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Building a System of Leading Indicators for Forecasting the Currency Crisis

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ABSTRACT

This research is devoted to the analysis of financial crises. We examine different classifications of crises, methods of forecasting, approaches to building systems of early warning indicators. To better understand the potential for predicting financial crises, we conduct our own empirical research, comparing logit model and random forest to predict currency crises in developing countries. We also identify the most relevant variables, whose dynamics may signal the currency crisis is approaching. We aim to compare the accuracy of econometric models and machine learning techniques in predicting currency crises in developing countries, and to identify a set of relevant indicators that could be used in a warning system. We use logit regression and random forest models. We compare the predictive power of these models using the ROC curve. The significance of variables in a random forest model is determined by the Shapley values. We found that the random forest model has slightly more accurate predictive power than the logit approach. Both models indicate that oil prices and commercial bank deposits are the most robust predictors of currency crises. The results obtained can be taken into account by economic institutions involved in financial system regulation, as we indicate the variables, which should be primarily taken into account when forecasting currency crises in developing countries.

Keywords: currency crisis; logit model; random forest; early warning system

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INTRODUCTION

Despite the best efforts of regulators, financial crises continue to occur with alarming frequency. Some of the most significant financial crises of recent history include the Great Depression of the 1930s, the Latin American debt crisis of the 1980s, the Asian financial crisis in the late 1990s, and the global financial crisis that began in 2007 and lasted until 2009. These crises have complex causes, often involving a combination of macroeconomic imbalances, weaknesses in the financial system's structure, and market inefficiencies.

Currently, methods for developing systems of leading indicators for financial crises are actively being studied in the academic literature. These methods allow us to predict future economic trends based on current and historical data, and identify potential risks in order to take proactive measures. Leading indicator systems can be based on various methods and models, including regression analysis, machine learning, and artificial intelligence. This allows us to process large amounts of data and identify relationships between different economic indicators.

The aim of this study is to identify economic indicators that would be most suitable for use in an early warning system for predicting currency crises in developing countries. Our research hypothesis is that there exists a specific set of indicators that can effectively detect currency crises in these countries in a timely manner.

The purpose of this study is to investigate financial crises and their causes. We will focus on economic and financial indicators that can be used as leading indicators for predicting future crises.

To accomplish this goal, we have set the following objectives:

1. Review the literature on the theoretical aspects of financial crises.

2. Identify a set of variables from existing empirical research that are significant for forecasting crises.

3. Explore methods for forecasting the likelihood of a financial crisis.

4. Compare traditional econometric approaches to forecasting currency crises with machine learning techniques.

5. Develop our own system of leading indicators based on the information gathered.

Monthly indicators for seven emerging market countries over the past 20 years, from 1st January 2002 to 12th January 2021, were used as the data for the empirical part of this study. The information was mainly obtained from the databases of the International Monetary Fund and the Organization for Economic Cooperation and Development.

The novelty of this work lies in several aspects. Firstly, it introduces a new set of indicators for empirical research into the potential factors that affect the likelihood of a currency crisis. This includes the addition of a “dollar index’. Secondly, it analyzes monthly data, rather than the more commonly used annual indicators. Thirdly, it compares two different methods of crisis forecasting — econometric and machine learning — and evaluates their results.

The structure of the paper is as follows: the first section discusses various types of financial crises and their characteristics, as well as the causes and consequences of these events. It also examines the views of researchers on how to construct a system of early warning indicators. The second and third sections describe the data collection and methodology used in the empirical research. Finally, the last part interprets the results and draws conclusions for economic policy.

CLASSIFICATION OF FINANCIAL CRISES AND THE MAIN APPROACHES TO THEIR FORECASTING

Financial Crises: Main Types, Causes, Consequences

A financial crisis is a state of the economy characterized by serious disruptions in the financial system, which can, in turn, cause significant losses for the population and businesses, as well as spread to other countries. There are several types of financial crises that differ from each other in which segment of the financial system they affect, what factors cause them, and what consequences they have. The main types of financial crises include currency crises, banking crises, and sovereign debt crises [1].

Currency crises occur when the value of a national currency declines dramatically. The causes of currency crises can be related to unfavorable changes in fundamental factors, such as low economic growth or lack of transparency in the markets. They can also be related to panic and lack of trust in the national currency [2]. Researchers define currency crises by various criteria, for example, by the degree of depreciation of the national currency or the intensity of market pressure during speculative attacks. Some studies claim that speculative attacks are the main cause of most currency crises [3]. These attacks are usually accompanied by a sharp depreciation of the national currency, a significant reduction in international reserves and an increase in interest rates.

Banking crises occur when banks are unable to meet their financial obligations to customers. These crises are often associated with high levels of debt, risky assets, and a lack of liquidity on the balance sheets of banks. Additionally, researchers have identified systemic banking crises, which are characterized by large-scale defaults of banks, a negative impact on the entire banking system, and an extended period of problems for the banking sector, such as decreased lending, deteriorated asset quality, and increased interest rates. Experts assess the severity of a banking crisis based on additional information about the banking system, economy, and political situation in a country [4].

