–2003; 2014–2019	1998–1999; 2008–2009; 2014–2015	2008–2009	1998–1999; 2014–2015
United Arab Emirates					
United Kingdom	2007–2011				
United States	1988; 2007–2011				
Uruguay	1981–1985; 2002–2005	1965; 1983–1986; 1988; 1990–1991; 2003	1957; 1963; 1965; 1967–1968; 1972; 1974–1975; 1983–1985; 1987–1990; 2002	1987–1988	1981–1985; 2002–2003
Uzbekistan			1996–1997; 2000; 2017		
Vanuatu					
Venezuela, RB	1994–1998	1983–1990; 1992–1994	1984; 1986–1987; 1989; 1993–1994; 1996; 2002; 2011; 2013; 2016	1983–1984	1992–1994
Vietnam	1997	1975; 1978; 1980–2005	1962; 1966; 1972; 1981; 1987–1989	1980–1981	
Virgin Islands					
Yemen, Republic of	1996	1990–2009; 2016–2018	1995	1995–1996	
Yugoslavia, SFR		1983–1991	1952; 1954; 1965; 1971; 1980–1981; 1983; 1987–1989; 1991	1983	
Zambia	1995–1998	1979–2018	1983; 1985–1986; 1989–1992; 1996; 1998; 2000; 2009; 2015	1995–1996	
Zimbabwe	1995–1999	1965–1980; 2000–2018	1983–1984; 1991; 1997–1998; 2000; 2003; 2005–2008	2000	

D Results

D.1 Currency crises

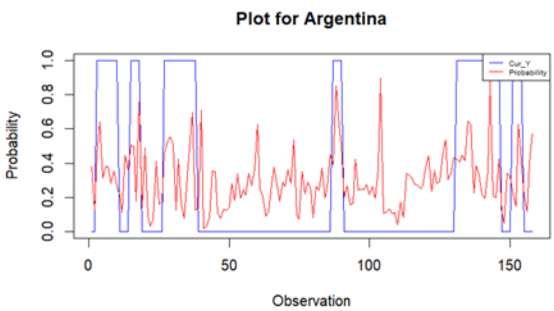

Figure D.1: Logit estimation of Argentina

```
> resultCur[["Argentina"]]
$Estimation
       name   Estimate Std.Error    zvalue           Pr
1 Intercept -1.0084732 0.2928928 -3.443148 0.0005749843
2         1  0.1834512 0.2092494  0.876711 0.3806436523
3         2 -3.9915058 1.6107508 -2.478041 0.0132106136
4         3 -0.8879399 0.5032364 -1.764459 0.0776547609
5         4  4.6851030 3.1679646  1.478900 0.1391670356

$AIC
[1] 175.0282

$BIC
[1] 195.3412

$R2
[1] 0.07220635

$index
```

