Early Warning System for Currency Crises Using Long Short-Term Memory and Gated Recurrent Unit Neural Networks

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Abstract

Currency crises, recurrent events in the economic history of developing, emerging and developed countries have disastrous economic consequences. This paper proposes an early warning system for currency crises using sophisticated recurrent neural networks, such as long short-term memory (LSTM) and gated recurrent unit (GRU). These models were initially used in language processing, where they performed well. Such models are increasingly being used in forecasting financial asset prices, including exchange rates, but they have not yet been applied to the prediction of currency crises. As for all recurrent neural networks, they allow for taking into account nonlinear interactions between variables and the influence of past data in a dynamic form. For a set of 68 countries including developed, emerging and developing economies over the period of 1995-2020, LSTM and GRU outperformed our benchmark models. LSTM and GRU correctly sent continuous signals within a two-year warning window to alert for 91% of the crises. For the LSTM, false signals represent only 14% of the emitted signals compared to 23% for logistic regression, making it an efficient early warning system for policymakers.

Keywords: currency crises, early warning system, neural network, long short-term memory, gated recurrent unit.
JEL Classification: F14, F31, F47.

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1 Introduction

Currency or balance of payments crises have been studied since the 1970s using the founding models of Krugman (1979) and Flood and Garber (1984), the drivers of the first-generation models. With many currency crises in the 1990s, the literature became considerable, and early warning systems were developed.

European countries suffered the crisis of the European Monetary System (1992-1993), leading to strong depreciations against the Deutsche Mark. Concerning emerging and developing economies, the collapse of the Mexican peso and its tequila effect on financial markets occured in 1994. In 1997, the Asian crisis led to strong capital outflows, revealing and amplifying certain fragilities (Kaminsky & Reinhart, 1996), while causing a domino effect on partner economies. The effect lasted until the beginning of the 2000s, amplified by the bursting of the dotcom bubble, leading to violent speculative attacks in Turkey and Argentina and the abandonment of their respective exchange rate regimes.

The consequences of these crises are multiple in number and can affect both the financial and real spheres (loss of central bank credibility, debt unsustainability, lack of capital, imported inflation, bankruptcy), with the main severity measure is the loss of GDP. Emerging and developing economies have suffered particularly from these depreciation episodes in the past, highlighting insufficient financial development, over-regulated markets, excessive dollarization of domestic and foreign assets and recurrent recourse to fixed exchange rate regimes due to the "fear of floating" (Calvo & Reinhart, 2000).

While some emerging countries were once again heavily impacted by the financial crisis of 2007-2009, they generally managed better than in the past, limiting their GDP loss to a level similar to that of advanced economies. The global financial crisis has revealed several deficiencies in financial system regulation, including systemic risk resulting from the interdependence of financial actors, sectors and countries, and an increased need for international cooperation. While recent crises may seem less severe than past episodes, their occurrence persists (the Turkish lira crisis and the collapse of the Argentine peso in 2018) with still disastrous consequences for the affected economies.

To warn of the future occurrence of a sudden drop in currency value and limit its effects, we need to build an efficient early warning system (EWS). The objective is to send a continuous signal over a given time window before the currency crisis episode begins. The EWS can be based on the monitoring of key indicators (Kaminsky et al., 1998) or on more synthetic approaches, for example, econometric models such as logit and probit regressions (Frankel & Rose, 1996; Gourinchas & Obstfeld, 2011), machine learning models (de Carvalho Filho et al., 2020; Ghosh & Ghosh, 2002) and deep learning models (Nag & Mitra, 1999; Peltonen, 2006). This system should accurately identify periods of vulnerability by sending continuous signals and managing the trade-off between sending multiple signals that also include false signals and sending reduced and less noisy signals that may lead to missing certain crises. Ideally, the warning system should not miss any crisis signals while minimizing false signals, as the cost of a missed signal is higher for policymakers. Focusing on the pre-crisis period, EWS models may have substantial value for policymakers by allowing them to detect underlying economic weaknesses and vulnerabilities, and implement preventive actions to reduce the risks of experiencing crises. In the wake of the 2008 financial crisis, proactive approaches to financial crises were strengthened in response to growing systemic risk. Early warning systems are part of this trend because the implementation of policies requires measuring the likelihood, magnitude, timing and determinants of crises.

This study develops three types of models that attempt to warn of the occurrence of a currency crisis in the two years preceding the collapse of a currency for 68 countries including developed, emerging and developing economies over the period of 1995-2020. First, logistic regression, a standard model in the EWS literature, and a random forest were constructed. These two models were used as benchmarks for the proposed approach based on two recurrent artificial neural networks: long short-term memory (LSTM) and gated recurrent unit (GRU). Both networks have grown in popularity in recent years. Initially used for natural language processing (speech recognition via Google Voice in 2015 and translation in some Google and Facebook applications in 2016 and 2017 owing to LSTMs), they have quickly spread to many fields, some of which are related to health or economics, notably through the prediction of financial asset prices (Claveria et al., 2022; Dautel et al., 2020) and systemic banking crises (Tölö, 2020). However, the performance of LSTM and GRU models compared to traditional econometric models in the context of currency crises has not been explicitly analyzed in the literature. The complex relationships between signals and predictors can be captured through a data-driven non-parametric and highly nonlinear methodology, such as random forest or artificial neural network. The second advantage of the proposed methodology is its adaptation to sequential data. Time-series forecasting often requires the inclusion of lagged variables to involve dynamic interactions in an artificial manner. Recurrent neural networks (RNN), such as LSTM and GRU, perfectly integrate this characteristic, owing to feedback loops and memory cells designed to identify short and long-term dependencies between variables. The RNN preserves the temporal order of the time series so that as observations pass through the network, it can identify the accumulation of vulnerabilities and send an alert when the vulnerabilities become too numerous or when a triggering event occurs. The contribution of these networks, compared to simple RNNs, lies in the construction of more complex cells, integrating a memory vector updated through a sophisticated gate mechanism. A simple recurrent neural network was constructed to identify the contribution of these new operations within the cells.

Feedback loops, which are characteristic of recurrent neural networks, make it possible to consider the sequential nature of time series and thus improve predictions. In the case of currency crises, a country that has experienced several currency crises in the past may be more likely to experience a new one even if its economic indicators deteriorate slightly. Thus, the thresholds for the deterioration of indicators would be specific to each country and would evolve over time according to each country's history. Similarly, according to the theory, a sharp rise in inflation can lead to substantial depreciation. An analysis of the evolution of inflation over previous periods makes it possible to identify whether the event is a one-off event or characteristic of a period of tension (accelerating rate of increase), thus having a relatively marked influence on the probability of crisis.

The contributions of this study can be summarized as follows. First, we used the expanding window method, which is an adaptation of cross-validation to time series, with a distinction between validation and test samples. During the training, the hyperparameters were adjusted according to the performance of validation sample. Once the optimal parameters were defined and the model was trained, its out-of-sample performance was measured on a test sample that was not known to the model. This allowed us to test the real generalization capacity of the models and guarantee the independence of the results. Second, currency crises remain episodic, which can hinder the training of the models while leading to good performance based on traditional metrics that are not adapted, such as accuracy. Two solutions were proposed in this study in addition to metrics adapted to the imbalanced dependent variable (F1 score, Precision, Recall): the lowering of the optimal alert threshold on the basis of the performances obtained on the F1 score, as done by Liu, Chen, and Wang (2022) with the ROC curve, and the use of the SMOTEENN algorithm, allowing the creation of artificial individuals of the minority class while deleting the least characteristic individuals of the majority class. Additional metrics oriented on the role of the EWS were also proposed, such as the persistence and continuity of warning signals, the timing of the first and last signals and the number of identified crises. Despite their performance, machine and deep learning models are often criticized for their lack of explicability. We addressed this problem by using the SHAP library in Python inspired by Shapley values from game theory to identify causal links between variables and to decompose the predictions obtained for each observation. Finally, our main contribution is the novel use of recurrent neural networks involving a memory vector that can retain long-term dependencies through a gate mechanism for the design of an EWS for currency crises. Thus, we contribute to the growing literature on machine and deep learning and improve reliability for policymakers of EWS for currency crises owing to neural networks adapted to sequential data, as expected by Tölö (2020).

The remainder of this paper is organized as follows. Section 2 presents multiple criteria for identifying currency crises and reviews the literature on EWS for financial crises. In Section 3, we describe all of the models developed in this study and the structure of the selected neural networks. Section 4 elaborates on the dataset used and the detailed methodology regarding the choice of alert window, data format, imbalanced target management as well as the training and testing procedures. Section 5 presents our empirical results on the test sample running from 2015 to 2020 and proposes an out-of-sample example of the contributions of the variables to the prediction. Finally, Section 6 concludes the paper.

2 Literature review

The objective of this section is to present the evolution of the literature on currency crises, both in terms of crisis definition and modeling approaches. This in-depth study made it possible to define benchmark models and an initial set of macroeconomic, financial and banking variables to be included.

2.1 Crisis criteria

To train a model to declare a warning signal, we must identify episodes of strong depreciation corresponding to currency crises. Various criteria have been proposed in the literature to define and identify currency collapses. There are two types of criteria for retrospectively dating currency crises: those based solely on the loss of value of the currency and those incorporating defense mechanisms against depreciation pressures.

The criterion proposed by Frankel and Rose (1996) is based only on the extent of currency value loss against the dollar. A collapse occurs when nominal depreciation reaches 25 percent or greater, which is at least 10 percent greater than the depreciation observed in the previous year.

$$\gamma_m = \frac{S_m}{S_{m-12}} - 1 \quad ; \quad \gamma_{m-12} = \frac{S_{m-12}}{S_{m-24}} - 1 \quad ; \quad \eta_m = \frac{\gamma_m}{\gamma_{m-12}} - 1$$

$$Frankel\ and\ Rose\ criterion:\ currency\ collapse\ occurs\ if\ \gamma_m \geq 25\%\ and\ \eta_m \geq 10\%.$$

S_m is the average nominal exchange rate in month m of a given country, expressed as units of local currency per unit of a foreign currency (USD).

By using only the currency value loss and its speed, there is a desire to consider only the attacks that have worked and thus rule out intermediate periods of tension. Frankel and Rose indicated that the thresholds used were arbitrary, although they were supported by sensitivity analysis.

Other authors have proposed a similar methodology using different thresholds. Milesi-Ferretti and Razin (2000) completed this criterion by adding a limit that the depreciation rate observed in the past year (γ_{m-12}) must not exceed. They proposed the following three definitions:

$$Definition\ 1:\ Currency\ collapse\ occurs\ if\ \gamma_m \geq 25\%,\ \eta_m \geq 100\%\ and\ \gamma_{m-12} \leq 40\%.$$

$$Definition\ 2:\ Currency\ collapse\ occurs\ if\ \gamma_m \geq 15\%,\ \eta_m \geq 10\%\ and\ \gamma_{m-12} \leq 10\%.$$

$$Definition\ 3:\ Definition\ 2\ +\ peg\ regime\ in\ m-12.$$

Milesi-Ferretti and Razin (2000) proposed Definition 1 as a complement to the Frankel and Rose criterion, adding a third condition and changing the second threshold to avoid capturing the large exchange rate fluctuations associated with episodes of high inflation. Definitions 2 and 3 focus on high-depreciation episodes preceded by relative exchange rate stability in the past year, corresponding to the implicit definition of a currency crisis in theoretical models.

Bussière et al. (2012) also proposed two new definitions, used in addition to traditional criteria, to distinguish between large depreciations and "mega-collapses". A "standard" currency crisis occurs when the annual change in the average exchange rate observed over the month (γ_m) is in the upper quartile of all depreciation episodes of the sample. A "mega-collapse" occurs when the depreciation (γ_m) is among the 6.25% greatest depreciation episodes observed in the sample.

These criteria can be extended by incorporating the international reserves differential and Central Bank interest rate differential with the country against which the domestic currency is quoted, as is the case with the Exchange Market Pressure index (EMP) proposed by

Eichengreen et al. (1996), derived from the foreign exchange market pressure index of Girton and Roper (1976).

$$EMP_t = w_1 \times \frac{\Delta E_t}{E_{t-1}} - w_2 \times (\frac{\Delta \bar{R}_t}{\bar{R}_{t-1}} - \frac{\Delta \bar{R}_{US_t}}{\bar{R}_{US_{t-1}}}) + w_3 \times (\Delta(i_t - i_{US_t}))$$

E_t the nominal exchange rate expressed as units of local currency per unit of a foreign currency (USD), $\bar{R}_t$ is the amount of international reserves R_t divided by base money, i_t is the policy interest rate and w_i is the weight assigned to each component.

However, the indicator is often simplified by omitting the differential aspect with the US (Kaminsky et al., 1998; Sachs et al., 1996).

$$EMP_t = w_1 \times \frac{\Delta E_t}{E_{t-1}} - w_2 \times \frac{\Delta R_t}{R_{t_1}} + w_3 \times \Delta i_t$$

A currency crisis occurs when the EMP is one to three standard deviations above its mean, according to the authors: one and a half for Eichengreen et al. (1994) and Eichengreen et al. (1996), two for Fratzscher and Bussière (2002) and Peltonen (2006), excluding the variation in the interest rate for the latter, and three for Kaminsky et al. (1998) and Berg et al. (2004). Using three standard deviations allows to consider only the most severe crises. Generally, the weights assigned to each component are such that the conditional variances of each component are equal. Periods of strong pressure on a currency, especially in the presence of non-flexible exchange rate regimes, most often lead to a reaction from policymakers who attempt to maintain parity by increasing the key interest rate or buying back depreciating currency to revalue it, thereby reducing their foreign exchange reserves. Thus, an increase in the EMP reflects increased depreciation pressure on the domestic currency.