Sovereign debt crises are defined as the inability of a country to pay its debt on time or restructure it on more favorable terms. There are crises of external and internal debt. Researchers identify debt crises using information about non-payments of principal or interest on time, or the use of restructuring or debt exchange on less favorable terms than the initial ones [5].

The classification of financial crises proposed by other researchers [6], in addition to the ones discussed above, also includes "Sudden Stop" crises. These are characterized by a sharp and significant reduction or halt in capital inflows into a country's economy. A crisis occurs when investors lose faith in a country's economic prospects and withdraw their investments en masse, leading to a substantial decrease in credit availability.

One difference between these two classifications is that more recent studies provide more detailed descriptions of each type of crisis, taking into consideration a wider range of factors that could lead to negative financial developments.

Both in [7] and in article [6], there is evidence that financial crises are often not isolated events, but rather interconnected.

In [7], the authors demonstrate that the relationship between banking crises and currency crises is mediated by several mechanisms. Firstly, when a banking crisis occurs, banks may sell their foreign assets in order to cover losses, which can cause a decline in the value of the national currency and subsequently lead to a currency crisis. Secondly, during a currency crisis, businesses may face difficulties in obtaining loans denominated in foreign currencies, leading to a banking crisis as they struggle to repay their debts. Additionally, if banks have invested in foreign assets that lose value due to the currency crisis, they may experience liquidity and solvency issues, further contributing to a banking crisis.

The researchers also draw attention to the fact that there is a connection between public debt, currency, and banking crises. Their study [8] shows that these crises tend to occur in the same month, due to common underlying factors that are not observable. The authors found that a banking crisis increases the risk of sovereign default in the future, while sovereign defaults do not seem to increase the likelihood of banking crises in the future. A delayed currency crisis also has a negative impact on the probability of a sovereign debt crisis. Additionally, the study identified an indirect impact of currency and banking crises on sovereign defaults through the worsening of macroeconomic variables. A currency crisis, for example, increases the likelihood of a debt crisis later by raising the real exchange rate. International illiquidity in banks also increases the probability of default if there is a banking crisis before a sovereign default. It is also worth noting that both macroeconomic indicators and the quality of institutions play an important role in determining sovereign defaults, as well as the delayed onset of banking crises. Specifically, sovereign defaults are more likely to occur in countries with increasing current account deficits, a high ratio of short-term external debt to reserves, and weak institutional structures [9].

Figure 1 shows the relationship between the different types of crises described in the literature. For example, a banking crisis can cause a loss of confidence in a country's financial system, which in turn can lead to a decrease in demand for the national currency. A depreciation of the national currency may increase the cost of servicing government debt and lead to a sovereign debt crisis. Accordingly, different types of crises can interact with each other and cause a chain reaction, exacerbating the unfavorable economic situation.

It is also important to consider the consequences of financial crises. One of the main long-term effects of these crises is the loss of public trust in the financial system, as noted by many researchers. For instance, the article [10] discusses how financial crises can lead to an increase in external debt, a reduction in credit availability, and ultimately, a loss of confidence in the country's economy and financial system. The article also suggests

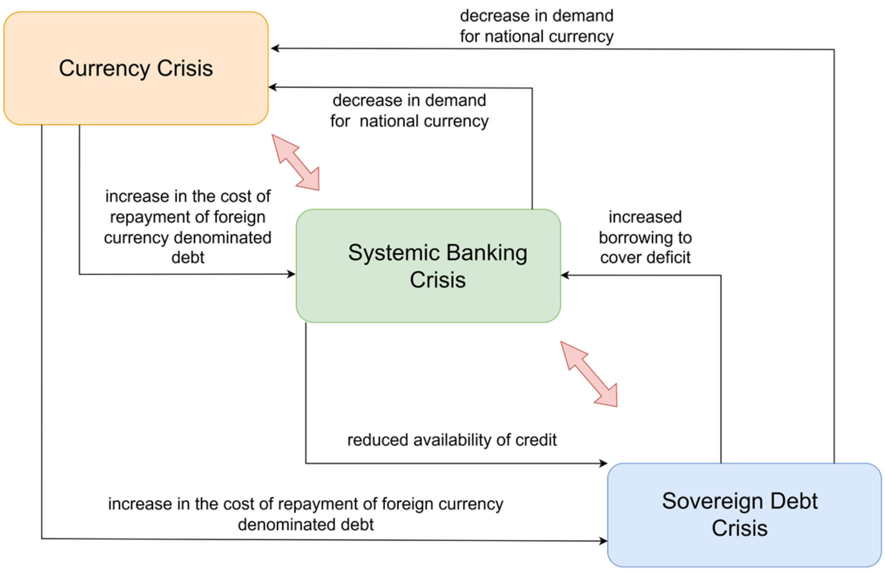

Fig. 1. **Interconnections Between Different Types of Financial Crises**

Source: Compiled by the author.

measures that developing countries can take to cope with financial instability, such as maintaining sufficient international reserves and a healthy banking system.