Figure D.2: Logit estimation of Argentina coeff

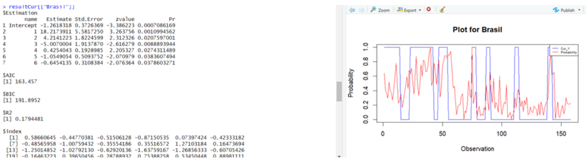

Figure D.3: Logit estimation of Brazil

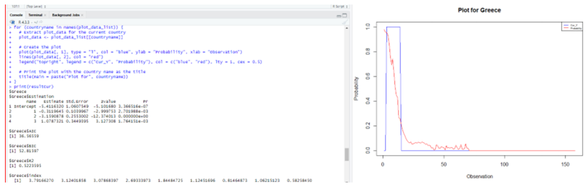

Figure D.4: Logit estimation of Greece

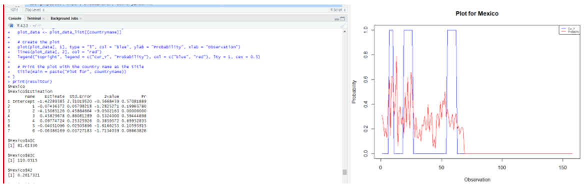

Figure D.5: Logit estimation of Mexico

Figure D.6: Logit estimation of Poland

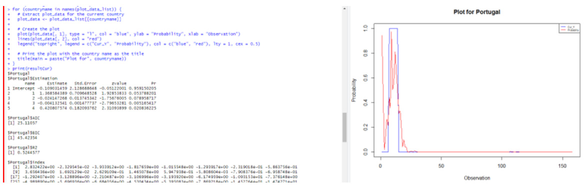

Figure D.7: Logit estimation of Portugal

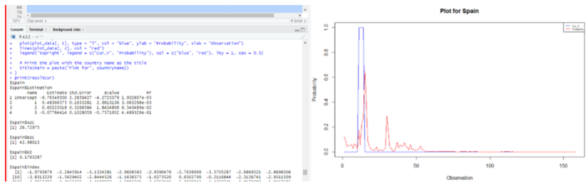

Figure D.8: Logit estimation of Spain

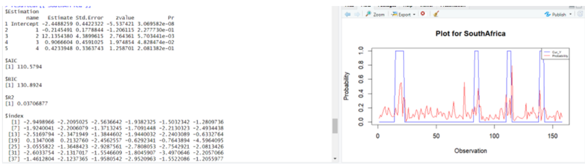

Figure D.9: Logit estimation of South Africal

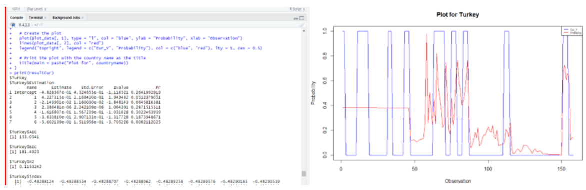

Figure D.10: Logit estimation of Turkey

D.2 Banking crises

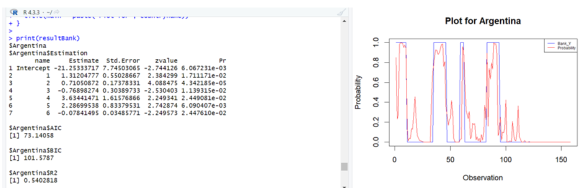

Figure D.11: Logit estimation of Argentina

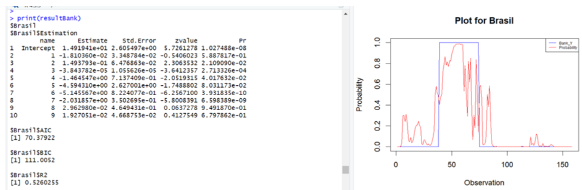

Figure D.12: Logit estimation of Brazil

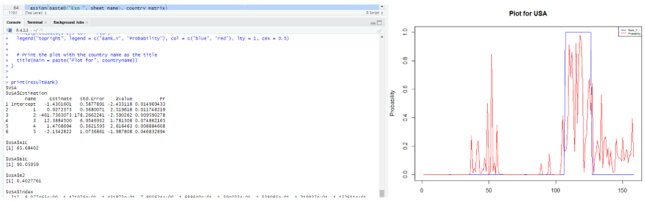

Figure D.21: Logit estimation of USA