In this first currency crisis study, the Frankel and Rose criterion was chosen for its popularity, explicability and simplicity of implementation, thereby removing the questions of weighting and the number of standard deviations to which the Exchange Market Pressure index is very sensitive, as explained by Pontines and Siregar (2008). The 25% and 10% thresholds limit attention to successful attacks. The binary crisis variable resulting from this dating exercise made it possible to construct the dependent variable of the early warning system, which is the signal before collapse.

Using a sample of 223 countries between 1990 and 2020 and the Frankel and Rose currency collapse criterion, Figure 1 shows a general decline in the occurrence of crises since the early 2000s, although they have increased on average since the 2008 financial crisis. Sub-Saharan Africa remains the most affected region over the entire time horizon of the graph, which implies a geographic contagion effect or link to the level of development. Another explanation may be reduced severity over time, leading to fewer crises identified by this criterion.

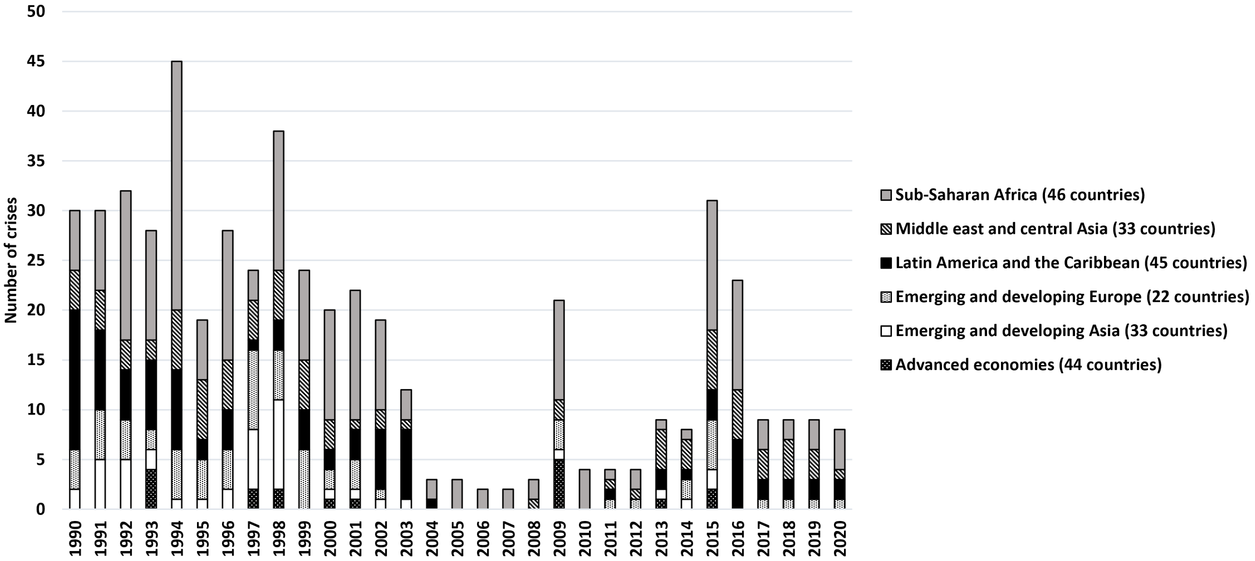

Figure 1: Currency crises (1990-2020) using the Frankel and Rose criterion.

2.2 Early warning system for currency crises

The literature on currency crises has been extensively developed since Krugman (1979) and the severe currency tensions observed in the following decades. Initially, their occurrence was attributed to weak economic fundamentals, such as expansionary monetary and fiscal policies, which were incompatible with the maintenance of a fixed parity (Mundell's impossible trinity). However, several other theories have emerged, leading to the inclusion of expectations, banking and financial indicators. Early warning systems are constructed in line with these considerations by including the indicators of these pre-crisis periods. We can distinguish two main categories of crisis warning methodology: the first is based on the individual monitoring of several key indicators, and the second is based on econometric, machine and deep learning models to predict the probability of crisis occurrence.

The seminal paper of Kaminsky et al. (1998) [KLR] is part of the first approach, popularized as the "Signals" approach. The survey produced by these authors highlights a list of economic indicators that are considered to herald future currency collapses given their unusual behavior. In line with this methodology, KLR retained 16 indicators[1], each of which was individually monitored. A signal was sent when an indicator deviated from its "normal" level by crossing the alert threshold, defined as the value associated with a defined percentile of the indicator's distribution (between 10% and 20%). The percentile used to define the threshold for a given variable was identical for all countries; however, the associated thresholds may differ. The optimal threshold had to be such that it maximized the transmission of good

[1] International reserves (USD), imports (USD), exports (USD), the terms of trade, deviations of the real exchange rate from trend (%), the differential between US and domestic real interest rates on deposits, "excess" real M1 balances, the money multiplier of M2, the ratio of domestic credit to GDP, the real interest rate on deposits, the ratio of nominal lending to deposit interest rates, the stock of commercial bank deposits (nominal terms), the ratio of M2 to gross international reserves, output, the index of equity prices (USD) and banking crises (dummy).

signals while minimizing the sending of false signals, that is, minimizing the noise-to-signal ratio. The indicators were then ranked according to their performance based on the noise-to-signal ratio, the persistence of their signals over the entire alert window and the time of the first signal. Their study confirmed that EWSs need a large and varied set of indicators, as the origins of crises can be multiple according to theory. Some variables have proven to be particularly successful, such as the real exchange rate, the banking crisis indicator, the stock index and the ratio of M2 to international reserves. Although the authors succeeded in building a powerful set of indicators to detect the origins of crises, their approach remains non-synthetic and does not lead to a unique and precise signal. Kaminsky (1999) considered this criticism by creating four composite indicators. One was the sum of the values taken by each of the monitored indicators (one if the variable has crossed its alert threshold and zero otherwise), weighted by the inverse of their noise-to-signal ratio. The probability of occurrence was then calculated by observing how often a certain value of the composite indicator was followed by a crisis in the warning window.

Out-of-sample tests were performed to test this signal approach. However, it provided mixed performance (Berg et al., 2004; Berg & Pattillo, 1999a, 1999b; Furman & Stiglitz, 1998; Mulder & Bussière, 1999). Berg and Pattillo (1999a) compared the performance of three EWS methodologies in the Asian crisis: the KLR approach, the probit model of Frankel and Rose (1996) and the cross-section country model of Sachs et al. (1996). In an attempt to replicate the KLR methodology as closely as possible, the results were inconclusive for the Asian crisis. While the predictive power remained weak, the approach allowed crises to be ranked in order of severity with some accuracy. In their comparative study, the KLR methodology performed the best, and the authors showed that by including the current account-to-GDP ratio and using the level of M2-to-reserves ratio rather than its growth rate, it was possible to improve its performance. In their second study, Berg and Pattillo (1999b) reproduced the KLR approach with these two new variables and then compared it with a transposition of the same approach into a probit model. In this multivariate probit framework, the explanatory variable took the value of one if a crisis has occured in the next 24 months and zero otherwise. This alternative proved to be more efficient, allowing for the creation of a composite warning indicator, testing the significance of the variables and the constancy of the associated coefficients over time and across countries.

Gourinchas and Obstfeld (2011) constructed a fixed effects panel specification for the indicators identified in the literature. In this "event study", each indicator was taken individually as a dependent variable of a model with four dummies as explanatory variables (dummy 1,2,3 and 4 respectively for default crisis, currency crisis, systemic banking crisis and 2008 crisis), taking the value one if a country has suffered a crisis and zero otherwise. This specification made it possible to observe the behavior of economic and financial variables around crisis periods, and thus the changes that herald future crises. For example, in the pre-crisis period, the model has identified a negative output gap, especially for emerging and developing economies, which is generally the consequence of actions taken by the Central Bank to defend the fixed parity. However, in their study, this approach was not used to directly predict the probability of crises, but to identify the variables to be included in a second model, which is panel logistic regression.

The Gourinchas and Obstfeld specification is therefore part of the second approach to forecasting currency crises, based on the relationship between a dependent variable (taking the value one if a crisis has occured in the following s periods and zero otherwise) and several dependent variables integrated simultaneously. Logit and probit regressions have gradually gained popularity (Berg & Pattillo, 1999a, 1999b; Chamon, Ghosh, & Kim, 2012; Eichengreen et al., 1996; Frankel & Rose, 1996; Fratzscher & Bussière, 2002) due to their synthetic nature, the possibility of interpreting the results directly in terms of probability, and the study of the significance of the coefficients and their constancy over time and across countries. In their event study, Gourinchas and Obstfeld failed to prove that an increase in upstream public debt contributed to the 2008 financial crisis. However, it is not impossible for a higher-than-normal level of public debt to increase an economy's vulnerability. The focus is to combine the effects of several indicators. Their model has proven to be successful in predicting currency crises, especially for developed economies. A currency crisis was more likely to occur in the next two years when domestic credit rose significantly above its trend and when the currency appreciated in real terms. For emerging countries, a decline in international reserves was an important warning criterion, giving credence to the shielding policy of increasing these reserves.

However, logistic regression can only consider linear interactions between variables, which can lead to the exclusion of certain indicators that are crucial for prediction. In recent decades, the development of data mining methods has benefited currency crisis literature, and new models have been developed to bring nonlinearity to the interactions among variables. Thus, forecasting models based on decision trees have emerged.

Ghosh and Ghosh (2002) used a binary recursive tree to predict currency crises in 40 developed and emerging economies. This algorithm allowed them to consider the structural vulnerabilities of each country and accordingly adapt the critical thresholds of certain variables. They showed that fragile governance makes countries more vulnerable to corporate sector weaknesses and deteriorating macroeconomic indicators, which can increase the probability of crises. They also identified the current account balance as the most important determinant of currency crises (top of the tree). Frankel and Wei (2004), set up a classification tree and showed that a high level of external debt does not necessarily lead to crises on its own, but it significantly increases the probability of a crisis if capital inflows are oriented toward the short-term and are not used to build up reserves. However, these trees can sometimes be overly simplistic and generally suffer from overfitting. In their working paper on forecasting periods of macroeconomic and financial stress in low-income economies, de Carvalho Filho et al. (2020) aggregated multiple decision trees into a random forest to increase their predictive power.

Models based on algorithms that seek to reproduce biological mechanisms (genetic algorithms and artificial neural networks) have also been tested for predicting financial crises and setting up early warning systems. Nag and Mitra (1999) proposed an artificial neural network (ANN) approach to warn of upcoming currency tensions in Malaysia, Thailand and Indonesia, three countries particularly impacted by the Asian crisis. For each of the three countries, a neural network including a recurrent mechanism (RNN) was built to capture dynamic features missed by traditional models. The optimal network hyperparameters and delays to be included were selected based on a genetic algorithm search procedure. This study showed promising results; however, it was not until the late 2000s that neural networks gained popularity. In his study on 24 emerging countries, Peltonen (2006) managed to outperform logistic regression with an ANN (including lagged variables), as did Sarlin (2014) with his multilayer perceptron (MLP) with backpropagation[2] in which the hyperparameters were defined by a genetic algorithm. To predict financial crises in BRICS countries (banking, currency and sudden stop crises), Nik et al. (2016) also constructed a MLP with backpropagation, focusing on studying the importance and significance of the normalized variables by interpreting the associated weights. The private sector domestic credit variables, both as GDP percentage and growth rate, had significant weights, as did the inflation rate, interest rates and economic growth. In their study of currency, banking and sovereign debt crises, Liu et al. (2022) compared logistic regression with seven machine and deep learning models, including both a random forest and an artificial neural network, for 165 countries from 1970 to 2017. Although the models appeared to perform well overall, the random forest outperformed the logistic regression and neural network. The ANN outperformed logistic regression only for currency crises.

Predicting time series requires considering dynamic relationships between variables, but this feature is omitted in traditional currency crisis early warning systems or artificially recreated through lagged variables. Recurrent neural networks such as those of Nag and Mitra are specifically designed to accommodate sequential series by incorporating a memory mechanism through feedback loops. However, in its simplest version, the RNN is only able to retain the near past (see the vanishing gradient problem described in Section 3) so that more sophisticated neural networks have been developed, such as LSTM and GRU networks. Two EWSs for the detection of systemic banking crises were built on the basis of a LSTM and a GRU for 17 developed countries by Tölö (2020) using logistic regression as a benchmark. The results showed that the predictions can be significantly improved with this type of recurrent network and became more robust. To the best of our knowledge, no other EWS dedicated to financial crises and, in particular, currency crises, is based on this type of model. If these models have been successful in forecasting financial asset prices (Claveria et al., 2022; Dautel et al., 2020; Ranjit et al., 2018) and other sequence problems, such as video, text and speech recognition (Wu et al., 2016), their contribution to currency crisis EWS remains to be demonstrated.

3 Model development

The objective of this section is to present the different models tested as well as the structures proposed for the neural networks.

[2] Updating the weights of each neuron according to its contribution to the prediction error, from the last layer to the first.