Other studies have found that financial crises can lead to a significant decrease in economic growth for several years after the event, resulting in a significant reduction in production and income for the population [11]. They confirm that these crises can cause a number of negative consequences, including a sharp reduction in lending and investment, a decrease in demand for goods and services, and an increase in unemployment.

There are several types of financial crises that can occur. This paper will focus on the following: systemic banking crises, currency crises, sovereign debt crises, twin crises (when two of these types occur simultaneously), and triple crises (when all three types occur).

Early Warning Systems for Financial Crisis

In recent years, there has been a significant focus in academic literature on the development of early warning systems (EWSs) for financial crises. During the last few decades, both developed and emerging economies have experienced numerous crisis episodes that have caused high costs not only within the country experiencing the crisis, but also among its trading and financial partners.

The most well-known system for predicting financial crises is the KLR model, proposed in [7]. The authors identified several variables that can indicate the possibility of a financial crisis. These include: the deviation of the real exchange rate from its trend, banking crises, exports, the stock market index, the M2 ratio to international reserves, output, the M1 money supply surplus, the M2 money supply multiplier, the ratio of domestic credit to nominal GDP, the real interest rate, the terms of trade, the real interest rate differential, the credit and deposit ratio, and imports and bank deposits.

In the future, in order to improve the effectiveness of the model for subsequent studies, a new category of indicators has been added to the original set of predictors — “global indicators”. These will include various macroeconomic variables, such as the US output, the output of the G7 countries, the dynamics of the Fed Reserve rate in the United States, and the dynamics of world oil prices [12]. While global indicators have a weak correlation with the domestic economic situation in a country, they can still be useful for improving the quality of predictive models. Changes in global indicators do not always reflect the current state of affairs in a specific country, but they can provide additional information that can help to make more accurate predictions.

The results of other work have shown that an early warning system based on a combination of several indicators provides a sufficiently high accuracy of forecasting financial crises in selected Asian countries [13]. In particular, the author notes that the growth rates of the money supply, bank deposits, GDP per capita and national savings correlate with such types of financial crises as banking, currency and debt. At the same time, the ratio of the M2 multiplier to foreign exchange reserves, the growth rate of foreign exchange reserves, the domestic real interest rate and inflation play an additional role in banking crises and some types of currency crises.

After the financial crisis of 2007–2009, many countries felt the effects of the global economic downturn. This led to a renewed focus on improving crisis early warning systems. In one study, researchers used a model to predict financial crises based on an analysis of over sixty potential variables [14]. However, of such a large pool of variables, only international reserves, inflation, and the real exchange rate turned out to be statistically significant for predicting various kinds of financial crises.

In another study, the authors examined various indicators based on both fundamental and financial variables [15]. The study found that debt levels, bank balance sheet size, GDP growth, inflation rates, money supply growth, stock price changes, and credit rates all provide early warning signs of potential crises. Additionally, the article highlighted the relationship between currency, government debt, and banking crises. A currency crisis can lead to government debt crises and banking crises due to significant declines in exchange rates and foreign exchange reserves, which threaten the liquidity and stability of the overall banking system.

In addition to the existing generally recognized leading indicators, it is also proposed to use world oil prices in a number of studies. It was revealed that oil prices significantly affect the movement of the value of the US dollar against other currencies from the 1970s to 2008 [16]. Moreover, the forecast results are consistent with the oil-exchange rate ratio: an increase in real oil prices leads to a significant decrease in the value of the US dollar against the currencies of oil-producing countries such as Canada, Mexico and Russia, while the national currencies of oil importers, such as Japan, become cheaper relative to the US dollar when the real The price of oil is rising.

Another study examined the relationship between the indicator of "economic openness" and the "sudden shutdown crisis", which are directly related to currency devaluation [17]. This article explores the impact of trade openness on the relationship between the current account and the real exchange rate, focusing on periods of significant problems in banks' balance sheets. The authors identified episodes of sudden stops in capital flows and sharp currency declines for a large sample of developed and developing countries between 1970 and 2011, and found that during these episodes, currency devaluation is associated with larger improvements in the current account in countries with more open economies for trade.

In general, it is worth noting that in all studies on the creation of a system of leading indicators to prevent financial crises, the authors relied on the original KLR model and supplemented it with their own variables.

Approaches to Forecasting Financial Crises

Various methods from both classical econometrics and machine learning are used to predict financial crises.

Econometric models are based on statistical analysis and are based on the assumption that the future behavior of agents can be predicted based on past data. Vector auto regression (VAR) and integrated moving average (ARIMA) autoregressive models are most often used to predict time series in finance, and Logit and Probit regressions are used to predict crisis events.

One of the first examples of using these models was presented in the article [7], where the author developed a crisis prevention method based on a signaling approach — a signal occurs when the value of a certain variable exceeds a set threshold. The main idea is that certain macroeconomic and financial variables tend to behave in different ways before and during a crisis. Subsequently, the EWS model was used to predict several financial crises, including the 1997 Asian Financial Crisis and the 2007–2009 global financial crises.