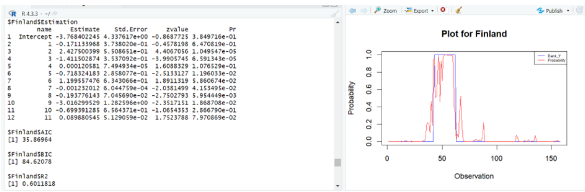

Figure D.13: Logit estimation of Finland

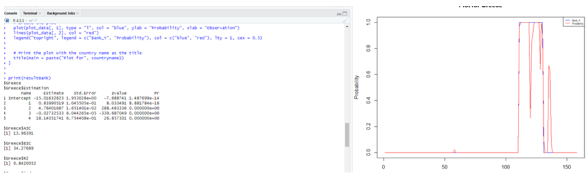

Figure D.14: Logit estimation of Greece

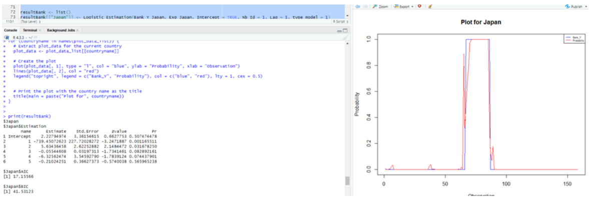

Figure D.15: Logit estimation of Japan

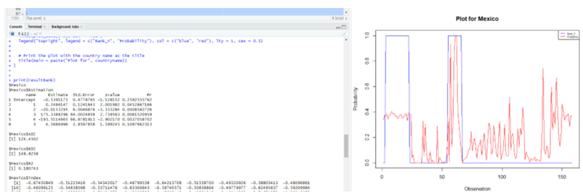

Figure D.16: Logit estimation of Mexico

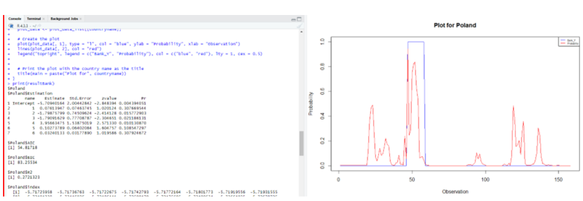

Figure D.17: Logit estimation of Poland

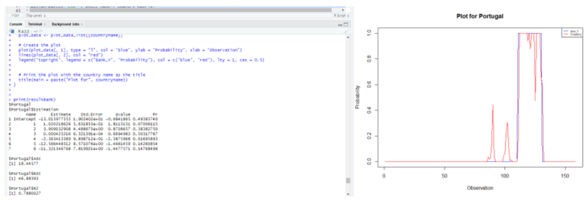

Figure D.18: Logit estimation of Portugal

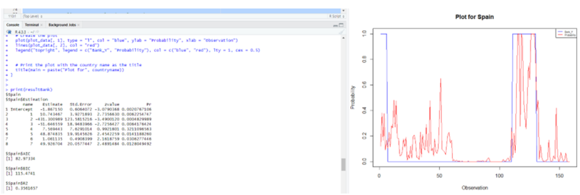

Figure D.19: Logit estimation of Spain

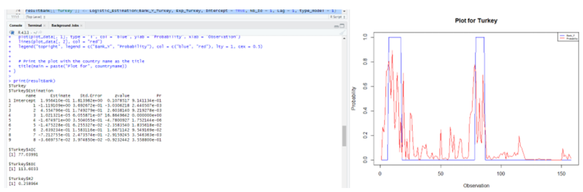

Figure D.20: Logit estimation of Turkey

D.3 Debt crises

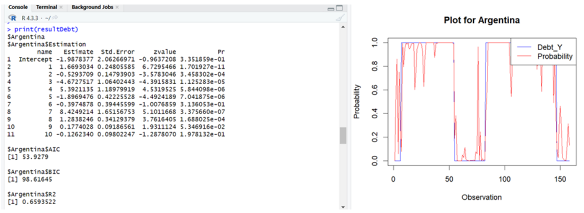

Figure D.22: Logit estimation of Argentina

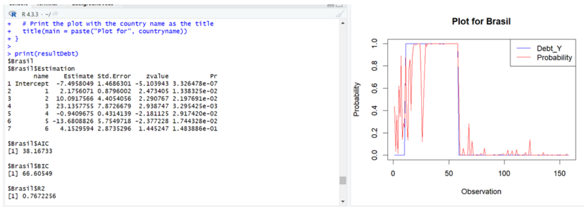

Figure D.23: Logit estimation of Brazil

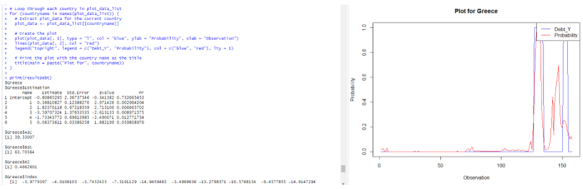

Figure D.24: Logit estimation of Greece