3.1 Logistic regression

Logistic regression is a model adapted to two-modality classification problems and is the predilection model of currency crisis EWS. It is one of the simplest models to set up and interpret because the interactions between the dependent and explanatory variables are linear. It predicts the probability of an event by optimizing the value of the coefficient assigned to each explanatory variable by maximizing the log-likelihood function of the sample. Thus, it is assumed that the probability of belonging to each of the two classes is a linear function of these input variables. During modeling, the bias and variance of the model should be reduced to improve the predictive quality, although they generally move in opposite directions. Adding a penalty parameter to the logistic regression can lead to better management of this trade-off, as is the case in ridge, lasso and elastic net regressions. In this study, all of these regressions were modeled using the Sklearn library in Python with hyperparameter optimization based on the Grid Search algorithm, allowing the best combination to be identified. Logistic regression appeared to be more efficient than the other types of regression mentioned previously and was chosen as the benchmark because of its significant use in the literature.

3.2 Random Forest (RF)

Random Forests are among the most powerful machine learning models and can be used for both regression and classification problems. These forests are composed of multiple decision trees to reduce the prediction variance that result from a single tree. The decision tree is an iterative algorithm that, at each iteration, splits the sample observations into k groups according to a defined threshold value for a particular model variable. The first division is obtained by choosing the most informative explanatory variable with respect to the target. This split results in subpopulations corresponding to the first node of the tree. The splitting process is then repeated several times for each sub-population (previously calculated nodes) until the final nodes are reached. Each tree composing the forest is trained on a sub-sample of observations and variables from a bootstrap selection to reduce the overfitting risk. Each is generated individually by the CART algorithm, and the forecasts are then aggregated using the bagging method, favoring performance generalization. The performance of RFs results from a trade-off between tree correlation and individual explanatory power. The more trees that are correlated, the higher the error rate of the forest. This correlation can be minimized by reducing the number of explanatory variables selected by the CART algorithm. However, reducing the number of variables also reduces the individual predictive power of each tree, thereby increasing the forest's error rate. In this study, the modeling was performed using the Sklearn library in Python.

3.3 Recurrent neural networks (RNNs)

Artificial neural networks are models originally inspired by the biological neural system by integrating statistical and optimization methods, allowing the machine to learn and make predictions. Neural networks consist of at least two layers of neurons (also called nodes): the input layer (explanatory variables) and output layer (prediction). Additional layers, called hidden layers, can also be added if the interactions between variables are more complex. Each node is connected to one or more nodes in the previous and next layers with associated weights and thresholds. The input variables are multiplied by their respective weights (a set of weights specific to each neuron) and then summed before passing through the activation function, which determines the output of the neuron and allows nonlinearity to be incorporated into the process. If this value is higher than the predefined threshold, the node is activated, and the information is transmitted to the nodes of the next layer. The mechanism is repeated as many times as there are layers, resulting in a prediction.

Two types of networks can be distinguished: feed-forward and recurrent neural networks. Feed-forward networks, as shown in Figure 2, are acyclic unlike RNNs. The first type is the simplest, as the information only circulates in one direction: from the input layer to the output layer, passing through the hidden layers if they exist.

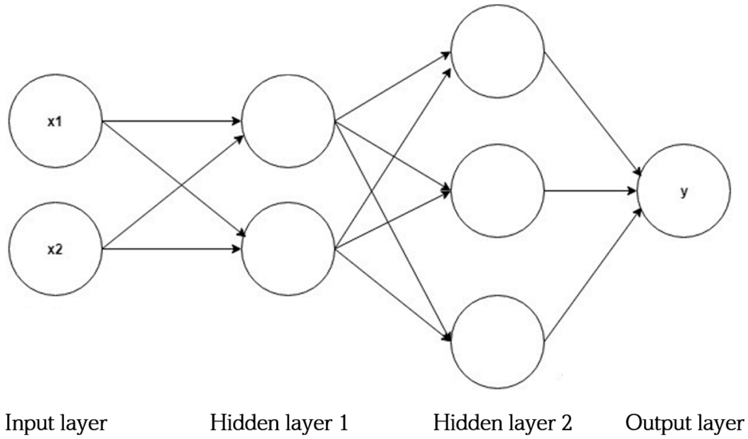

Figure 2: Fully connected feed-forward neural network.

RNNs, as shown in Figure 3, are designed to adapt to sequential data, owing to their feedback loops. The input variables and data transformed during the previous iterations in the network (also called the hidden state) allow us to obtain a prediction that consider the sequence order and related dependencies. In other words, they can retain the state from one iteration to the next and use their own output as one of the input for the next iteration. Therefore, the points are not treated independently but are seen as sequences by the model.

With each new passage through the network, the predicted value is compared to the expected value to calculate the prediction error. This error is minimized by modifying the network weights according to the importance of the contribution of the associated nodes (update proportional to the partial derivative of the error function with respect to the current weight). This procedure, called the backpropagation algorithm, is repeated until the loss function minimum is reached. To do this, an optimization algorithm such as the descending gradient is used, which is capable of identifying the minimum of any convex function by converging to it at a speed depending on its parameterization (learning rate).

However, simple RNNs, also called "vanilla", have a limitation during the learning phase: the vanishing gradient problem. When the weights are extremely small (less than one), their

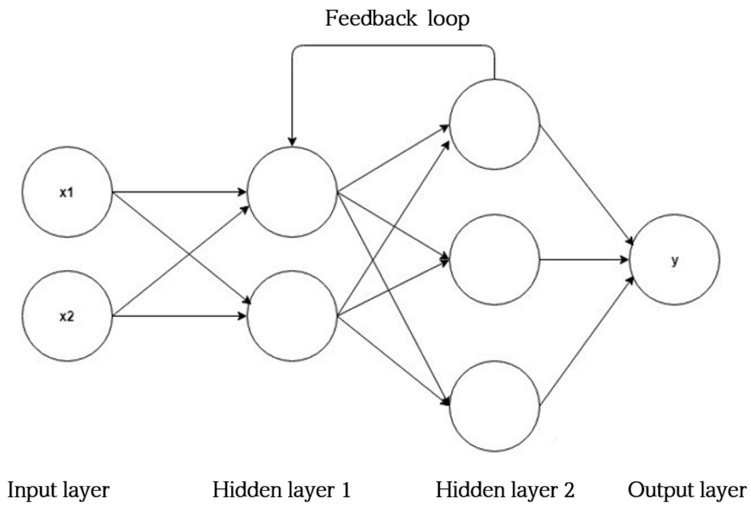

Figure 3: Recurrent neural network.

successive multiplication at each time step causes the gradient to decrease exponentially until it reaches zero (or causes the gradient explode if the weights are very large), causing the network to stop learning early. Indeed, the descent of the gradient allows the RNN parameters to be updated; and the more the gradient decreases, the more insignificant the updates become, contributing to retaining only the near past. For this reason, recurrent networks have evolved to include an updated memory vector owing to a gate mechanism that enables the retention of information for an extended time, as with the LSTM (Hochreiter & Schmidhuber, 1997) and GRU (Cho et al., 2014). These networks reduce the risk of explosion or vanishing gradients by using an additive gradient combined with a gate mechanism.

All recurrent networks are built as a chain repeating an identical cell (or node), the structure of which is quite simple for standard recurrent networks. In a standard RNN cell, two inputs are necessary to produce the output, as shown in Figure 4: the input variables corresponding to the explanatory variables (x_t) and the previous hidden state (h_{t-1}) corresponding to the last output of the cell. These components are weighted and summed before passing through the activation function (tanh). The process is slightly more complex in the LSTM and GRU cells. For LSTM, three inputs are needed to perform the prediction: again the observed explanatory variables (x_t) and the output of the cell from the previous time step (h_{t-1}), the latter corresponding to the short-term memory, and the long-term memory (C_t), which contains the long-term dependencies between the model variables. This long-term memory is updated by the gate mechanism. This mechanism is also found in GRU, which is a simplified version of LSTM.

The LSTM and GRU cells attempt to keep track of all past information that has passed through the network while forgetting irrelevant information, thanks to a memory vector called the cell state (horizontal line running through the top of the LSTM and GRU diagrams in Figure 4). The contribution of LSTMs and other sophisticated recurrent networks lies in this cell state, which passes through all cells of the network while undergoing only minor transformations. Thus, the information relative to the more distant time step can easily be stored in memory in an unchanged form. Information can be added or deleted from this memory vector owing to gate regulation. LSTM has three gates: Forget Gate, Input Gate and Output Gate. The Forget Gate decides which information should be deleted from the long-term memory used in the previous time step (C_{t-1}) based on the new information available (x_t and h_{t-1}). The Input Gate identifies which new relevant information from the explanatory variables (x_t) and short-term memory (h_{t-1}) should be stored in the long-term memory (C_t). Through these two gates, the cell state (C_{t-1}) is updated (C_t). Finally, the Output Gate filters the information available (x_t, h_{t-1}, C_t) to create the output of the cell (h_t), which is also used as short-term memory during the next time step.

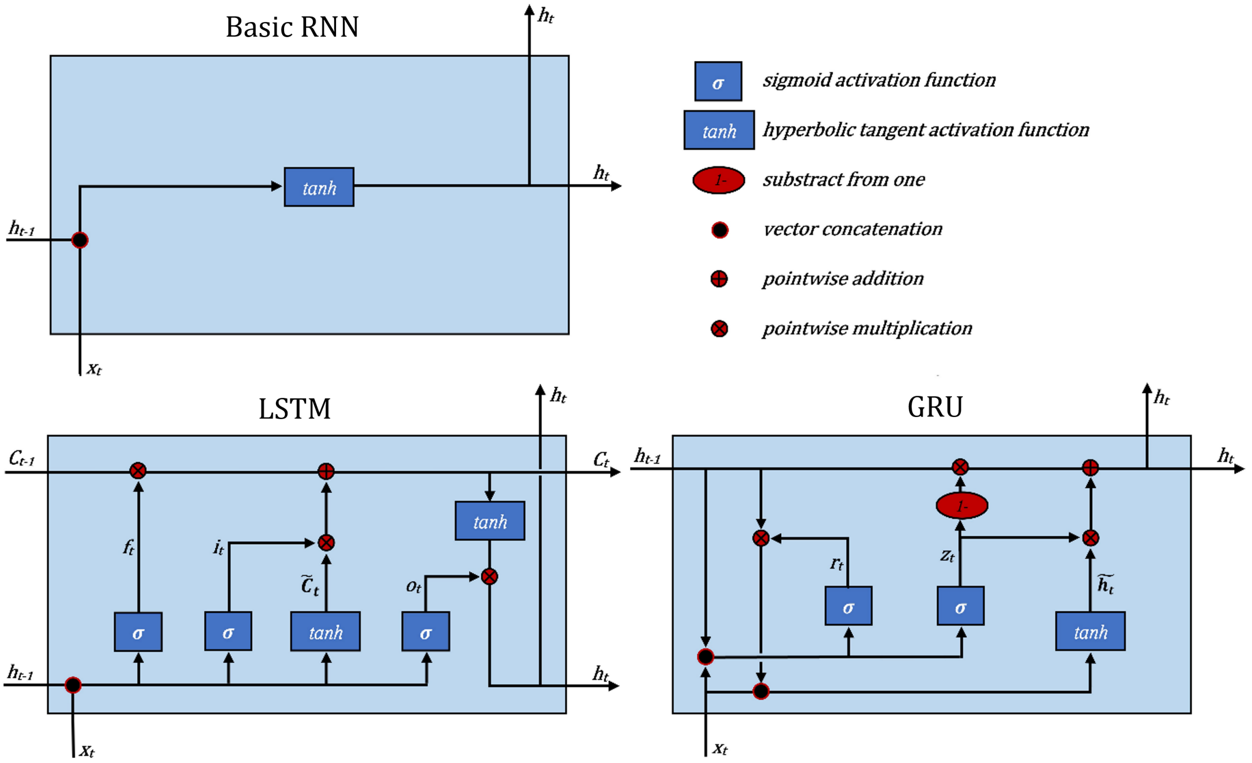

Figure 4: Basic RNN, LSTM and GRU cells.

The performance of these networks is based on the efficiency of the filters applied to the data and associated weights. During the learning phase, the optimal weights are defined using backpropagation to improve prediction. The deletion and addition of information in the cell state as well as the cell output are the result of successive filtering processes performed by the activation function(s) of each gate. In a LSTM cell, the first filtering step occurs in the Forget Gate. The received inputs pass through the sigmoid activation function, generating a value between zero and one. A value close to zero indicates that the corresponding variable is irrelevant. The resulting vector is then multiplied by the cell state vector, such that the information already contained in the long-term memory and now judged to be less relevant is given a less important place in the memory. Simultaneously, the Input Gate filters the same inputs as the Forget Gate owing to the two activation functions, sigmoid and tanh (values between -1 and 1), to add new information in the long-term memory. First, the inputs pass through the sigmoid function to filter out irrelevant information by assigning them a value close to zero. These same inputs are then passed through the tanh function, which indicates the extent of the updates to be made to the long-term memory given the new information at its disposal. The tanh function can be negative; therefore, it is possible to decrease the impact of a component of the cell state. The vectors produced by the sigmoid and tanh functions are then multiplied and added to the cell state vector to update it. This double operation allows us to identify the variables that have particularly changed with respect to the state maintained in the long-term memory (tanh filtering) and to decide wheter these changes have an impact on the forecast (sigmoid filtering). Finally, a filtering step is applied to build the output of the cell in the Output Gate. At this stage, the network contains a large amount of information, including an updated cell state. Once again, the tanh and sigmoid functions are used to filter the available information in the same manner as before and produce the output. It should be noted that during the learning phase, the optimal weights are identified, thereby giving more or less importance to the variables and consequently impacting the values produced by the activation functions.