The Logit and Probit models have their limitations. They may be sensitive to the choice of variables that the researcher determines independently, which means they are not specific. In addition, these models assume a linear relationship between factors and the likelihood of a crisis. Some researchers have also found that standard regressions may not be able to capture vulnerabilities resulting from a combination of macroeconomic and financial factors.

Machine learning methods are based on learning algorithms based on data. These methods can be used to predict crises based on a variety of factors, including macroeconomic data, financial market data, socio-economic and political factors. Among the machine learning methods, classification algorithms such as decision tree, random forest, gradient boosting, and neural networks are most often used to predict financial crises.

Decision trees are created using the binary partitioning method, where each node is divided into two branches representing different outcomes or solutions. As a result of using this approach, it is possible to identify unique combinations of factors and threshold values of variables, exceeding which threatens a financial crisis [18].

A more accurate approach to predicting financial crises is using the "random forest" method, which creates multiple decision trees and combines them to produce forecasts. Each tree in the forest is trained on different subsets of data, and the results of all the trees are combined to produce a final forecast. The research results have shown that a random forest provides high prediction accuracy and is superior to other machine learning methods such as neural networks and the support vector method [19]. A random forest has several advantages over individual decision trees, as it can improve the accuracy of model prediction by averaging the predictions of multiple decision trees, which helps reduce the variance and systematic error of the model. A random forest is less susceptible to overfitting compared to individual decision trees, because each decision tree is trained on a slightly different subset of data. In addition, a random forest allows you to evaluate the importance of each feature in predicting the target variable.

Using gradient boosting to predict financial crises is another machine learning method that can be used to predict financial crises. This method combines several weak models and increases their weight to obtain a strong model (for several examples of using boosting algorithms for financial data, see [20]). It works by sequentially adding new models to existing ones, with each new model correcting errors that were made by previous models. In one of the papers, the authors use a random forest and gradient boosting to predict financial crises using financial indicators, economic indicators, and news. The results demonstrated the effectiveness of both methods, but found that a random forest provides higher prediction accuracy than gradient boosting [21].

Neural networks are also a useful tool for predicting financial crises. They consist of neurons, which are elementary information processors, connected by connections that transfer signals between them. Neurons and connections form layers, each with a specific role in data processing. An example of this is the use of neural networks to forecast crises based on economic and financial data [22].

In this process, historical financial data are used as input for training the neural network. The output is a prediction of the likelihood of a future crisis. The quality of the model is evaluated using cross-validation, and optimal parameters are selected. This method is advantageous over other methods because it better handles complex nonlinear interactions between financial indicators.

In general, all the methods considered have both advantages and disadvantages, and the choice of a particular method depends on the objectives of the study and the availability of data. Some researchers suggest combining different methods to achieve more accurate and reliable forecasts [23].

DESCRIPTION AND PRELIMINARY ANALYSIS OF THE DATA

Our research is devoted specifically to forecasting currency crises. To identify currency crises, we use the criteria proposed in the study [8]. A currency crisis is said to have occurred when the national currency depreciates by more than 10% in the current month, after a period of relatively stable exchange rates. This is defined as an average absolute percentage change over the previous 12 months of less than 2.5%.

Table 1 presents statistics on currency crises in seven emerging economies from January 2002 to December 2021. These countries include Colombia, Mexico, Türkiye, Brazil, Indonesia, Russia, and South Africa. All of these countries have experienced serious currency crises in the past with significant economic implications. As a result, there were a total of 22 crisis episodes in this sample.

As a basis for a set of potential predictors of currency crises, we took the list of indicators proposed in the KLR model [7] and supplemented it with statistically significant indicators from [9, 16, 17].

At the same time, some corrections were made to the data set in the KLR model.

1. The KLR model uses the ratio of the current account to GDP, but we have taken the ratio to international reserves. Also, instead of the ratio of domestic credit to GDP, the percentage change in domestic credit was taken.

2. The M1 excess money supply was omitted from the set of variables due to its high correlation with the monetary multiplier.

3. Export and import as separate variables are not used, unlike the standard KLR model. Instead, the "openness of the economy" indicator is used, calculated as the ratio of exports and imports to GDP.

4. The inflation indicator has good predictive abilities, but is mainly significant in relation to banking crises [9, 15]. Inflation was not used in our set of predictors.

5. Global oil prices and the dollar index were added as global factors.

As a result, we have obtained the following final set of predictors for currency crises in developing countries:

M2 multiplier: An increase in the monetary multiplier can lead to an increase in lending and faster economic growth, but if the money supply grows too quickly, inflation can occur, which would negatively affect the exchange rate.

Domestic credit: An increase in domestic credit can lead to an outflow of capital from a country and a worsening of the economic situation. This can then become a catalyst for a currency crisis.

Commercial bank deposits: A decrease in deposits may be accompanied by a decrease in lending and lower economic growth rates, increasing the vulnerability of the national currency.