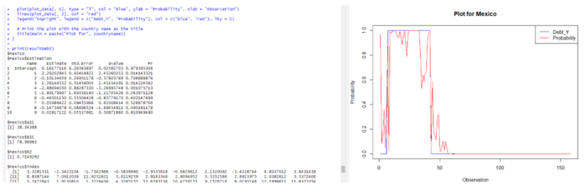

Figure D.25: Logit estimation of Mexico

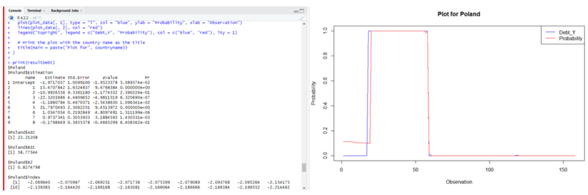

Figure D.26: Logit estimation of Poland

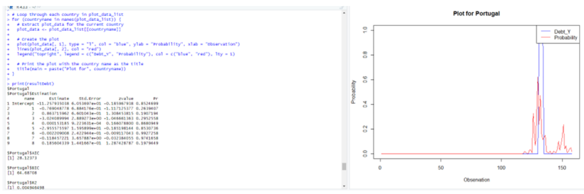

Figure D.27: Logit estimation of Portugal

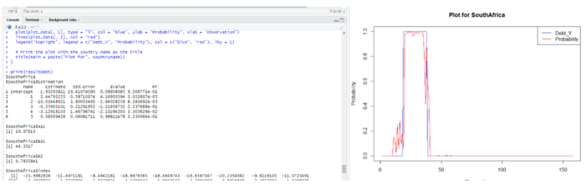

Figure D.28: Logit estimation of South Africa

Figure D.29: Logit estimation of Turkey

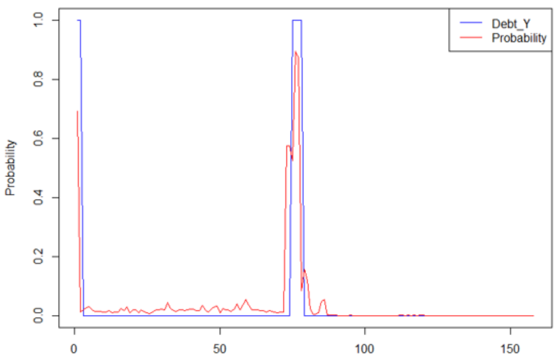

Figure D.30: Logit Estimation for Turkey

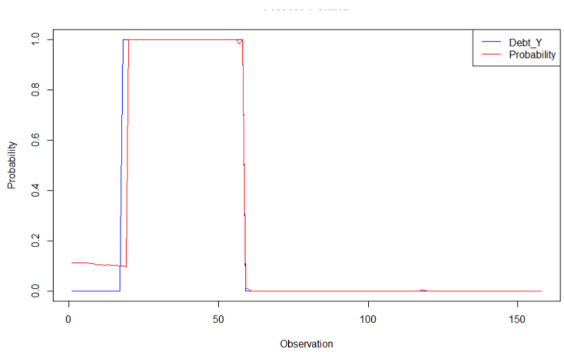

Figure D.31: Logit Estimation for Poland

E Forecast financial crises

E.1 Forecast currency crises

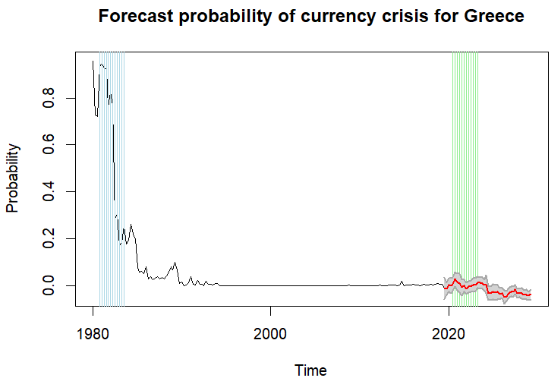

Figure E.1: Currency crises Probability for Greece

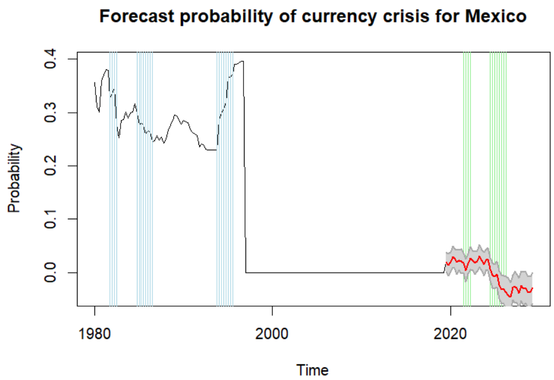

Figure E.2: Currency crises Probability for Mexico

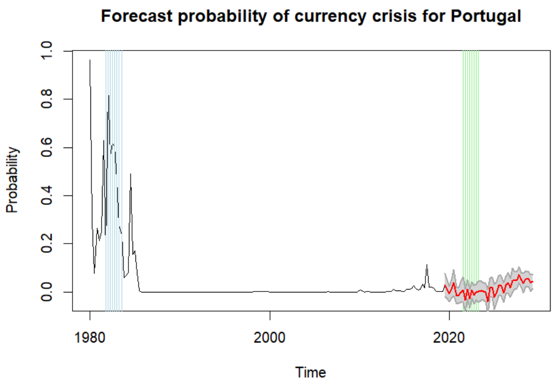

Figure E.3: Currency crises Probability for Portugal

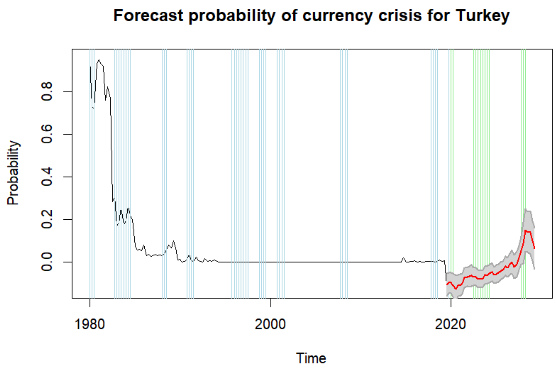