The GRU is a compromise between a simple RNN and a LSTM because it limits the risk of exponential gradient decay owing to a gate mechanism but contains only one memory vector; thus, it does not distinguish between short and long-term memory. However, unlike traditional RNN, the hidden state (h_t) integrates short and long-term dependencies. Requiring fewer parameters than LSTM, the training of a GRU is generally simpler and faster. This type of network includes two gates: the Update Gate and the Reset Gate. First, the Reset Gate determines how much of the memory produced in the previous time step (h_{t-1}) should be combined with new variables (x_t) to provide a new hidden state (h'_t). The Update Gate retains information relevant to the current and future predictions from the previous hidden state (h_{t-1}) and the new state proposed by the Reset Gate (h'_t), creating the final hidden state (h_t). Thus, long-term dependencies can be retained by the model if the Update Gate decides to retain a significant proportion of the previous hidden state (h_{t-1}).

LSTM and GRU neural networks, which are close in structure, are generally in competition and are particularly efficient in time series and textual analysis. In this study, these two types of networks were built using the Keras and TensorFlow libraries in Python. Six networks were constructed: two simple RNNs, the first with one hidden layer and the second with two hidden layers, and two LSTMs and GRUs, again with one and two hidden layers, respectively. The structures are shown in Figures A1, A2 and A3. Each neural network built has many-to-one form: the network receives a sequence of inputs and generates a unique output in the form of a probability transformed into an integer value according to a defined threshold. Adding layers increases the complexity of the networks. The hyperparameters were defined using the Bayesian optimization algorithm, testing combinations of hyperparameters available in Table 1 so that the objective function was maximized.

Hyperparameters	Values
Neurons	5-45, step=5
Layers	1,2
Epochs	50-1000, step=10
Dropout	0-0.5, step=0.05
Recurrent dropout	0-0.5, step=0.05
Activation function	Tanh, Softsign
Recurrent activation function	Sigmoid, Softmax
Optimization objective	F1 score, Precision at Recall
Early stopping	With (200), without
L2 regularization	0, 0.001, 0.01

Table 1: Hyperparameter space.

4 Data collection and preprocessing

4.1 Signal window

In this study, we aim to warn of the possible occurrence of a crisis in a given window and not to identify its precise timing. To do so, we defined a warning window of eight quarters before the collapse of a currency, during which a continuous signal must be sent by our models in the form of a probability transformed into a binary variable according to a defined threshold (0.5 in the standard case). Thus, each quarter corresponds to a tranquil period (dependent variable equal to zero) or to an alert period corresponding to the pre-crisis period (dependent variable equal to one). If the probability predicted by the model is transformed into one, the model predicts a crisis in the next eight quarters. The two-year warning window is a standard in the literature and is found in KLR and Berg and Pattillo (1999b). This two-year window offers the advantage of being sufficiently distant from the event to take preventive measures without being disconnected from it.

No treatment of post-crisis bias has been performed, such as suppressing crises and subsequent observations over several years after the currency collapse (Demirgüc-Kunt & Detragiache, 1998; Gourinchas & Obstfeld, 2011) or assigning a particular value to these observations and transforming the target into a three-modality variable (Fratzscher & Bussière, 2002). When no treatment is assigned to these post-crisis observations, they are treated as observations of tranquil periods during which economic indicators are healthy and sustainable, despite that they are in a period of adjustment toward a "normal" level. As a result, these periods can be wrongly considered indicators of future crises. We chose not to delete any of the observations to avoid breaking the order of the sequences and altering the memory mechanism of the tested neural networks. In theory, LSTMs and GRUs can identify cycles of events in a sequence and thus integrate this post-crisis period while focusing on the alert mechanism in the pre-crisis period. In this study, the notions of crisis episodes and currency crises (generally comprising several episodes) were confounded, but the switch to a target with more than two modalities could constitute a source of improvement for the continuation of this work.

4.2 Data collection

The study is based on quarterly data from Q1 1995 to Q4 2020 for 68 currencies quoted against the US dollar as the base currency, including currencies of developed, emerging and developing economies (complete list available in Table B1). The dataset was derived from Datastream, IMF International Financial Statistics and the Global Economy.

In line with the previously presented literature, particularly the KLR paper, current and capital accounts, and international, monetary, real, fiscal and development variables were incorporated into our models. A first attempt to materialize the contagion phenomenon was also tested through six dummies for the six major world regions according to the IMF World Economic Outlook[3], taking a value of one if a crisis occurred in one of these regions during the last eight quarters and zero otherwise. The full list of variables tested is presented in Table B2.

KLR identified indicators for which the particular dynamics in the pre-crisis period herald a collapse in the value of a currency. The early nature of these indicators make it possible to partially remove the question of endogeneity, assuming that their characteristic dynamics are sufficiently early for them to be considered determinants of crises and not consequences. However, the criteria for identifying crises are such that it is sometimes necessary to wait several months before the associated extreme thresholds are reached, even though the consequences are already materializing.

Depending on the model, the final set of indicators differed in line with the results of the variable selection algorithms (recursive feature elimination, mean decrease impurity and permutation feature importance). For the regressions, the full set of variables was used; for the random forest and neural network models, an identical subset of variables, including nominal and real exchange rate growth rates, real exchange rate deviation from its trend, ISO code, inflation rate, inflation differential with the US, CPI volatility, M2 growth, M2 to international reserves and public debt to GDP performed better. From the variables included in the dataset, we expected a characteristic dynamic in the pre-crisis period, the time pattern of which may differ according to the indicators. Therefore, it was necessary to include several lags for each variable. However, this can lead to collinearity problems in logistic regression models, contrary to recurrent neural networks, for which these multiple lags are the basis of the performance. Thus, a time window of seven quarters (current and past six quarters), selected based on the performance obtained with the F1 score, was used for the 11 variables included in the recurrent neural networks.

4.3 Data preprocessing

Feature scaling

Prior to modeling, the dataset was standardized so that all variables were on the same scale. Standardization generally increases the performance of models, especially when they are

[3] (1) Advanced Economies; (2) Emerging and Developing Europe; (3) Middle East and Central Asia; (4) Emerging and Developing Asia; (5) Latin America and the Caribbean; (6) Sub-Saharan Africa.

highly sensitive to differences in scale across variables. For regression models, standardization provides coefficients of comparable sizes that can be used as indicators of the importance of the variables. Algorithms based on decision trees are indifferent to scale issues because the decision nodes are split based on the behavior of one variable at a time. Standardization, therefore, does not particularly increase the performance of these models but does not hinder their learning. Finally, for neural networks, standardization makes it possible to bring the data into ranges more comparable to those of the activation functions ([0:1], [-1:1]), facilitating the achievement of a zero value by the gradient during the training phase. To maintain a real independence between the sample on which the models was trained and the one on which the final performance was measured, the standardization was built on the training data only and then applied to the test sample.

Imbalanced classification target management

Owing to the scarcity of currency crises, the dependent variable in this study contained few observations taking the value of one. The imbalanced nature of the target to be predicted may imply learning difficulties, especially for machine learning models that tend to neglect the minority class. Predicting warning signals rather than crises directly made it possible to partially compensate for this drawback: crises represent 2.7% of the global sample, while warning signals correspond to 9.6%. However, this was still insufficient; therefore, two techniques have been considered, supplemented by an adapted performance measurement criterion (F1 score).

It is possible to act upstream of the modeling by combining oversampling and undersampling techniques thanks to the SMOTEENN library proposed by Python. The SMOTEENN algorithm, as shown in Figure 5, combines two sampling techniques: the Synthetic Minority Over-sampling Technique (SMOTE), which creates artificial individuals of the minority class, and Edited Nearest Neighbors (ENN), which removes the least representative individuals of the majority class or of the two classes, each of them using the K-nearest neighbors algorithm. However, this method can only be used with models that do not explicitly include the sequential nature of the series as a parameter because the artificial individuals created can not be replaced in the order of the sequence. Thus, this method has only been used in regressions and random forests.

Another simpler solution may be to act on the prediction by lowering the probability threshold beyond which the probabilities predicted by the models are assigned to signals (by default, fixed at 0.5), forcing the model to artificially increase the proportion of predicted signals. The 0.5 threshold value may imply that policymakers assign equal weight to missed signals that could lead to inaction on their part and false signals that could lead to unnecessary actions and expenditures. The many episodes of crisis have led policymakers to become proactive and the implementation of EWS itself implies that they are less likely to miss crises, sometimes at the cost of more false alarms. The threshold was lowered based on the average performance obtained on the validation samples for the F1 score, as done by Liu et al. (2022) with the ROC curve. This alternative was tested for all of the models.

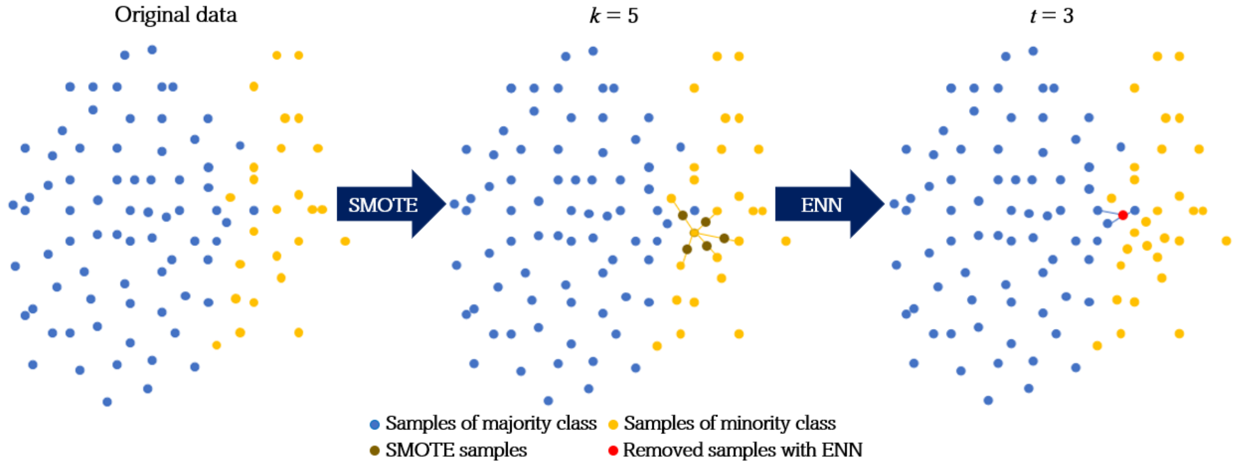
Original data
$k = 5$
$t = 3$
SMOTE
ENN
● Samples of majority class
● Samples of minority class
● SMOTE samples
● Removed samples with ENN

Figure 5: SMOTEEN algorithm.

Training and validation procedure

Cross-validation is generally the best method to train a model while limiting overfitting. It consists of subdividing the sample k times into a training sample on which the model is fitted and a validation or test sample to measure the performance of the model on unseen data. By training and evaluating the model on different samples, variability is reduced, and selection bias and overfitting are limited. Training and validation samples are generally constructed using a random selection of observations, which is incompatible with the study of time series, where order matters. Therefore, the expanding window method, which is an adaptation of cross-validation to time series, was used in this study. The sample was divided into a training sample starting at the first available observation up to a certain date and a validation sample comprising the following observations up to a given date. This prevents data leakage, that is, the use of future data to predict the past. As with cross-validation, the operation was repeated several times, with the difference that the number of observations contained in the training window increased with each new training (expanding window), incorporating more recent data. The validation window maintained a fixed size but slided toward the most recent observations as the training sample grown. Thus, in the last training iteration, the training sample included all observations contained in the validation sample except the most recent ones.

To guarantee real independence between model learning and performance evaluation and limit overfitting, in this study, the validation and test samples correspond to different observations, as recommended by Sarlin (2014). The training phase comprising the training and validation samples was based on data from Q1 1995 to Q4 2014, respecting the split shown in Figure 6 for each of the four training iterations.

The hyperparameters and structure of the models were optimized according to the average performance obtained from the validation samples. The test sample, which runs from Q1 2015 to Q4 2020, allowed the final performance of each model to be evaluated without it having been used during training. Similar to Nag and Mitra (1999), this allowed the independence of the results to be guaranteed and the generalization capacity of the models to be tested.

All of the models adopted in this study were constructed according to this method.

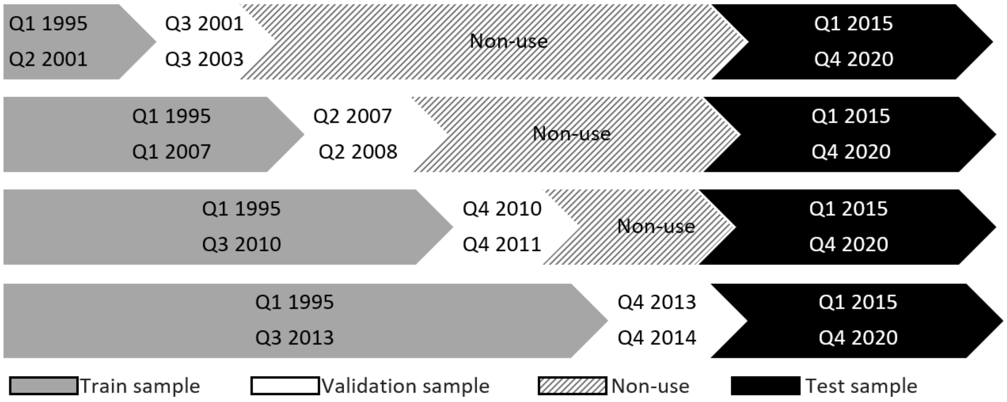

Figure 6: Training and testing procedure.