The ratio of the current account to international reserves: Deterioration in

Table 1

Currency Crises in Developing Countries Between 2002 and 2021

Countries	Currency Crises
Colombia	September, 2008; December, 2014; March, 2020
Mexico	October, 2008; March, 2020
Türkiye	May, 2004; June, 2006; October, 2008; August, 2018
Brazil	October, 2002; September, 2008; March, 2015; March, 2020
Indonesia	November, 2008; March, 2020
Russia	January, 2009; May, 2012; November, 2014; March, 2020
SOUTH AFRICA	June, 2006; October, 2008; March, 2020

Source: Compiled by the author.

the terms of trade may worsen the crisis by reducing the country's export earnings and increasing the cost of imports, leading to a balance of payments crisis.

Real exchange rate volatility: If the exchange rate becomes volatile, it can lead to a deterioration in the current account and make the country vulnerable to external shocks.

International reserves: A decrease in international reserves may make it impossible to cover its external obligations or maintain the stability of the national currency in the face of speculative attacks.

Change in real GDP: Lower economic growth rates during a currency crisis may worsen the economic situation in the country.

Stock market index: A decline in national stock market indexes may lead to a flight of capital from the country to more stable markets, which could be accompanied by a depreciation of the national currency.

Openness of the economy: On the one hand, high levels of openness can lead to increased international trade and inflows of foreign capital. However, it also increases the country's vulnerability to external shocks.

Real interest rate: An increase in the interest rate could lead to an influx of capital into the economy, reducing the likelihood of a crisis. However, it could also increase the cost of servicing external debt and decrease demand for loans within the country, potentially negatively affecting economic growth.

World oil prices: Falling oil prices could lead to a trade deficit, a lack of foreign exchange reserves, and a worsening exchange rate for countries that rely heavily on exporting raw materials.

The dollar index: The strengthening of the dollar leads to lower export and higher import prices, which worsens the trade balance in commodity-exporting countries, increasing the risk of a currency crisis. The dollar index is calculated for six currencies of developed countries (euro, yen, pound sterling, Canadian dollar, Swedish krona and Swiss franc). The results of the study [24] showed that changes in the dollar exchange rate reflect changes in global risk sentiment and global demand for risky assets.

The appendix table provides a comprehensive list of variables utilized in the study, along with their sources and units of measurement. All data was collected on a monthly basis, except for GDP values, which were estimated from annual data using interpolation.

Prior to constructing models to identify the most significant indicators for predicting currency crises, we conducted a preliminary analysis of the data [25].

At the first stage, a test was conducted to test the hypothesis that there were statistically significant differences between the average values of certain variables during the crisis period and the pre-crisis period. *Table 2* shows that significant differences in average values were observed for variables such as international reserves, bank deposits, real GDP, the stock market index, the degree of openness of the economy, exchange rate volatility, and world oil prices. Significant differences in average values between groups with normal economic conditions and those at the beginning of the crisis were observed at a significance level of 5%.

However, we cannot conclusively state that there are no significant differences in the average values for other explanatory variables between the crisis period and the pre-crisis.

At the second stage, we performed a test for multicollinearity among the features in the linear regression model. *Table 3* shows several indicators of multicollinearity, including the variance inflation factor (VIF), the square root of VIF, the tolerance, and the R-squared values for each independent variable.

Table 3 shows that the variance inflation factors (VIF) values only slightly exceed 1, indicating a moderate correlation between the variables. Therefore, it was decided to retain all indicators as potential predictors of currency crises in the study.

METHODOLOGY

The Logit Model

We are building a logistic regression model based on a basic dataset containing 12 variables. We have pre-standardized the data. Logistic regression is a statistical model used to predict the probability of a binary outcome. In our case, we are predicting the presence or absence of a crisis. The model has random effects, meaning that the parameters can vary from country to country. This allows us to account for the individual characteristics of each country that may affect the likelihood of a crisis.

$$CurrencyCrisis_{i,t} = \beta_0 + \beta_i X_{i,\,t-k} + \varepsilon_{i,t}, \tag{1}$$

где $CurrencyCrisis_{i,t}$ — is a binary dependent variable that takes the value 1 if there was a currency crisis in country *i* in month *t,* and 0 otherwise;; β_i — a matrix of regression coefficients; $X_{i,\,t-k}$ — a matrix of explanatory variables with values of *k* lags back, which are associated with the probability of a currency crisis;; $\varepsilon_{i,t}$ — is an error term that captures any accidental or unexplained change in the probability of a currency crisis.

To solve the problem of endogeneity in the model, it is necessary to use lags. Initially, one lag was taken for each variable, and then, sequentially, by increasing the number of lags for variables, the change in Log likelihood and the Akaike criterion (AIC) were analyzed. The best combination of these two parameters is obtained using the following model:

$$\begin{aligned} CurrencyCrisis_{i,t} = {} & \beta_0 + \beta_{1i} IntReserves_{i,t-3} + \beta_{2i} BankDeps_{i,t-3} + \\ & + \beta_{3i} RealGDP_{i,t-1} + \beta_{4i} ShareIndex_{i,t-1} + \beta_{5i} MMmult_{i,t-3} + \\ & + \beta_{6i} DomCredit_{i,t-3} + \beta_{7i} TradeBal_{i,t-3} + \beta_{8i} Opennes_{i,t-2} + \\ & + \beta_{9i} DevOfExRate_{i,t-2} + \beta_{10i} IntRate_{i,t-1} + + \beta_{11i} DXY_{i,t-1} + \\ & + \beta_{12i} OilPrices_{i,t-1} + \varepsilon_{i,t}. \end{aligned} \tag{2}$$