Figure E.4: Currency crises Probability for Turkey

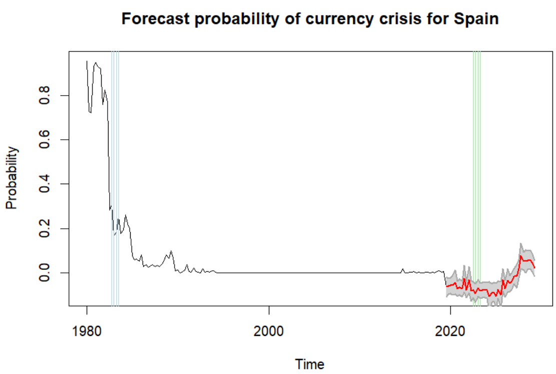

Figure E.5: Currency crises Probability for Spain

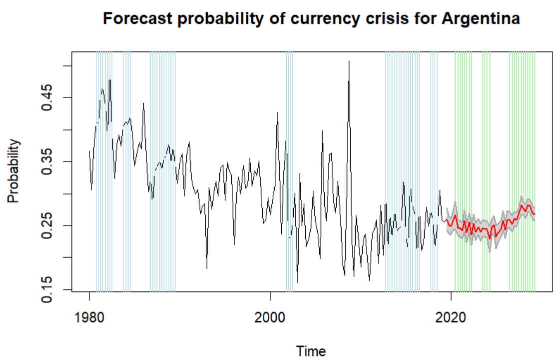

Figure E.6: Currency crises Probability for Argentina

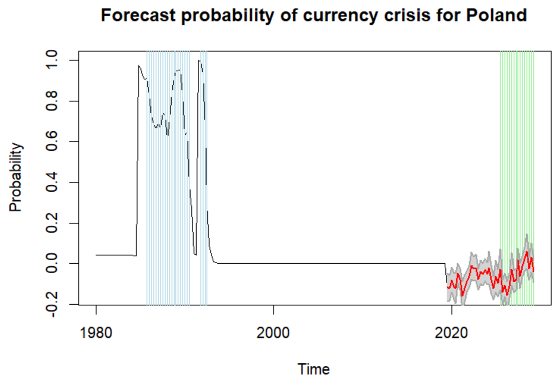

Figure E.7: Currency crises Probability for Poland

E.2 Forecast Banking crises

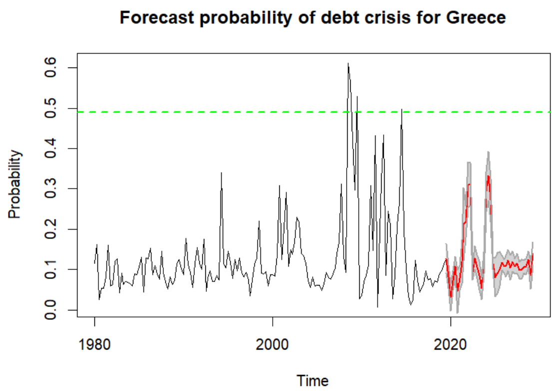

Figure E.8: Banking crises Probability for Greece

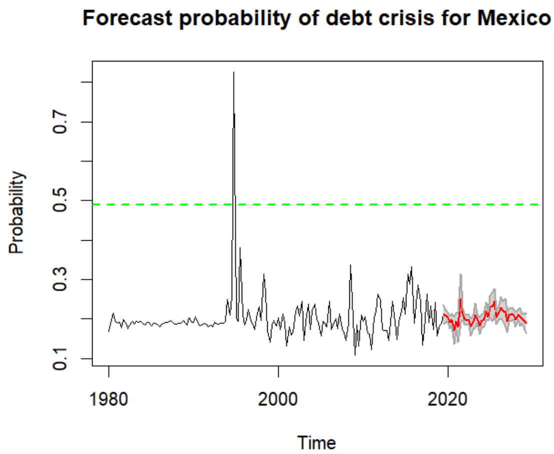

Figure E.9: Banking crises Probability for Mexico

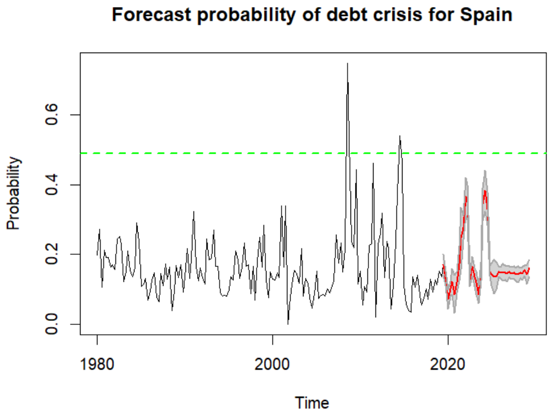

Figure E.10: Banking crises Probability for Portugal

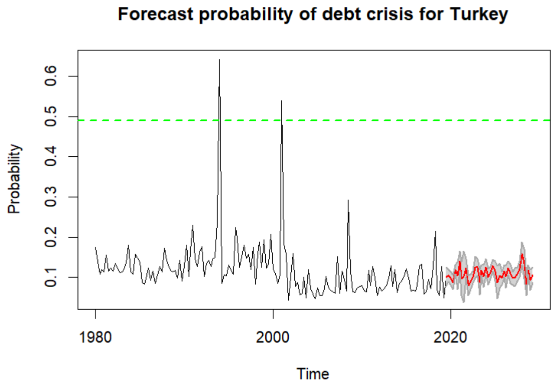

Figure E.11: Banking crises Probability for Turkey

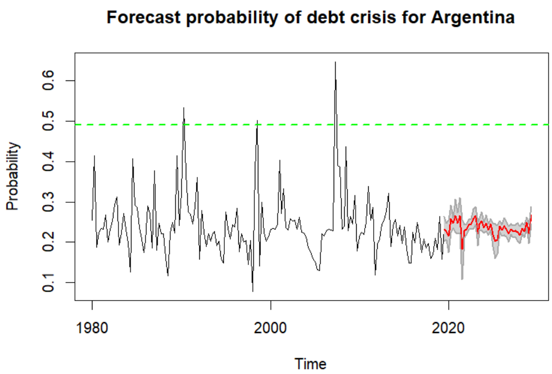

Figure E.12: Banking crises Probability for Argentina

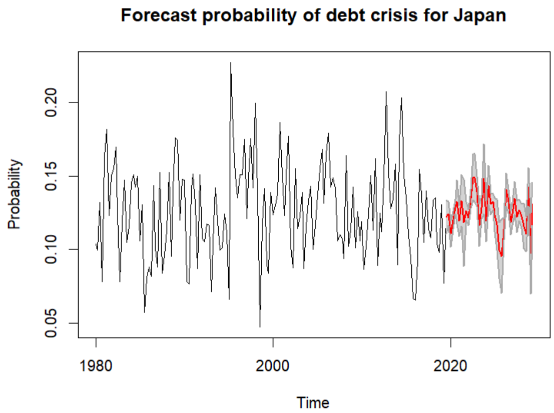

Figure E.13: Banking crises Probability for Japan