5 Experimental evaluation

5.1 Performance criteria

To compare the performance of each model on this classification problem, a set of performance metrics including precision, recall, F1 score and area under the ROC curve (AUC) were used. While the AUC is traditionally a decisive criterion, it can lead to high performance even though few good warning signals are predicted by the models in the presence of an imbalanced target. In fact, when the minority class (in terms of proportion) is associated with a small number of observations (small sample size), ROC curve estimates may become unreliable. The three criteria of precision, recall and F1 score have the advantage of considering this particularity by basing their construction on the confusion matrix (Table 2).

		True class	
		Crisis (within 8 quarters)	**No crisis (within 8 quarters)**
Predicted class	**Signal was sent**	True Positive (TP)	False Positive (FP)
	No signal was sent	False Negative (FN)	True Negative (TN)

TP: number of crisis signals rightly sent.
TN: number of quarters correctly identified as tranquil.
FN: number of missed crisis signals.
FP: number of crisis signals sent during tranquil periods.

Table 2: Confusion matrix.

$$Precision = \frac{TP}{TP+FP} \quad ; \quad Recall = \frac{TP}{TP+FN} \quad ; \quad F1\ score = \frac{2 * Precision * Recall}{Precision + Recall}$$

The precision metric rewards the sending of true warning signals, indicating the occurrence of a crisis within two years, while penalizing false signals, that is, quarters for which a signal was sent but a crisis did not occur within two years. Thus, the quality of the forecast increases with precision.

The recall criterion, also known as sensitivity, highlights the number of good signals sent by the model while penalizing the missed signals, that is, the quarters for which the model did not send a signal even though a crisis occurred in the two years that followed. Recall is particularly relevant in this study beacuse the cost of not signaling a crisis is higher than that of a false signal for policymakers.

The F1 score offers the advantage of combining the two metrics presented above, forming a synthetic indicator, such as the KLR adjusted noise-to-signal ratio. This metric allows for valuing the sending of true signals by penalizing both noise (false signals) and missed true signals, making it possible to focus the performance measurement on the minority class. Therefore, the F1 score was the decisive criterion for comparing the performance of models, increasing with prediction quality.

5.2 Results

5.2.1 Global performances

For each model (logistic regression, random forest, simple RNN, LSTM and GRU), three specifications were tested on a cross-country panel dataset. For logistic regression and random forest, the standard specification is compared to two specifications that consider the imbalanced character of the target: one by lowering the probability threshold of assignment to each class and the other using the SMOTEENN algorithm to increase the ratio of the minority class to the majority class. For neural networks, a specification with one hidden layer is compared to an identical specification with a lower probability threshold and a model with two hidden layers.

Metrics
Information on the performance of each model on the test sample from Q1 2015 to Q4 2020 is presented in Table 3. The performance of all models is acceptable, with F1 scores above 0.70, except for the random forest *(1)*. Sophisticated neural networks[4] appear to perform significantly better, with F1 scores above 0.80 for the single-hidden layer with no change in the probability threshold of assignment to a class specifications (LSTM *(1)* and GRU *(1)*). The best version of the standard model in the literature, namely logistic regression *(1)*, still appears to be a good candidate for the implementation of an EWS for currency crises with a F1 score of 0.73. However, of all of the signals sent, 77% were true (precision), and only 70% of true signals were identified (recall). For the one-hidden layer GRU *(1)*, 83% of the signals sent were true, and 79% of the expected signals were identified, which represents a considerable margin of improvement. Recall is the second most decisive performance criterion because an undetected crisis represents a higher cost for policymakers than does a false signal. Based on the F1 score alone, sophisticated neural networks were systematically more efficient than

[4] LSTM and GRU

logistic regressions, random forests and simple RNNs, regardless of the number of hidden layers or the technique used for managing the imbalanced target.

The simple RNN shows acceptable performance, with a F1 score of 0.76 in its two-hidden layer specification (model *(3)*), which is higher than the scores of logistic regressions and random forests but still below LSTM and GRU, regardless of the specifications chosen. The LSTM and GRU networks represent an improvement over basic recurrent neural networks in that they have both reduced noise and increased the number of good signals emitted. It should also be noted that for LSTM and GRU, the best performance was obtained owing to a specification with only one hidden layer against two for the best simple RNN. The more complex mechanism governing the LSTM and GRU cells allowed for the use of fewer deep networks, facilitating learning.

	F1	**Precision**	**Recall**	**AUC**
Logistic regression				
(1) standard	0.73	0.77	0.70	0.84
(2) probability threshold 45%	0.72	0.74	0.71	0.84
(3) SMOTEENN 20%	0.71	0.66	0.76	0.86
Random forest				
(1) standard	0.59	0.86	0.45	0.72
(2) probability threshold 30%	0.75	0.79	0.72	0.85
(3) SMOTEENN 40%	0.71	0.70	0.71	0.84
Simple RNN				
(1) 1 hidden layer	0.73	0.72	0.74	0.85
(2) 1 hidden layer + probability threshold 40%	0.73	0.69	0.78	0.87
(3) 2 hidden layers	0.76	0.77	0.75	0.86
LSTM				
(1) 1 hidden layer	0.81	0.86	0.76	0.87
(2) 1 hidden layer + probability threshold 40%	0.80	0.82	0.78	0.88
(3) 2 hidden layers	0.78	0.76	0.80	0.89
GRU				
(1) 1 hidden layer	0.81	0.83	0.79	0.89
(2) 1 hidden layer + probability threshold 35%	0.78	0.72	0.86	0.91
(3) 2 hidden layers	0.77	0.70	0.86	0.91

Table 3: Metrics for test sample.

With respect to the imbalanced target to be predicted, only the performance of the random forest was affected. In its standard specification *(1)*, the random forest failed to integrate this characteristic, leading to poor performance (F1 score = 0.59). The use of the SMOTEENN algorithm with a ratio of the number of observations in the minority class to the number of observations in the majority class reaching 40% after resampling (model *(3)*) significantly improved the predictive power of the model, but lower the probability threshold to 0.30 proved to be the most effective (model *(2)*). Logistic regression appeared insensitive to this imbalanced characteristic of the target, showing comparable results regardless of the model and inducing probabilities that were not concentrated around 0.5. Single-hidden layer neural networks were also insensitive to this particularity because they had already taken it into account during the optimization phase of the parameters, aiming at maximizing the F1 score or the precision for a defined recall score.

Identified crises

Although the metrics listed in Table 3 allow the measurement and comparison of the performance of each model, they are sensitive to the definition of the problem studied. Indeed, the models were trained to send continuous warning signals over a two-year warning window before a crisis occured; therefore, the above-mentioned metrics increased with the number of good signals identified. However, the final objective was to identify the maximum number of crises, and the model that has predicted the greatest number of signals was not necessarily the one that has identified the greatest number of crises. A model that is well trained to recognize "standard" crises, which are more recurrent, will send signals over almost the entire alert window associated with the crises in question and may not send any signal before a crisis with more atypical characteristics. For the best specification of each of the models on the basis of the F1 score, Table 4 shows the number of crises identified by each of them, that is, for which at least one signal was sent during the alert window. The results are presented with respect to the previously used country classifications. The test sample contained 22 crises, with at least one in each of the six regions. The models performed well, missing a maximum of only 4 crises for the simple RNN. We see that the random forest managed to identify 20 crises, similar to the single-hidden layer LSTM. Similarly, the logistic regression identified 19 crises, similar to the single-hidden layer GRU. Sophisticated neural networks stood out not by the number of identified crises but by the precision of the signals sent; the signals sent were more reliable because they were less noisy with false signals and were more numerous during the alert window. The simple RNN, which had a F1 score of 0.76 for its two-hidden layer specification, is the poorest performing model. The simple RNN has sent signals that were most often continuous over the entire alert window, but it seemed to adapt less well to the particularities of each currency.

Regardless of the model used, the collapse of the Som (Kyrgyzstan's currency) in Q4 2015 was not anticipated. Several explanations can be proposed for this phenomenon. On one hand, the year-on-year depreciation of the Som in Q4 2015, the first component of the Frankel and Rose criterion, was just over one percentage point above the 25% threshold of the criterion. The second component was above the 10% threshold, although it remained relatively low compared with the other crises in the sample. On the other hand, the Q4 2015 crisis was the first observed for the Som in the available sample. We can assume that the unprecedented nature of the event for the currency studied and the fact that it was not very representative compared with the other crises in the sample may have misled the models. Using the SHAP library in Python (described in Section 5.2.2), it was possible to measure the contribution of the explanatory variables to the probability predicted by the neural networks. The "ISO" variable (encoded variable of the country names) showed a negative contribution (decrease in predicted probability) in relation to the infrequency of crises in the country. M2 growth and the ratio of M2 to international reserves, considered sustainable by the networks, largely compensated for the deterioration of the other monetary variables (inflation rate, inflation differential with the US and CPI volatility) and a slight overvaluation of the real exchange rate compared with its trend.

If we compare the neural networks, the missed crises are globally the same (KGZ and NAM are common to the three networks, and MYS is common to the GRU and simple RNN) because of their similar functioning. Only the simple RNN was unable to alert to the drop in the Swedish krona in Q1 2015. The main reason for this was the granting of a large weight to the "ISO" variable, limiting the probability of a crisis occurring because the country had never experienced one in the past.

	Crises	**Logit**	**RF**	**RNN**	**LSTM**	**GRU**
Advanced Economies	2	2	2	1	2	2
Emerging and Developing Europe	5	5	5	5	5	5
Middle East and Central Asia	4	3	3	2	3	2
Emerging and Developing Asia	1	1	1	1	1	1
Latin America and the Caribbean	5	5	4	5	5	5
Sub-Saharan Africa	5	3	5	4	4	4
Total	22	19	20	18	20	19
Missed crisis		KGZ NAM ZAF	KGZ MEX	KGZ MYS NAM SWE	KGZ NAM	KGZ MYS NAM

The results are presented for the best specification of each type of model, based on the F1 score (standard logistic regression, random forest with a 30% probability threshold, standard RNN with two hidden layers, standard LSTM with one hidden layer and standard GRU with one hidden layer).

Table 4: Identified crises in the test sample (Q1 2015-Q4 2020).

In their signals approach, KLR used different sample sizes depending on the availability of data for each of the leading indicators. While, on average, their sample contained 61 crises as opposed to 22 in this study, it should be noted that their study was not conducted out-of-sample as was the case here. The best performing models in terms of detected crises, the random forest with a probability threshold set at 30%, and the standard LSTM with one hidden layer managed to identify 91% of the crises in the sample, while KLR identified an average of 70%.

Capacity for generalization

During the training phase, each model was tested on four different validation samples to identify the combination of hyperparameters that performed best on average and thus promote the generalization of the models on unseen data. Neural networks offered more stable performance, displaying reduced box plots compared to the other models in Figure C1, indicating a superior generalization capacity regardless of the period used.

Comparison to the literature

Table 5 compares our results with those of Berg and Pattillo (1999b) and Peltonen (2006). We compared the performance of our benchmark model, the standard model of the EWS literature, and our best LSTM and GRU specifications to the KLR signal model reconstructed by Berg and Pattillo as well as their probit model. As recurrent neural networks are absent from the related literature, we compared our results with those of Peltonen's ANN.

The differences in results should be interpreted with caution because the estimation sample (including temporality and countries), the criterion for identifying crises, the duration of the alert window, the variables included in the models and the probability threshold may differ across studies. Our out-of-sample results appear stronger than those in the existing literature, both for logistic regression and neural networks, outperforming the KLR model. The globally performing model of Berg and Pattillo as well as that of Peltonen seem to be affected by the imbalanced character of the target to be predicted, leading to a high accuracy but a low recall (reaching 25% for the KLR model and 3.6% for the ANN). Our models were trained over a longer period with more countries so we were able to correct this defect, allowing the identification of more than 70% of warning signals, regardless of our model. Our models are also less sensitive to noise, with only 14% of the signals sent as false for the LSTM, as opposed to 61% for Berg and Patillo's probit model and 72% for Peltonen's ANN. Our models appear to be more efficient overall (identification of alert and tranquil periods), more precise during alert periods, and less noisy.

	Logit[1]	**LSTM**[1]	**GRU**[1]	**BP**[2]**-Signal**	**BP**[2]**-Probit**	**P**[3]**-Probit**	**P**[3]**-ANN**
Percentage of observations correctly called[(a)]	95.0	96.5	96.4	69.0	76.0	89.2	89.0
Percentage of pre-crisis periods correctly called[(b)]	70.0	76.1	79.0	25.0	16.0	0.0	3.6
Percentage of tranquil periods correctly called[(c)]	97.6	98.7	98.2	85.0	93.0	99.9	99.5
False alarms as percentage of total alarms[(d)]	23.4	13.9	16.8	63.0	61.0	100.0	71.4

[1] The models selected are the best performing ones based on F1 score, that is, the standard logistic regression and the standard single-hidden layer LSTM and GRU. Crises were identified using the Frankel and Rose criterion for a 8-quarter alert window. The out-of-sample period runs from Q1 2015 to Q4 2020 for 68 countries.

[2] BP corresponds to Berg and Pattillo (1999b). The signal model is a reproduction of the KLR model (weighted sum of indicators), whereas the probit model is a regression using a set of variables identical to that in KLR. The specifications retained are those of the 25% threshold for a 24-month alert window using the EMP criterion. The out-of-sample period runs from May 1995 to December 1997 for 23 countries.