Table 2

Descriptive Statistics and T-test for Pre-crisis and Crisis Periods

Variable	Obs.	Mean(0)	St. Dev. (0)	Mean (1)	St. Dev. (1)	p-value
IntReserves	1673	0.01	0.00	−0.03	0.01	0.00 ***
BankDeps	1673	0.01	0.00	0.02	0.01	0.00 ***
RealGDP	1668	0.00	0.00	−0.02	0.01	0.00 ***
ShareIndex	1669	0.01	0.00	−0.12	0.02	0.00 ***
MMmult	1673	0.00	0.00	0.01	0.01	0.17
DomCredit	1675	0.01	0.00	0.02	0.00	0.28
TradeBal	1680	0.00	0.00	−0.01	0.01	0.30
Opennes	1673	0.01	0.00	0.06	0.02	0.00 ***
DevOfExRate	1680	0.56	7.17	180.96	137.10	0.00 ***
IntRate	1673	0.01	0.00	0.01	0.00	0.29
DXY	1673	0.00	0.00	−0.03	0.02	0.10
OilPrices	1673	0.01	0.00	−0.22	0.04	0.00 ***

Source: Compiled by the author.

Note: Obs.— observations; Mean — average value; p-value — the p-value value. *** significance at the level of 1%, ** significance at the level of 5%, * significance at the level of 10%.

After the regression analysis, we performed a Hausman test to determine whether it was appropriate to use random effects. The results of the test indicate that there is no statistically significant difference in the coefficients between the fixed effects model and the random effects model. This suggests that the random effects model is acceptable and that unobserved heterogeneity does not significantly impact the results.

Table 4 presents the results of models based on formula (2). To demonstrate the usefulness of including global variables (the international interest rate, the dollar index, and world oil prices), we compared two specifications: one without global variables and one with them.

When global variables were introduced, the log-likelihood in Model 2 increased and the Akaike Information Criterion (AIC) decreased, indicating a better fit of the model. A likelihood ratio test was also performed, and the p-value was found to be less than 5%, indicating that the additional variables in Model 2 significantly improved the model's fit compared to Model 1.

The regression analysis results confirm the findings of previous empirical studies. Increases in international reserves, bank deposits, real GDP, the stock market index, the money multiplier, and world oil prices all reduce the likelihood of a currency crisis. On the other hand, increases in domestic credit

Table 3

Results of Multicollinearity Tests

Variable	VIF	VIF (SQRT)	Access	R-squared
IntReserves	1.14	1.07	0.88	0.12
BankDeps	1.5	1.23	0.67	0.33
RealGDP	1.05	1.03	0.95	0.05
ShareIndex	1.22	1.1	0.82	0.18
MMmult	1.04	1.02	0.96	0.04
DomCredit	1.51	1.23	0.66	0.34
TradeBal	1.06	1.03	0.94	0.06
Opennes	1.05	1.03	0.96	0.05
DevOfExRate	1.01	1	0.99	0.01
IntRate	1.04	1.02	0.96	0.04
DXY	1	1	1.00	0.00
OilPrices	1.18	1.09	0.84	0.16
Средняя VIF	1.15			

Source: Compiled by the author.

and the US dollar index increase the likelihood of such a crisis.

The most statistically significant variables are bank deposits, domestic credit, international reserves, and global variables such as world oil prices and the US dollar index.

The highest statistical significance is observed in indicators of the volume of bank deposits, domestic credit, international reserves, as well as global variables, namely, world oil prices and the dollar index.

The Random Forest Model

Due to the fact that logistic regression does not account for non-linear relationships between variables, we decided to use machine learning techniques, in particular the random forest algorithm, as an alternative.

The random forest algorithm has been shown to be effective in predicting different types of financial crises in numerous studies [19, 24]. A random forest is built based on a large number of decision trees trained on different samples of the training dataset. After

Table 4

Results of Logit Models' Estimation

Variable	Lag	Model 1	Model 2
IntReserves	3	–.41**	–.47**
BankDeps	3	–.67***	–.61 ***
RealGDP	1	–.12	–.14*
ShareIndex	1	–.68***	–.37
MMmult	3	–.34*	–.41*
DomCredit	3	.56***	.54***
TradeBal	3	–.30	–.35
Opennes	2	–.29	–.39
DevOfExRate	2	–.38	–.45 *
IntRate	1		.32
DXY	1		.42**
OilPrices	1		–.58***
Observtions		1644	1644
Log likelihood		–95.57	– 89.50
AIC		213.15	207.00

Source: Compiled by the author.

Note: *** — significance at the level of 1%, ** — significance at the level of 5%, * — significance at the level of 10%.

the decision trees are grown, their forecasts are averaged to obtain the final result of the probability of a crisis.