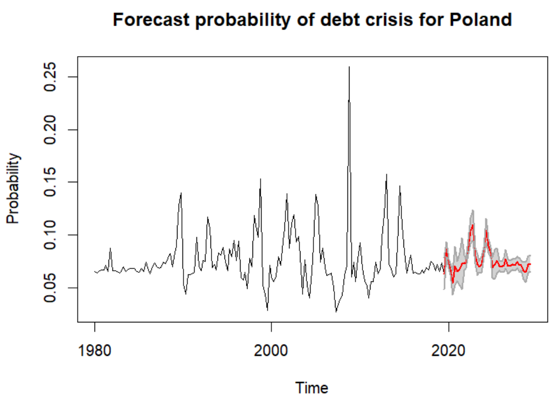

Figure E.14: Banking crises Probability for Poland

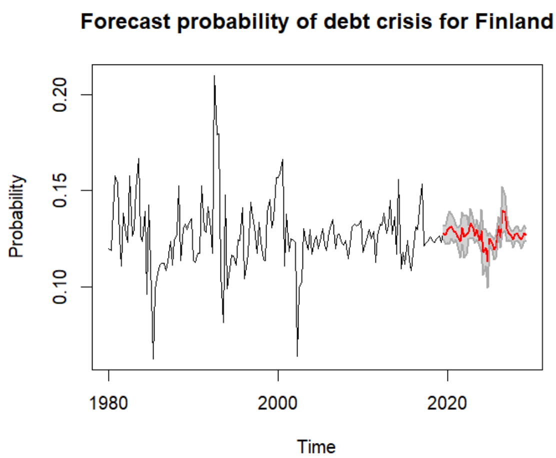

Figure E.15: Banking crises Probability for Finland

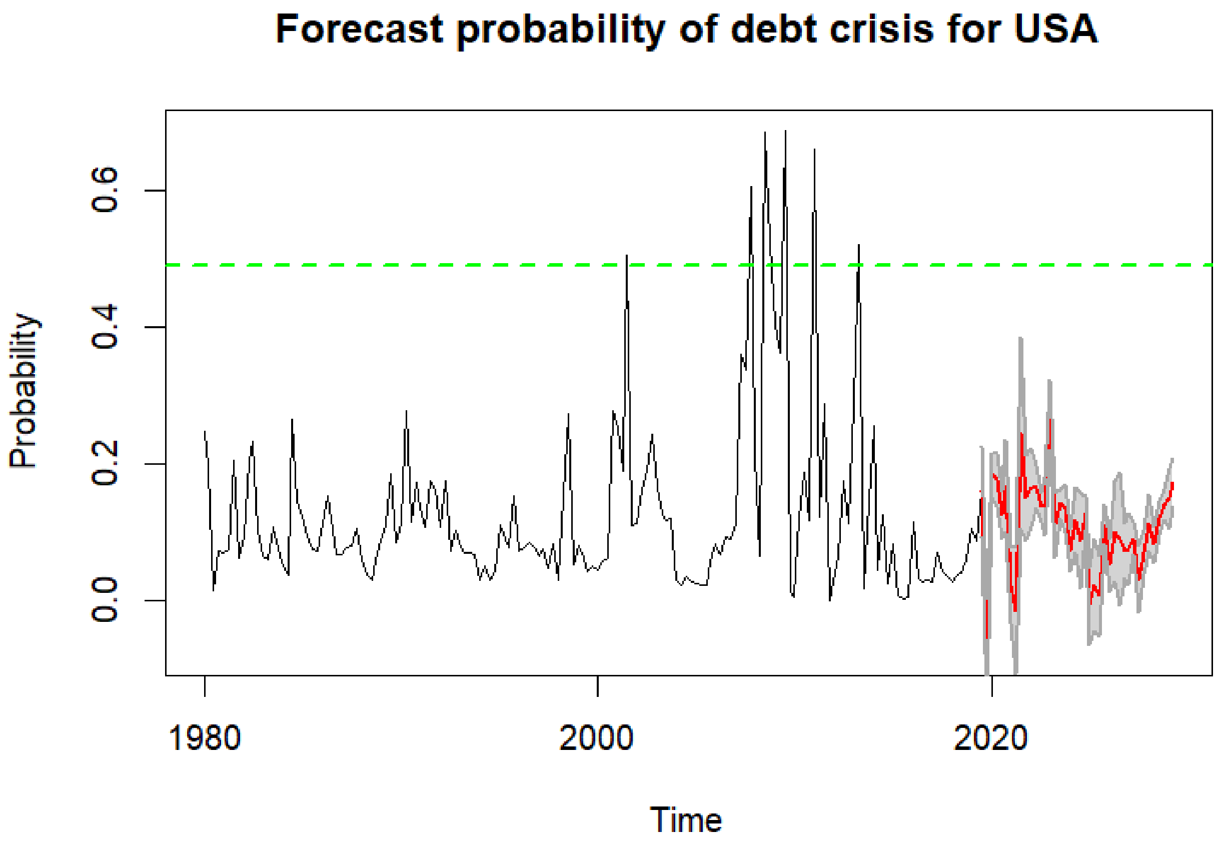

Figure E.16: Banking crises Probability for USA

E.3 Forecast Debt crises

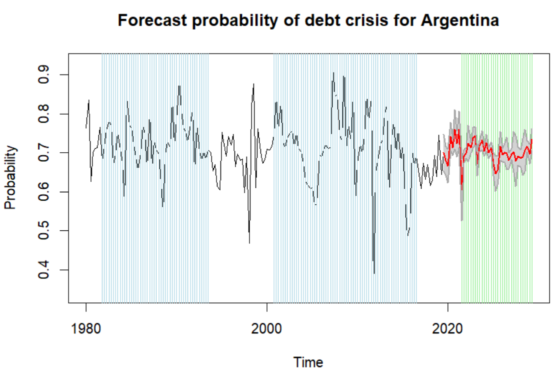

Figure E.17: Debt crises Probability for Argentina

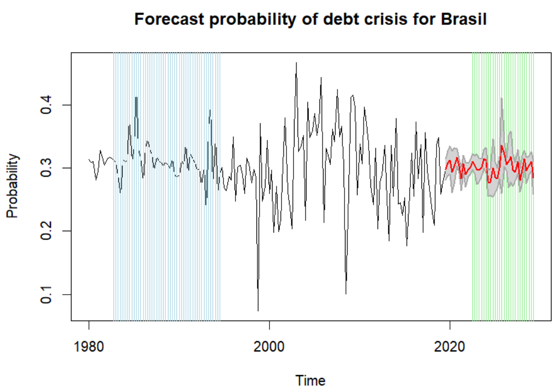

Figure E.18: Debt crises Probability for Brazil

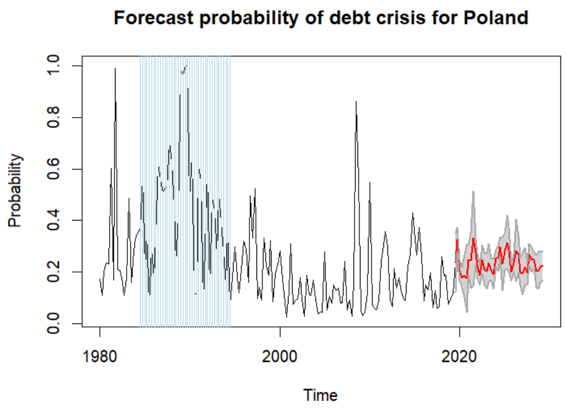

Figure E.19: Debt crises Probability for Poland

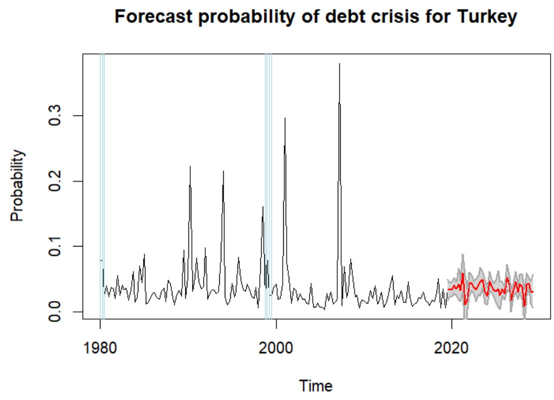

Figure E.20: Debt crises Probability for Turkey

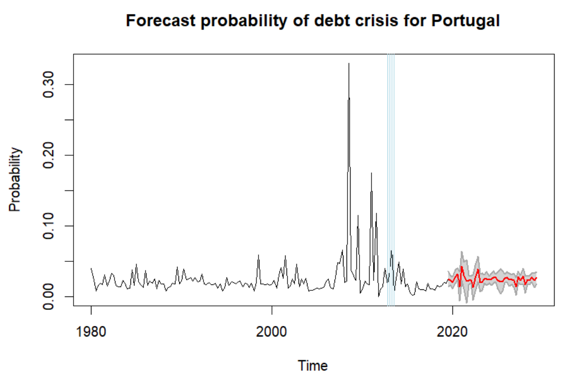

Figure E.21: Debt crises Probability for Portugal

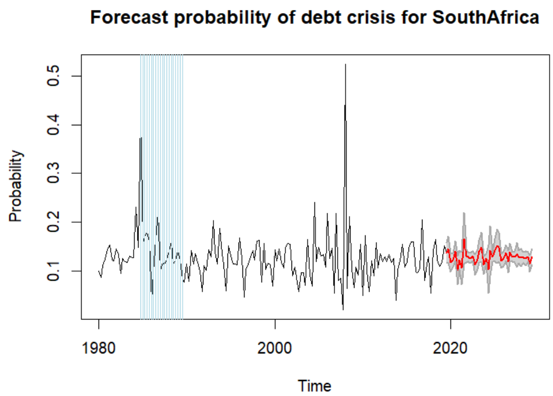

Figure E.22: Debt crises Probability for South Africa

E.4 Forecast model evaluation

Debt	MAE	MSE	RMSE
Brazil	0.049	0.003	0.058