[3] P corresponds to Peltonen (2006). The author compares two specifications, a probit model and an artificial neural network (ANN). The specifications chosen are those of the 25% threshold for a 3-month alert window using the EMP criterion. The out-of-sample period runs from December 1997 to December 2001 for 24 countries.

[(a)] Number of identified true signals and true tranquil periods / number of samples (accuracy)

[(b)] Number of identified true signals / number of expected signals (recall or sensitivity)

[(c)] Number of identified true tranquil periods / number of tranquil periods (specificity)

[(d)] False signals sent / number of signals sent

Table 5: Comparison of out-of-sample performances.

Sophisticated-single-hidden layer neural networks were the best performing models here, with comparable results for LSTM and GRU based on the metrics. Increasing their complexity by adding a second hidden layer slightly decreased the overall performance, with F1 scores reaching 0.78 and 0.77 for LSTM *(3)* and GRU *(3)*, respectively, but allowed for the identification of more true signals (higher recall). These two types of neural networks outperformed their predecessor (simple RNN), trained on an identical dataset with Bayesian optimization, demonstrating the contribution of the gate mechanism in the network cells. In terms of identified crises, LSTM seems to be the best candidate, although its performance is comparable to that of random forest *(2)*. The sophisticated neural networks in this study allowed for the identification of more than 85% of the crises depending on the specification chosen, similar to the benchmark models; however, they are characterized by their precision in the emitted signals and the lesser occurrence of false signals, which increase their reliability. It should also be noted that neural networks and random forests performed on a more limited number of variables (11 variables) than logistic regressions (33 variables), which could allow the study to be easily extended to other countries and over time.

5.2.2 LSTM and GRU : detailed performances

EWS metrics

In this study, neural networks appear to be the best candidates for the implementation of an early warning system for currency crises. However, the performance criteria used above are not sufficient on their own to identify the best EWS. Additional measures specific to EWSs, such as the number of crises identified, signal continuity, and timing of the first and last signals, may prove decisive.

Information on the performance of the single and two-hidden layer networks on the test sample is presented in Table 6. The objective of the EWS is to send as many good warning signals as possible. In this sense, the GRU with two hidden layers appears to be the best performing, with 118 good signals identified out of the 138 expected. However, its F1 score was penalized by the 51 false signals sent, which increases the uncertainty of policymakers concerning the reliability of the model predictions. LSTM with one hidden layer is more reliable because only 17 false signals were sent, 10 of which were attributed to post-crisis bias. All neural networks (and all models in this study) were affected by this bias, which could be improved in future studies by switching to a three-modality target after an in-depth study on the duration of this bias.

	LSTM		**GRU**	
	1 hidden layer	**2 hidden layers**	**1 hidden layer**	**2 hidden layers**
True signals to be identified	138	138	138	138
True signals sent by the model	105	110	109	118
Missed true signals by the model	33	28	29	20
False signals sent by the model	17	34	22	51
of which related to post-crisis bias	10	22	7	27
Number of crises to be identified	22	22	22	22
Number of crises identified by the model	20	20	19	20
Missed crises (no signal sent)	KGZ, NAM	KGZ, SWE	KGZ, NAM, MYS	KGZ, SWE
Average % true signals sent/expected signals	69%	72%	73%	78%
Average % continuous true signals sent/expected signals	68%	71%	71%	78%
Average number of quarters of delay for the first signal sent	1	1	0	0
Average number of quarters in advance for the last signal sent	1	0	0	0

Table 6: EWS metrics on the test sample.

If the number of good signals sent is an important criterion, the ultimate objective was to succeed in identifying each crisis, that is, sending at least one signal before each of them. Each model managed to warn of 20 crises of the 22 crises in the test sample, excepting the GRU with one hidden layer, which missed three crises. The latter appeared to be the best performing model based on the precision, recall and F1 score. For all models, the collapse of the Som (Kyrgyzstan) against the dollar in Q4 2015 was not anticipated. More complexity (i.e., adding an additional hidden layer) allowed us to anticipate the fall of the Namibian dollar against the US dollar in Q4 2015.

Policymakers can take preventive action if they have confidence in the EWS, and signal continuity over the entire warning window can strengthen it. KLR studied the persistence and timing of the signals. Focusing on a two-year warning window, they showed that, on average, all indicators sent the first signal between a year and a year and a half before a crisis erupts. Their measure of signal persistence is different from ours because it compares the average number of signals sent during the alert window relative to tranquil times. In this study, persistence or continuity is the average number of good signals emitted compared to the number of expected signals for each alert window. Thus, a continuity indicator close to 100% tells policymakers that long signals should be watched carefully (under the condition that the noise metric is low) and that the first signal issued precisely suggests a crisis coming in eight quarters, completing the timing indicator. For all crises detected by the two-hidden layer GRU, the signals sent represented, on average, 78% of the alert window and were continuous over 78% of the alert window on average. GRUs also appear to be more accurate than LSTMs because the first signal for each alert window was, on average, sent in the first quarter of the window (no delay) and the last one at the end of the window[5]. However, the two-hidden layer GRU sent signals beyond the window because it was very sensitive to post-crisis bias.

The two-hidden layer GRU appears to perform better here, with a higher proportion of good-predicted signals, and showed some signal continuity. However, the signals sent were also noisier and altered by post-crisis bias. LSTMs were less sensitive to noise but slightly less accurate over the warning window. Finally, the single-hidden layer GRU is the least efficient, missing three crises, whereas the others miss two.

SHAP values

As is the case of traditional models, it was possible to assess the overall importance of the variables (Figures D1 and D2), the direction of the correlations (Figures D3 and D4) as well as identify, for a specific signal, the variables that have contributed to the predicted probability by measuring the impact of past observations (Tables D1 and D2). This has been done using SHapley Additive exPlanation (Lundberg & Lee, 2017), also known as the SHAP value, inspired by game theory (Shapley, 1953). Deep learning models, although powerful, are at first sight more difficult to explain because of the large number of parameters involved as well as the stacking of several hidden layers. The use of SHAP values allowed us to compensate for this weakness by precisely identifying the causes of crises, which could allow policymakers to implement adapted policies. The base value corresponds to the average payoff deduced from

[5] It does not guarantee that the signal was emitted continuously between the first and last emitted signals.

the set of possible combinations of players in the framework of comparative game theory. Similarly, for econometric, machine or deep learning models, the base value corresponds to the average probability predicted by the model for the entire sample based on the average contributions of each explanatory variable. Therefore, the SHAP value is the difference between the contribution of a variable to a given prediction and its average contribution to all predictions. The probability predicted by the model for a given observation is the sum of the base value and SHAP values of all explanatory variables for that observation.

Figures D1 and D2 show the importance of the variables, and Figures D3 and D4 show the direction of the correlations with the target for the LSTM and GRU with one hidden layer. A correspondence table with the variable names is presented in Table B3. The blue dots correspond to indicators with low values, and the red dots correspond to indicators with high values. The x-axis indicates the sign and magnitude of the contribution to the model-predicted probability. Negative contributions decrease the probability of a crisis. The variables are ranked in order of importance. The top three most important variables were identical for both models, including the deviation of the real exchange rate from its trend, real exchange rate growth rate and the encoded ISO code. The deviation of the real exchange rate often appears to be a good indicator of future crises, as shown by Kaminsky et al. (1998) and Gourinchas and Obstfeld (2011). The overvaluation of a currency relative to its trend with the US dollar can increase the vulnerability of an economy by reducing the competitiveness of its exports and maintaining a current account deficit, which can be decisive in emerging and developing economies. The real exchange rate growth rate is positively correlated with the warning signals, meaning that the currencies under study were gradually losing value before their collapses, probably because of a sharp rise in inflation and persistent speculative attacks. Finally, the appearance of the ISO code in the top three implies structural fragilities, leading to history repeating itself.

Tables D1 and D2 present the contributions of present and past variables (up to six quarters back) to the sending of a warning signal in Q3 2017, one year before the collapse of the Turkish lira in Q3 2018. For LSTM, the base value was 0.074 and the predicted probability for the third quarter of 2017 was 0.839. For GRU, the base value was 0.0723 and the predicted probability was 0.7451. The sum of the contributions of the variables over the seven quarters and the base value corresponds to the model prediction. The variables in red increased the predicted probability, whereas those in blue decreased it. For both LSTM and GRU, all indicators seemed to deteriorate, increasing the probability of a signal above the alert threshold. The sending of a warning signal was particularly influenced by the real exchange rate growth rate, public debt to GDP ratio and encoded ISO code. Monetary variables such as CPI volatility, M2 growth rate, inflation rate and inflation differential with the US reinforced the sending of a warning signal with greater weight in more recent quarters. The Turkish lira had already suffered currency crises in the past (2001 and 2015) in addition to other episodes of extreme depreciation that did not fully satisfy the Frankel and Rose criterion (the 2008 financial crisis and post-crisis period). Therefore, the evolution of the Turkish exchange rate was historically destabilizing for the country, making the lira a vulnerable currency due to a lack of confidence. The real exchange rate depreciation fluctuated during the alert window but remained positive, reaching ranges comparable to past crises and tensions. The ratio of public debt to GDP has continued to decrease since the GFC, reaching about 27% in 2015, compared to over 45% in 2008. At the beginning of the warning window, public debt was thus relatively low, but the trend has reversed, and it started to increase because of the impact of depreciation on external debt (representing almost 40% of public debt). Finally, in an open economy such as Turkey's, depreciation can represent gains in competitiveness but can also lead to an increase in prices through imported inflation (pass-through effect), which occurred in early 2017. Therefore, the crisis of 2018 was the result of the country's history and mistrust in the Turkish lira leading to indebtedness in foreign currency, which proved to be very risky in the face of an already depreciated currency reinforcing price increases.

6 Conclusions and future work

This study has investigated the implementation of an early warning system for currency crises over a two-year warning window for 68 countries, including developed, emerging and developing economies over the period of 1995-2020 using the Frankel and Rose criterion. The objective was to evaluate the performance of sophisticated recurrent neural networks, representing the state of the art in terms of financial asset price prediction models, compared to traditional models, such as logistic regressions and random forests. The advantage of these models lies in a gate mechanism that allows the memory vector to retain information over an extended period and to distinguish between short and long-term dependencies. Thus, the LSTM and GRU models have been tested for the first time for the implementation of an EWS for currency crises and compared to the traditional models of the associated literature, which are still widely used.

For all of the models tested, the performances were acceptable, meaning that the calibration of past data is a good way to forecast the future in the case of currency crises. LSTM and GRU outperformed traditional models and simple recurrent neural networks, both based on standard metrics such as the AUC and metrics adapted to the imbalanced nature of the target, such as the F1 score, in line with the growing literature on the use of machine and deep learning for predicting financial crises. It should be noted that the imbalanced specificity was integrated by neural networks during the parameter optimization phase and, therefore, did not reduce the predictive power of the models. The best LSTM and GRU constructed offered similar performances and allowed for the warning of 20 of the 22 crises of the test sample, as did the best random forest, compared to 19 crises for the logistic regression. The traditional models built also performed well in terms of the number of detected crises and showed performances superior to those in the past literature. This can be explained by the availability of data over a longer history and for a larger number of countries, thus improving the training of the models. However, neural networks outperformed these traditional models in terms of precision and continuity of signals throughout the alert window and were characterized by less noisy signals (representing 14%, 17% and 23% of the emitted signals for LSTM, GRU and logistic regression, respectively), making them more reliable EWSs for policymakers.

All models were sensitive to post-crisis bias, concentrating false signals after the collapse of a currency due to the continued deterioration of economic and financial indicators. The treatment of this bias could be improved in future studies by conducting an appropriate study on the duration of this bias and switching to a three-modality target.

As with traditional models, it was possible to explain precisely how neural networks led to a prediction and to identify the contributions of past variables to the current prediction owing to SHAP decomposition. Each of the constructed networks was based on a limited number of variables from the initial set, including only variables related to the real and nominal exchange rates (growth rate and deviation from trend) and monetary, fiscal and development variables. The deviation of the real exchange rate from its trend appeared here as the most decisive variable, which is in line with the literature presented in this paper. The nonlinear nature of the operations within the neural network cells also allowed us to obtain warning signals motivated by variables that had less importance for the whole sample, as in the example of Turkey. This made it possible to detect crises of various origins. The accurate results of our two neural networks, in addition to being superior to those of traditional models, were also interpretable, which made it possible to identify the causes and vulnerabilities leading to crises.

The proposed contagion variable, which included six dummy variables taking the value of one if a currency crisis had occurred in the last eight quarters for each of the six IMF regions, did not perform well here. However, the contagion mechanism could be materialized in future studies through an exchange rate correlation variable, which is assumed to increase during periods of tension.

Finally, one may wonder whether the valuable results obtained can be generalized to all types of financial crises. This could be the subject of comparative studies and the implementation of new types of neural networks, as the associated literature is constantly growing.

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All authors declare that they have no conflicts of interest.

Data availability statement
The data that support the findings of this study are available from Datastream, IMF International Financial Statistics and the Global Economy. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors with permission from Datastream and the Global Economy.

