Central Bank Review 20 (2020) 99–107

Contents lists available at ScienceDirect

Central Bank Review

journal homepage: http://www.journals.elsevier.com/central-bank-review/

An optimal early warning system for currency crises under model uncertainty☆

Mamdouh Abdelmoula M. Abdelsalam [a], Hany Abdel-Latif [b], *

[a] Minufia University, Egypt
[b] Swansea University, UK

ARTICLE INFO

Article history:
Received 13 December 2019
Received in revised form
28 February 2020
Accepted 13 March 2020
Available online 26 March 2020

JEL classification:
E44
F31
F47
G01

Keywords:
Financial crises
Currency crises
Early warning
Uncertainty
Egypt

ABSTRACT

This paper assesses several early warning (EWS) models of financial crises to propose a model that can predict the incidence of a currency crisis in developing countries. For this purpose, we employ the equal weighting (EW) and dynamic model averaging (DMA) approaches to combine forecast from individual models allowing for time-varying weights. Taking Egypt as a case study and focusing only on currency crises, our findings show that combined forecast (EW- and DMA-based EWS), to account for uncertainty, perform better than other competing models in both in-sample and out-of-sample forecasts.

1. Introduction

Financial crises are recurrent phenomena which come in different shapes and forms. Currency crises, debt crises, and banking crises are examples. Financial crises can cause severe economic damage not only to their country of origin but also across borders. Output declines, chronic poverty struggle, international reserves dry up, and aggravating government debt are merely some symptoms of long-lasting impacts of financial crises. The financial crisis of 2007–2008, which ignited in the US and engulfed other advanced and emerging economies through various trade and financial links, is a prominent example of how financial crises can get nasty. A decade after the crisis and the world economy is yet to recover from its impacts. The International Monetary Fund (IMF) finds persistent output losses even after a decade of the outbreak of the recent global crisis (IMF, 2018).

Economists have been trying to develop systems of indicators that can predict financial crises. Such indicators or early warning systems (EWSs) are designed to detect financial crises at an early stage. Although they are essential in almost every country, the importance of EWSs becomes paramount in developing countries which lack competencies and institutional settings that can facilitate optimal utilization of resources. Well functioned EWSs could help developing countries in their quest to further integrate into the world economy while avoiding costs of financial crises. Thus, the ability to identify adequate EWSs should be an integral part of their economic agenda. Besides, EWSs can suggest suitable policy interventions that could prevent severe crises or at least minimize their adverse impacts.

Many central banks and international organizations developed EWS models aimed at anticipating the timing of a financial crisis

☆ We are grateful for valuable comments from the editor and two anonymous referees as well as from Don Webber, Chahir Zaki and participants and anonymous reviewers for the Economic Research Forum Annual Conference in Kuwait. Mamdouh Abdelsalam acknowledges financial support from the Economic Research Forum (ERF).

* Corresponding author. Economics Department, Swansea University, Swansea SA1 8EN, UK.

E-mail address: h.abdel-latif@swansea.ac.uk (H. Abdel-Latif).

Peer review under responsibility of the Central Bank of the Republic of Turkey.

https://doi.org/10.1016/j.cbrev.2020.03.002

and ensuring the safety of the financial system (Bussière and Fratzscher, 2006). The financial soundness indicators (FSI) and macro-prudential indicators (MPI) are examples of early warning indicators adopted by the IMF. However, most of these indicators are designed primarily for more mature financial sectors in developed economies. For example, as contemporaneous indicators, FSIs pose difficulties if there are delays in data collection, which is a serious challenge in most developing countries. Besides, while the FSIs and MPIs usually require the availability of high-frequency data, aggregate data is only produced at a lower frequency (i.e., annually or quarterly at best for some indicators). Therefore, there is a need to formulate indicators that suit the nature of developing economies as well as to assess current EWS models and identify the most efficient model.

Against this backdrop, the current paper aims to assess several EWS models of financial crises and propose an optimal model that can predict the incidence of financial crises in developing countries. Many approaches are suggested by the existing literature to design EWSs. The majority of these approaches have been established based on author-selected model specifications (Frankel and Saravelos, 2012). Variant modeling approaches of designing EWSs come under four categories: probit and logit models (Eichengreen et al., 1995); non-parametric signaling models (Kaminsky et al., 1998); cross-country quantitative and qualitative analyses (Edwards and Santaella, 1993); and modern approaches such as binary recursive trees (Ghosh and Ghosh, 2003) artificial neural networks, and Markov switching models. A significant shortcoming in the above approaches is the absence of explicit modeling of uncertainty embedded in the adopted theoretical model. Raftery (1995) finds that inflated confidence levels usually exist when taking uncertainty into consideration. Moreover, existing approaches do not offer clear selection criteria for robust EWSs.