Argentina	0.070	0.010	0.100
Greece	0.025	0.001	0.034
Mexico	0.055	0.004	0.066
Poland	0.103	0.015	0.124
Portugal	0.019	0.001	0.033
South Africa	0.025	0.001	0.032
Turkey	0.018	0.000	0.020
Average	0.034	0.002	0.041

Table 19: Evaluation metrics for debt crises forecasts

Abstract:

Being in an era where unpredictable financial crises happen, it is necessary to understand which financial indicators should be included win an Early Warning System (EWS). The purpose of our master thesis is to identify the key Variables that enhance the accuracy of an EWS for currency, banking, and debt crises. In first stage, we reviewed the current literature to have a full understanding of the difference between types of crises and to acknowledge the different EWS methods that exists. Secondly, we proceeded in empirical research where we started by testing the Relationship between the variables using a bivariate regression, a correlation and multicollinearity analysis. Subsequently, we proceeded in the implementation of a logit regression model to establish our EWS, followed by a specification model. Our results showed that for the currency crises the most significant variables are the CPI energy, short-term interest rate, exchange rate, industrial production and the 3-Month Treasury bill. For banking crises, we identified the exchange rate, CPI, short-term interest rate, 3-Months Treasury bill and the 10-Year constant maturity. For debt crises, the most significant variables are the CPI, exchange rate, 10-Year constant maturity and the 3-Month Treasury Bill. Once we have identified the most significant variables, we have performed forecasts for each type of crises for the next decade and conducted model evaluations.

Keywords: Financial crises; Early Warning System; Logistic estimation model; Dynamic model

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