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Appendices

A Structure of neural networks

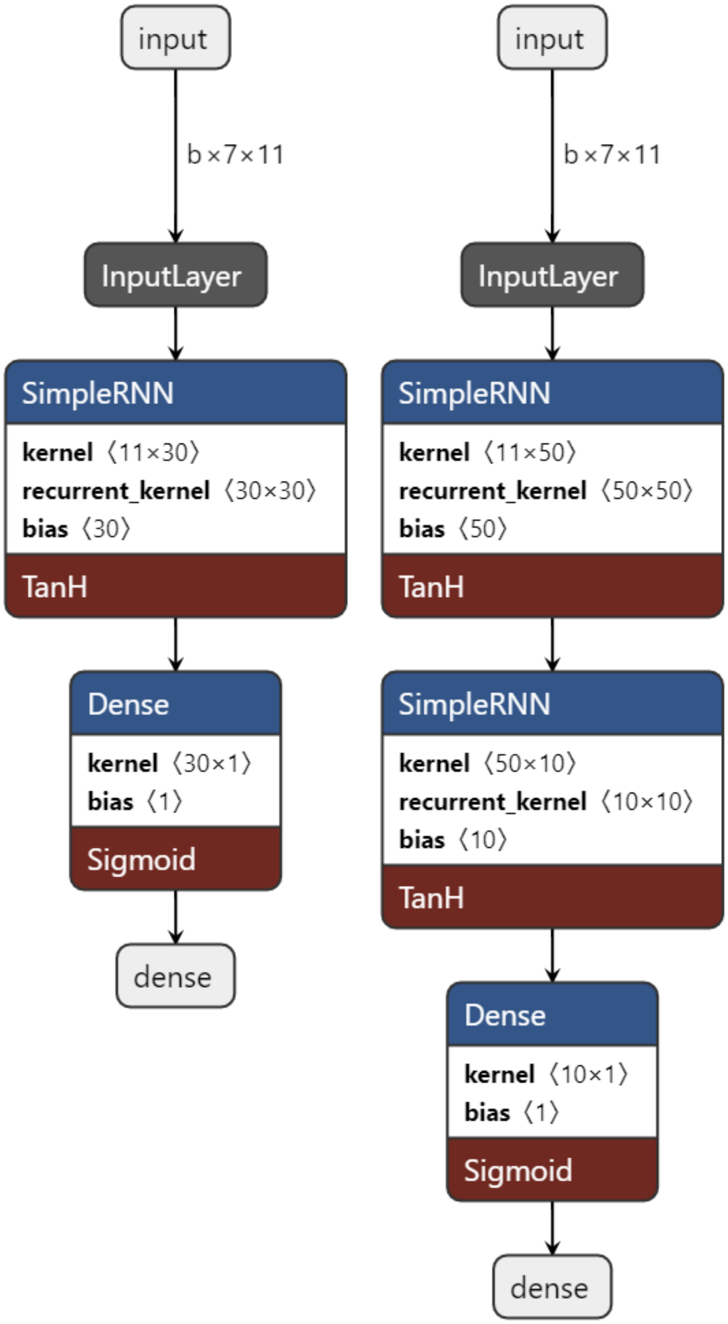


Figure A1: Simple RNN proposed structures.

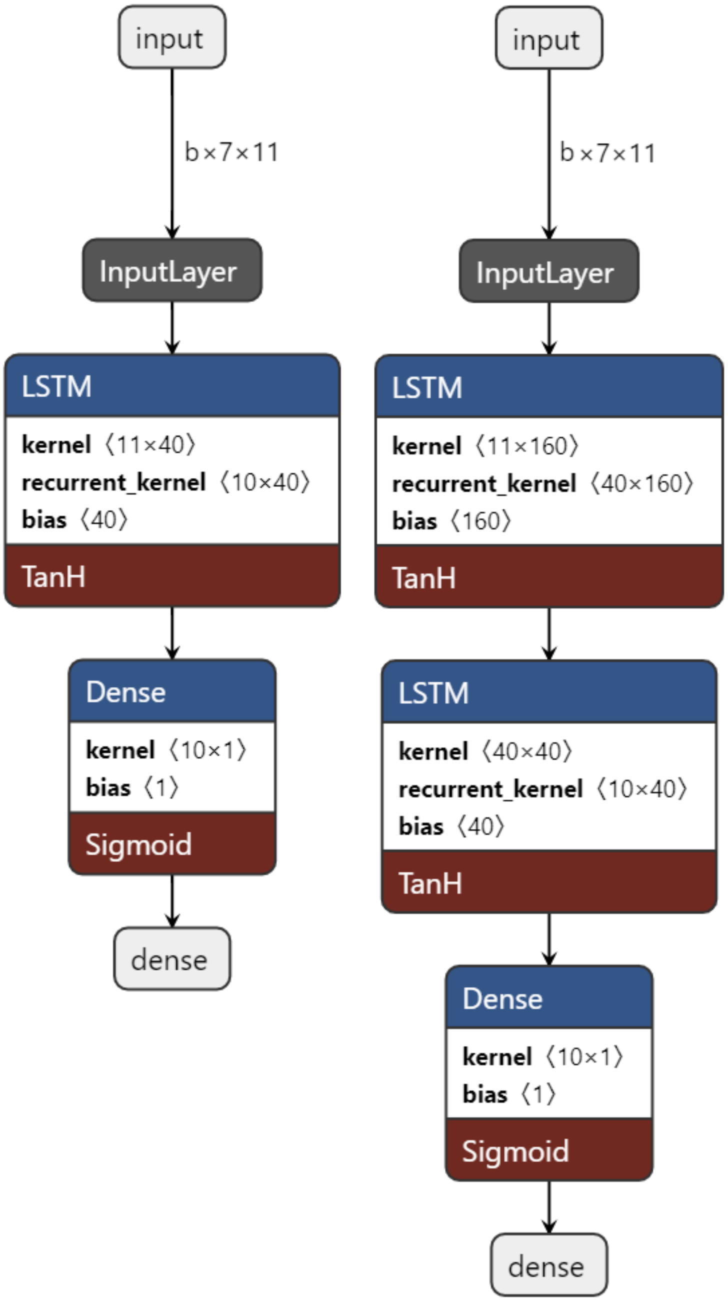


Figure A2: LSTM proposed structures.

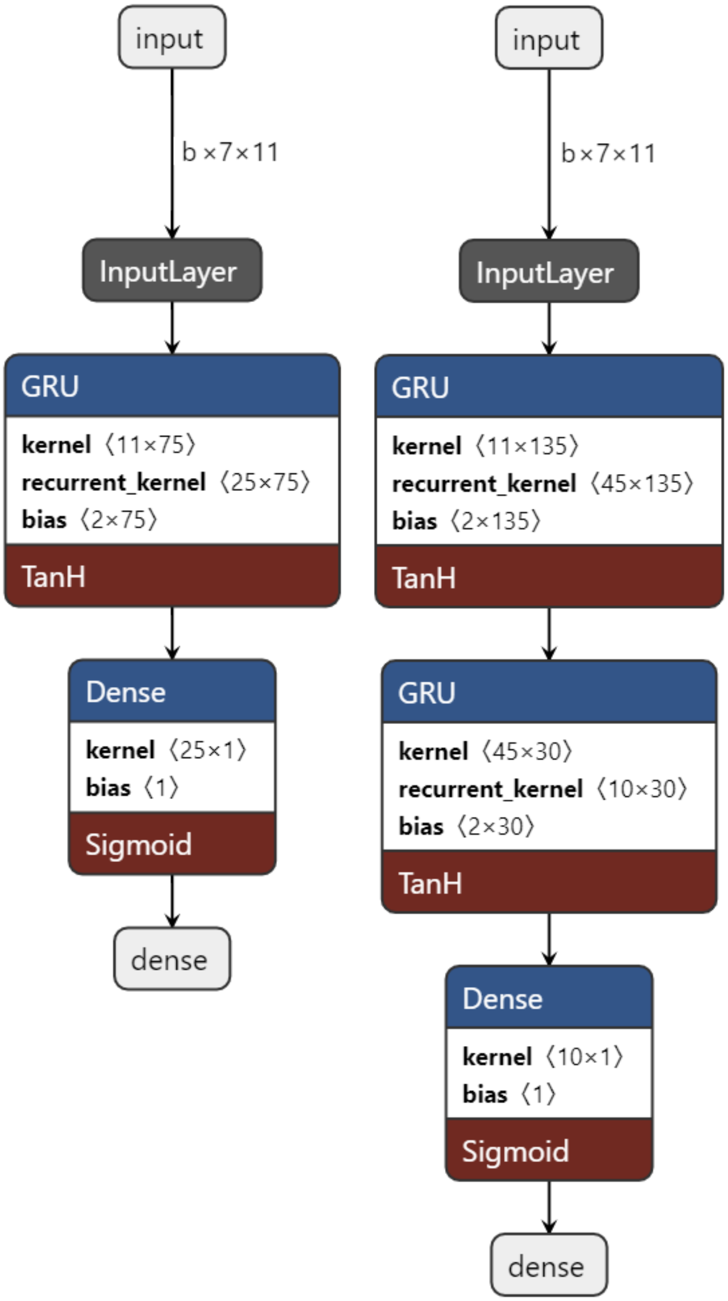


Figure A3: GRU proposed structures.

B Composition of the dataset

IMF World Economic Outlook regions	Countries
Advanced Economies	Australia, Canada, Switzerland, Czech Republic, Germany, Denmark, Eurozone*, Finland, France, United Kingdom, Iceland, Japan, South Korea, Netherlands, New Zealand, Singapore, Sweden, United States, Norway
Emerging and Developing Europe	Albania, Bulgaria, Belarus, Hungary, Moldova, Northern Macedonia, Poland, Romania, Russia, Serbia, Turkey, Ukraine
Middle East and Central Asia	Armenia, Egypt, Georgia, Jordan, Kazakhstan, Kyrgyzstan, Kuwait, Morocco, Tunisia, Israel
Emerging and Developing Asia	China, Hong Kong, Indonesia, India, Malaysia, Philippines, Thailand
Latin America and the Caribbean	Argentina, Brazil, Chile, Colombia, Dominican Republic, Guatemala, Jamaica, Mexico, Peru, Paraguay
Sub-Saharan Africa	Botswana, Cape Verde, Ghana, Kenya, Mauritius, Namibia, Nigeria, Rwanda, Uganda, South Africa

* Includes Germany, Austria, Belgium, Spain, Finland, France, Greece, Ireland, Italy, Portugal, Netherlands, Cyprus, Estonia, Latvia, Lithuania, Malta, Luxembourg, Slovenia and Slovak Republic since 1999.

Table B1: IMF WEO country classification.

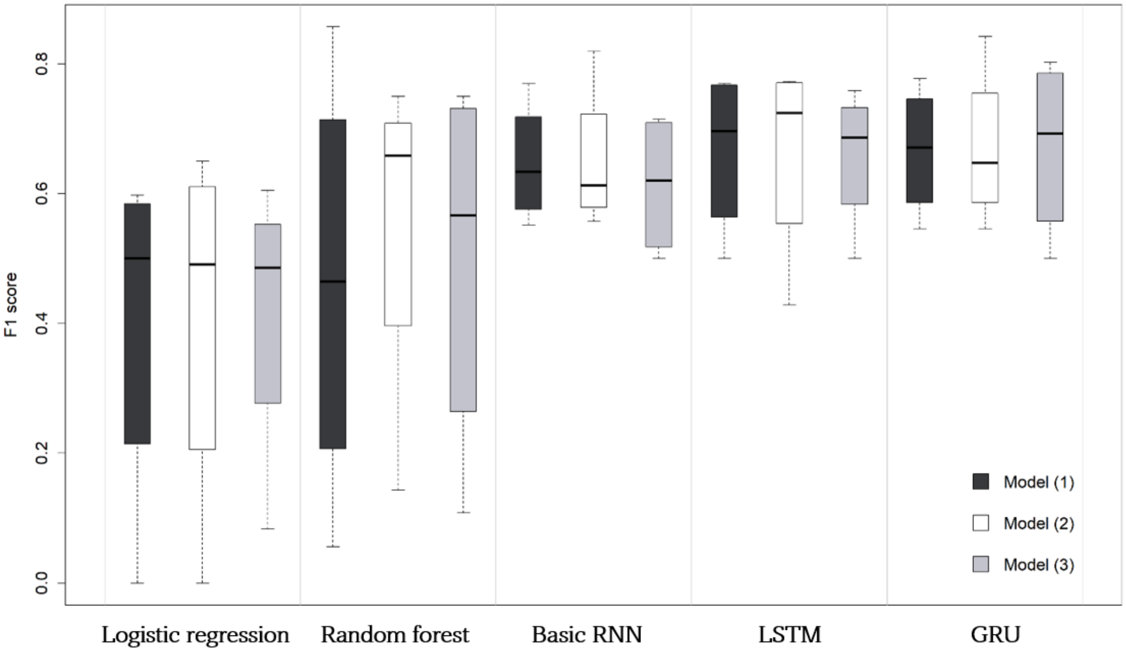
	Variables
Current account	Exports to GDP, imports to GDP, terms of trade, current account to GDP, nominal and real exchange rate level and growth, exchange rate volatility, real exchange rate deviation from its trend, international reserves growth
Capital account	Interest rate, interest rate growth
International	Differential between domestic and US real GDP growth, inflation and interest rate
Monetary	Inflation, CPI volatility, domestic credit to the private sector to GDP, M2 growth, M2 to international reserves
Real	Real GDP growth, output gap
Fiscal	Public debt to GDP
Level of development	World Economic Outlook classification in six regions, ISO code (label encoding)
Contagion	Six dummies equal to one if a crisis has occurred in one of the six WEO regions within the last eight quarters (one hot encoding)

Table B2: Initial set of variables.