To address these issues, the current paper attempts to identify an optimal EWS under model uncertainty. The extensive research on early warning indicators which lacks consensus on a universally accepted theoretical model or empirical approach underpins the associated model uncertainty (see Adams and Metwally (2019)). As such, we propose a statistically motivated approach to address such model uncertainty by utilizing the equal weighting (EW) and dynamic model averaging (DMA) approaches. Following Raftery et al. (2010), we combine forecasts from different EWS models based on the predictive likelihood of each model as approximate to the past forecasting performance. One of the advantages of applying the EW and DMA approaches is to allow for time-variant weights to be attached to different models. By doing so, we propose a more robust way of identifying the best model explains likely risks facing a specific country.

Taking Egypt as a case study and focusing only on currency crises, we show how our EW- and DMA-based EWS models perform better than other competing models. The Egyptian foreign exchange market provides an excellent case to study currency crises. Supported by the IMF, the Egyptian economy has been through several economic reform programs since 1991. These programs targeted macroeconomic imbalances and foreign exchange market distortions. Despite being commended by the IMF staff for notable improvements in the foreign currency market, Egypt has witnessed several currency crises, most notably those of 2001 and 2016. For example, the Egyptian pound has lost more than 30% of its value against the US dollar due to fallen demand for tourism and increased demand for foreign currency to finance national projects. Additional drops in the value of the Egyptian pound have occurred after the 2011 uprising. The Egyptian pound has further fallen in value from around 6 pounds for one US dollar in 2012 to more than 19 for the same one dollar at the end of 2016. The recent developments in the Egyptian currency unmasked acute foreign currency shortages due to the exchange rate regime rigidity and the presence of a parallel market for foreign exchange. In particular, in 2016, the Egyptian Central Bank announced a policy shift toward a liberalized exchange rate regime aiming to quell any distortions in the domestic foreign currency market. We argue that recurrent currency crises in Egypt could have been avoided or at least muted by adopting a well functioning forward-looking warning system. For these reasons, we believe the Egyptian foreign currency is unique and an excellent case for assessing different prediction models.

We thus contribute to the existing literature in two main ways. First, we assess alternative approaches for designing EWSs with decision-makers degree of risk-aversion towards the risk of default. Second, we suggest utilizing the EW and DMA approaches to obtain more robust signals for currency crises in developing countries. More specifically, we show how the EW- and DMA-based EWS models can be used to overcome the uncertainty associated with the adopted theoretical model.

This paper proceeds as follows. Section 2 reviews the existing literature. Section 3 explains our methodology. Section 4 summarises the dataset and variables of interest. Section 5 presents the empirical results. Section 6 discusses our robustness checks. Finally, section 7 concludes.

2. Literature review

A first step towards developing an effective EWS is to precisely distinguish between 'usual' fluctuations and what is a financial crisis. Currency crises, for example, and associated sharp depreciation, are usually attributed to speculative attacks that force monetary authorities to take several measures to defend the value of their currency. These preemptive measures include selling international currency reserves, sharply increasing interest rates, and erecting more restrictive capital controls. Identifying a proper definition of the crisis of interest is usually followed by an examination of the leading causes of the crisis. Using a broad set of indicators, one needs then to decide which statistical technique would be most appropriate when designing an EWS.

Many theoretical models attempt to explain the causes of currency crises. Early models that build on the work of Krugman (1979) and Flood and Garber (1984) show that pegged currencies can be subject to sudden speculative attacks if there is a substantial public debt financed by central bank credit or if investors anticipate that the peg is about to change. Another strand of theoretical models attribute currency crises to doubts around to what extent the government is planning to maintain the exchange rate. These models show that uncertainty around possible policy changes in the foreign exchange market can create multiple equilibria, which in turn triggers currency crises (Frankel and Rose, 1996). The third group of theoretical models is motivated by the 1997 Asian crisis show how balance sheets mismatches and fluctuations in exchange rates can bring about currency crises (e.g., (Chang and Velasco, 1999)). They show that vulnerabilities stemming from large outstanding debts dominated in foreign currency can lead to a banking-currency 'twin' crisis.

In addition to the theoretical research cited above, empirical research on predicting currency crises has flourished, especially after the Mexican and Asian crises. This strand of research attempts to identify some indicators and uses (parametric and non-parametric) statistical methods that could assist in identifying highly vulnerable countries. Much of this research uses binary outcome models (such as Probit and Logit models) to estimate the probability of the incidence of a currency crisis given a wide range of macroeconomic indicators (see Goldstein et al. (2000); Kumar et al. (2003)). For instance, Goldstein et al. (2000) report several indicators that can help to predict currency crises such as high ratios of money supply (M2) to international currency reserves and large current-account deficits.

In addition to the widely cited discrete outcome models, empirical research on predicting currency crises employs other methods such as the multiple indicators multiple causes (MIMC) approach, and Markov switching models. For example, while Rose and Spiegel (2012) use the MIMC approach, Abiad (2003) employ Markov switching models to craft EWS models. Savona and Vezzoli (2015) propose a new algorithm for regression tree models to obtain predicted probabilities for each country.