In our case, we chose the following hyperparameters to build a random forest model:

- The minimum sample size was set to 10;
- The number of decision trees was set to 100;
- The maximum depth was set to 10;
- The number of features was set to 10.

The ratio of training and test data is 70 to 30 of the total sample.

Shapley values are used to determine the contribution of each variable to the final forecast of the model. This allows you to understand which variables have the greatest predictive value. Shapley regression will be used to assess the economic and statistical significance of predictors [26]:

$$CurrencyCrisis = Logit\left(\Phi_{n\times k}\left(x\right)\hat{\beta}\right)+\hat{\varepsilon}, \qquad (3)$$

где $CurrencyCrisis$ — is a binary dependent variable that takes the value 1 if there is a currency crisis and 0 otherwise; $\Phi_{n\times k}\left(x\right)$ — Shapley's values; $\hat{\beta}$ — A coefficient that measures the similarity between predicted crisis probabilities and actual crises; $\acute{\varepsilon}$ — is the error term that captures the change in the probability of a currency crisis.

Thus, the nonlinear and unobservable predictor function in the machine learning model is transformed into a linear parametric space using Shapley values. In the context of machine learning, this model can be seen as a combination of variables working together to achieve the goal of predicting an outcome. Shapley regression calculates the contribution of each variable to the prediction by adding

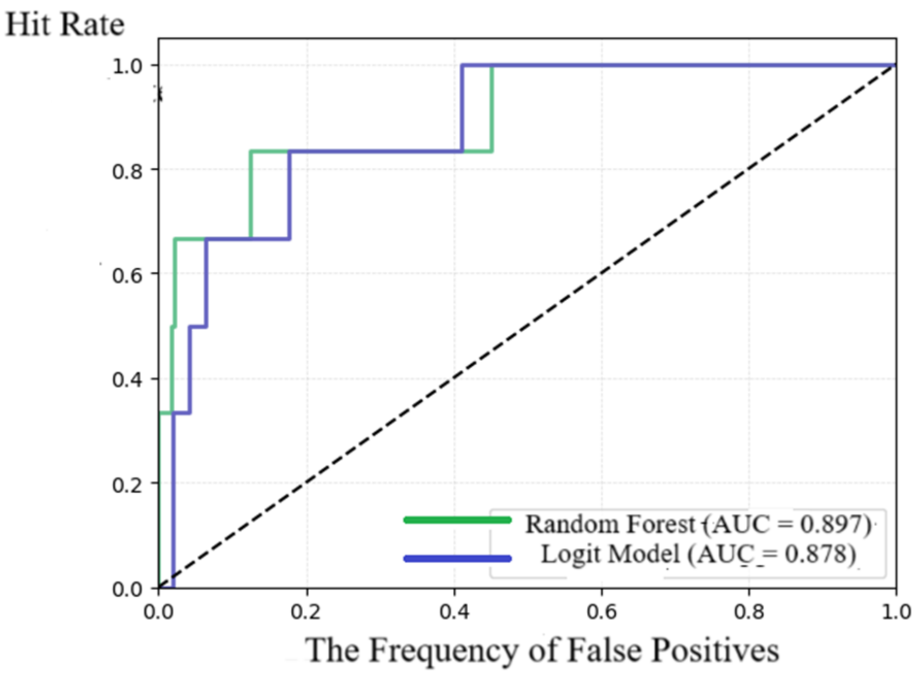

Fig. 2. **Comparison of the Forecasting Power of the Logit Model and Random Forest**

Source: Compiled by the author.

them sequentially to the model. This allows us to evaluate the importance of each variable and understand how they interact. Additionally, Shapley regression helps solve the "black box" problem in machine learning when it is hard to understand which variables influence the prediction.

COMPARISON OF THE EFFECTIVENESS OF THE "RANDOM FOREST" AND THE LOGISTIC MODEL IN PREDICTING CURRENCY CRISES

In this part of the study, we compare the results of logistic regression and the "random forest" model. As the main indicator of the quality of the models, we will use the ROC curve, which illustrates the balance between errors of the first and second kind. Judging from *Figure 2*, the ROC curve for the random forest model lies slightly above the graph for logistic regression. This suggests that the random forest model turns out to be more effective for predicting crises than logistic regression, but there is little improvement in forecast accuracy.

Figure 3 shows the Shapley values for determining the most significant predictors of currency crises. Based on the results obtained, the most important indicators are world oil prices, real GDP and bank deposits, while the least significant are international reserves, trade balance and domestic credit.

Table 5 shows the final set of predictors that turn out to be significant for predicting currency crises in developing countries, selected according to the Logit model and the random forest model.

CONCLUSIONS

This study aimed to identify leading indicators that can be used to predict currency crises in developing countries. A set of variables was initially selected from the KLR model, and then additional significant variables were added based on empirical studies. Additionally, global factors such as world oil prices and the dollar index were included in the explanatory variable set.