Name in the model	Variable
exr_r_cycle	Deviation of the real exchange rate from its trend
texr_r4	Real exchange rate growth rate (annual %)
texr4	Nominal exchange rate growth rate (annual %)
texr1	Nominal exchange rate growth rate (quarterly %)
tm2_4	M2 growth (annual %)
m2_res	M2 to international reserves
infl	Inflation rate (annual %)
dinfl	Inflation differential with the US
vol_cpi	CPI volatility
debt_ge	Public debt to GDP
ISO	ISO code (encoded)

Table B3: Feature names.

C Capacity for generalization



Model (1) refers to the standard specification (with one hidden layer for neural networks).
Model (2) refers to a specification with a lower probability threshold for assignment to class 1.
Model (3) refers to a specification using the SMOTEENN algorithm for logistic regression and random forest and a standard specification with two hidden layers for neural networks.

Figure C1: Box plot of F1 scores during cross-validation (expanding window).

D Analysis of SHAP values

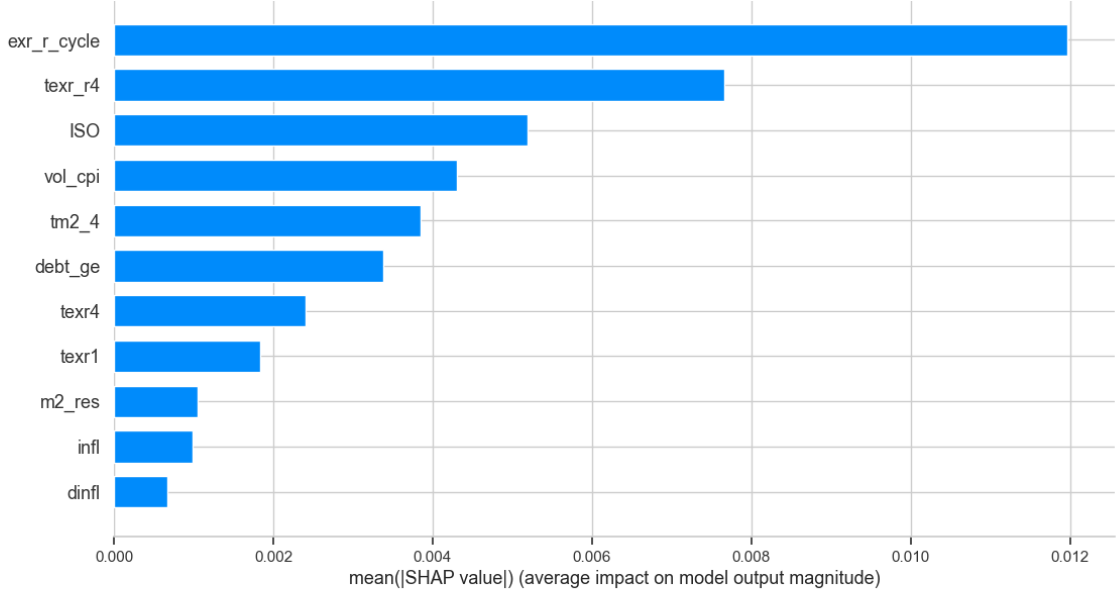


Figure D1: One-hidden layer LSTM, feature importance.

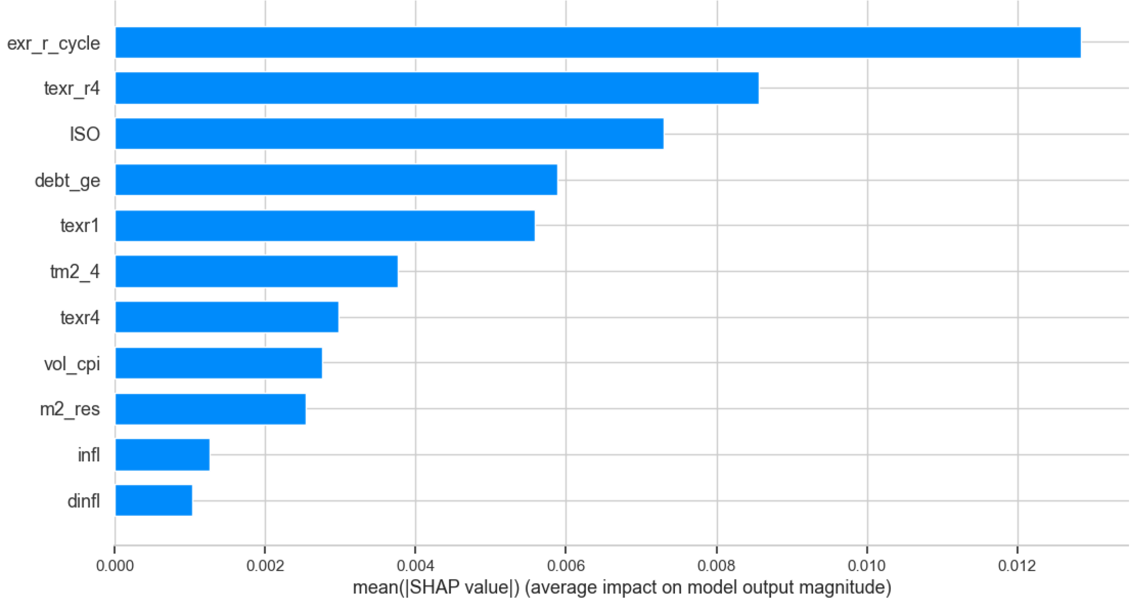


Figure D2: One-hidden layer GRU, feature importance.

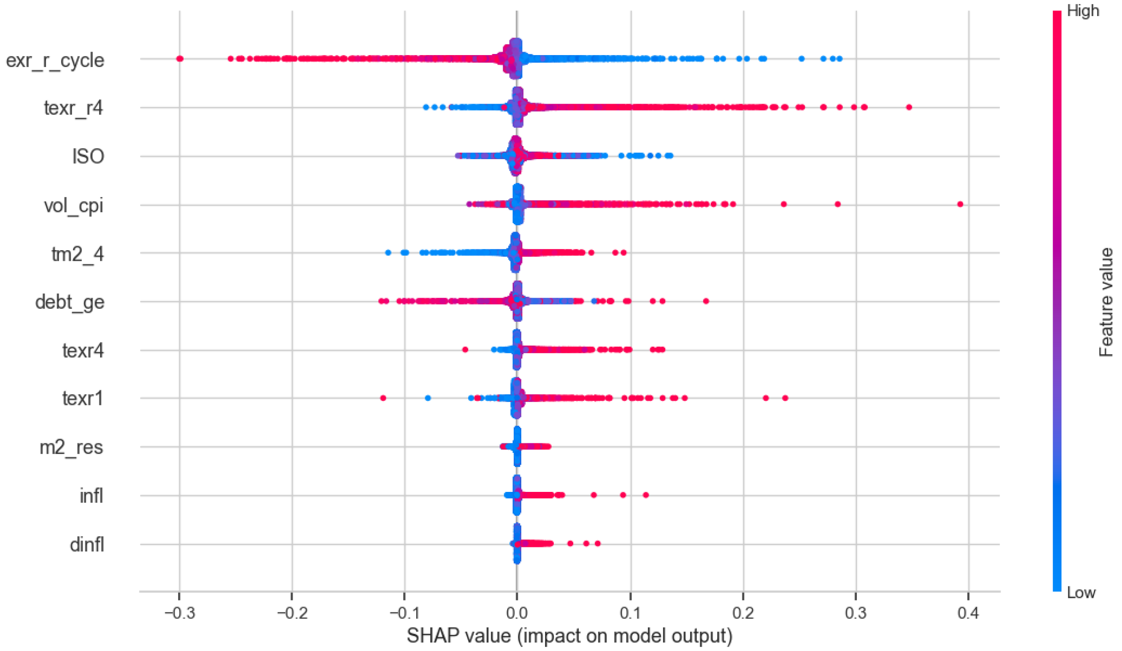


Figure D3: One-hidden layer LSTM, feature importance, additional.

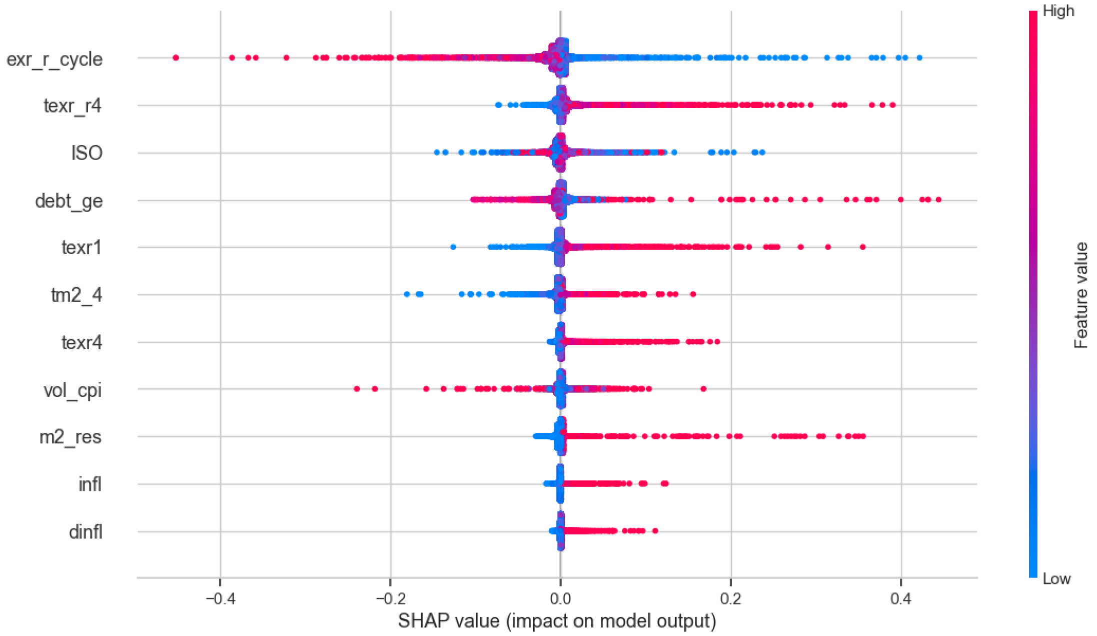


Figure D4: One-hidden layer GRU, feature importance, additional.

	Q1 2016	Q2 2016	Q3 2016	Q4 2016	Q1 2017	Q2 2017	Q3 2017	TOTAL feature
texr4	1,00	0,80	0,30	0,70	1,30	1,10	2,30	**7,50**
texr_r4	2,70	2,10	-0,10	2,60	5,60	3,40	3,50	**19,80**
exr_r_cycle	-0,20	1,60	2,60	-1,60	-7,00	-1,00	8,00	**2,40**
texr1	0,20	0,20	0,30	0,40	0,90	-0,10	-1,00	**0,90**
ISO	0,70	3,90	5,90	3,50	2,10	2,20	1,00	**19,30**
infl	0,20	0,10	0,10	0,10	0,20	0,40	1,20	**2,30**
dinfl	0,00	0,10	0,10	0,10	0,10	0,20	0,80	**1,40**
vol_cpi	-1,30	-0,20	0,50	1,30	1,20	1,50	4,30	**7,30**
tm2_4	0,70	0,20	-0,20	0,60	0,50	1,10	2,70	**5,60**
m2_res	0,20	0,10	0,00	-0,10	-0,20	0,30	0,30	**0,60**
debt_ge	1,70	2,70	2,10	1,00	0,40	0,60	0,90	**9,40**
TOTAL quarter	**5,90**	**11,60**	**11,60**	**8,60**	**5,10**	**9,70**	**24,00**	**76,50**
							Base value	**7,40**
							Predicted probability	**83,90**

Table D1: Contribution of the variables from the current and past time steps to the sending of a signal in Q3 2017 by the one-hidden layer LSTM one year before the collapse of the Turkish lira (Q3 2018).

	Q1 2016	Q2 2016	Q3 2016	Q4 2016	Q1 2017	Q2 2017	Q3 2017	Total feature
texr4	0,69	0,48	0,29	0,63	1,29	2,10	2,31	**7,80**
texr_r4	2,33	1,34	0,16	1,90	4,80	7,50	5,86	**23,88**
exr_r_cycle	-0,17	0,39	0,17	0,36	-3,69	-2,18	7,47	**2,35**
texr1	0,24	-0,24	0,38	1,83	5,07	-2,78	-2,45	**2,06**
ISO	0,41	1,76	2,14	0,46	-1,54	-1,99	7,26	**8,51**
infl	0,06	0,05	0,07	0,01	-0,01	0,42	1,45	**2,04**
dinfl	0,06	0,04	0,04	-0,04	-0,15	0,14	1,37	**1,47**
vol_cpi	0,07	0,08	0,06	0,27	0,61	2,23	2,91	**6,23**
tm2_4	0,05	-0,02	-0,09	-0,02	0,10	1,28	2,99	**4,30**
m2_res	0,04	0,03	0,03	-0,01	-0,10	-0,30	-0,54	**-0,85**
debt_ge	0,18	0,62	0,77	1,57	2,45	3,28	0,62	**9,50**
Total quarter	**3,96**	**4,55**	**4,01**	**6,97**	**8,83**	**9,70**	**29,25**	**67,28**
							Base value	**7,23**
							Predicted probability	**74,51**

Table D2: Contribution of the variables from the current and past time steps to the sending of a signal in Q3 2017 by the one-hidden layer GRU one year before the collapse of the Turkish lira (Q3 2018).