Logistic regression and random forest models were used as the main research methodologies. The ROC curve was employed

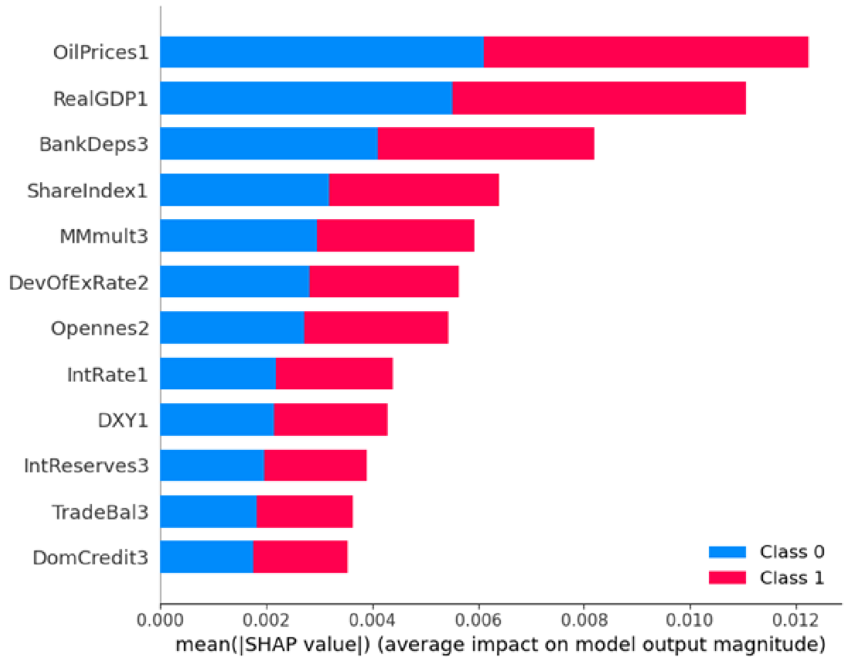

Fig. 3. **Variable Importance Ranking Based on Shapley Values**

Source: Compiled by the author.

Table 5

Relevant Predictors for Currency Crises in Developing Countries

Variable	Logit	Random Forest
Currency Crisis (Currency Crisis)		
M2 multiplier (MMmult)		**
Domestic credit (DomCredit)	***	
Commercial bank deposits (BankDeps)	***	***
The ratio of the current account to reserves (TradeBal)		
Revaluation of the real exchange rate (DevOfExRate)		**
International reserves (IntReserves)		
Real GDP (RealGDP)		***
Stock market (ShareIndex)		***
Openness of the economy (Opennes)		**
Real international interest rate (IntRate)		**
The dollar index (DXY)		
World oil prices (OilPrices)	***	***

Source: Compiled by the author.

Note: *** — significance at the level of 1%, ** — significance at the level of 5.

to compare the predictive power of the two models. Based on the findings, the random forest model was found to provide more accurate forecasts for the onset of currency crises than traditional logistic regression.

As for the set of leading indicators, world oil prices and commercial bank deposits were found to be the most reliable for predicting currency crises. These variables were identified as important by both the Logit regression model and the random forest method. This paper compares the traditional econometric approach with the machine learning method in predicting currency crises and forms a final set of predictors for use in a system of leading indicators for developing countries. The results show that world oil prices are the most significant among the "global variables" and commercial bank deposits perform best among the country-specific indicators.

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APPENDIX

Table

Data Sources for Relevant Variables

Variable	Definition	Unit
Currency crisis (CurrencyCrisis)	Nominal exchange rate (00ae IMF IFS)	Dummy variable
M2 multiplier (MMmult)	M2 money supply (34 plus 35 IMF IFS) relative to the monetary base (14 IMF IFS)	Percentage change
Domestic credit (DomCredit)	Internal claims (line 32 of the IMF IFS)	Percentage change
Commercial Bank Deposits (BankDeps)	Transferable deposits (24 plus 25 IMF IFS) divided by CPI	Percentage change
The ratio of the current account to reserves (TradeBal)	Ratio of exports minus imports (OECD Statistics) to International reserves (1L IMF IFS)	Relation to international reserves
Revaluation of the real exchange rate (DevOfExRate)	Deviation of the nominal exchange rate (00ae IMF IFS) divided by CPI from the trend using the Hodrick-Prescott filter (parameter 129000)	Percentage deviation
Международные резервы (IntReserves)	International reserves (1L IMF IFS)	Percentage change
Real GDP (RealGDP)	Nominal GDP (99B IMF IFS) divided by GDP deflator (99C IMF IFS)	Percentage change
Stock Market (ShareIndex)	Cumulative Stock Index (OECD Statistics)	Percentage change
Openness of the economy (Opennes)	The ratio of exports and imports (OECD Statistics) to nominal GDP (99B IMF IFS)	Relation to GDP
Real International Interest Rate (IntRate)	The US Federal Funds rate minus the US inflation rate (lines 60B and 64 of the IMF IFS)	Percentage change
Dollar Index (DXY)	The USD Index (Investing.com)	Percentage change
World oil prices (OilPrices)	Brent Oil Futures (Investing.com)	Percentage change

Source: Compiled by the author

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