Other empirical research uses a non-parametric signal extraction approach in which certain macroeconomic and financial variables are monitored for unusual behavior. These models would then signal an alarm should these indicators surpass a particular threshold value. In this family of models, a key challenge arises from the difficulty in setting the 'right' threshold. While shallow threshold values can help to avoid missed crises with increased chances of false alarms, relatively higher limits would minimize the incidence of false alarms but with higher risks of unreported crises. Lin et al. (2008) specify two different threshold values for each indicator: mild and drastic threshold values. However, the choice of the threshold levels is somewhat arbitrary. Casu et al. (2011) set the threshold value at a certain multiple of standard deviations from the indicator's long-run mean. Again, such a dynamic choice of the threshold value does not address the main issue as it is expected to be dependent on the sample properties.

Moreover, research examining currency crises in Egypt is scarce. A few studies examine currency crises in Egypt including El-Shazly (2006, 2011), Al-Assaf (2017), and Adams and Metwally (2019). For example, employing only four indicators between January 1995 to January 2003, El-Shazly (2011) uses a probit model to construct an early warning system for currency crises in Egypt. Using a similar approach (i.e., logit model) and a relatively longer series (January 1980 to December 2015),Al-Assaf (2017) construct an early warning system for currency crises in Egypt and Jordan. More recently, Adams and Metwally (2019) also employ a probit model based on data collected between 1977 and 2017 to identify important indicators in predicting currency crisis episodes in Egypt. None of the previous studies examining currency crises in Egypt assesses the predicting performance of competing models as we do.

A few research papers compare model performance in crisis prediction as we do in this study. While Berg and Pattillo (1999), Comelli (2014) find that discrete outcome models provide better forecasts of currency crises compared to the signal approach, Budsayaplakorn et al. (2010) show that although both families of methods are of similar performance, the signal approach slightly outperforms discrete outcome models. More recently, Ari and Cergibozan (2018) find that the Markov approach is superior to the logit model when predicting currency crises in Turkey. As such, mixed results of the assessment of EWS models of currency crisis have also been reported in the findings of Berg et al. (2005). Candelon et al. (2012) propose a model-free framework with the aim of comparing the relative performance of alternative methods of EWS.

The above cited EWS models do not explicitly account for uncertainty. The multitude of candidate theories and approaches investigated in this strand of research highlight the associated model uncertainty. Frankel and Saravelos (2012), for example, provides a summary of 83 (theoretical and empirical) papers that investigate different EWS models. To fill in this gap in the literature, we aim to identify an optimal EWS for currency crises under model uncertainty. Focusing on the Egyptian currency as an interesting case study as discussed earlier in the introduction, we show that our proposed EW- and DMA-based EWS models outperform other competing models in both in-sample and out-of-sample forecasts.

3. Methodology

The econometric analysis aims to assess the predictive power of different individual models (Probit, Logit, Grompit, and Switching regression model) and combine different forecasts in order to improve the captured predictions for currency crises.

As highlighted earlier, the majority of currency crisis models build on a binary dependent variable. Considering a 14-month prediction period, the outcome variable y_t is a dummy variable that takes the value of one in the month when a crisis episode starts as well as in the following 14 months, while it takes the value of zero otherwise. This window length provides enough span for policymakers to overcome existing disturbances in the foreign exchange market.

The estimated probabilities of a currency crisis in different models depend on a constant plus other explanatory variables, as follows.

$$p_t = Pr(y_t = 1|x_t) = 1 - F(-'x_t\beta) \tag{1}$$

where x_t denotes the given exogenous variables, β is a vector of estimated coefficients and F is a cumulative function for the underlying density function. The log likelihood function is captured using the following form:

$$lnL(\beta) = \sigma_t\{y_t.ln[1 - F(-x\beta)] + (1 - y_t.ln[1 - F(-x\beta)])\} \tag{2}$$

Following the study of Hamilton (1989), Markov Switching (MS) regression models became a common approach for modeling time series data which suffers from structural breaks as is the case with most macroeconomic data. Although these models are linear in each regime based on a specific state for real data, they are nonlinear in all regimes.

The MS modeling approach for predicting currency pressures has several desirable properties. Firstly, there is no need to define episodes for currency crises as forecast probabilities can be defined and estimated simultaneously, which removes the need to define a currency crisis arbitrarily. Secondly, more knowledge about currency variations can be captured when using an index for currency pressures, rather than utilizing a binary variable. Thirdly, if well defined and specified, the MS provides an appropriate approach for capturing currency crises.

Moreover, typical MS models assume that data on a given series usually incorporate two different regimes: normal times and crisis times. Although these states are unobservable, they can be captured by a latent variable z_t, which takes the value of one in crisis times and zero during normal times. Thus, the attributes of the observable variable or the index of the foreign exchange market pressure y_t are changing based on the value of the latent variable z_t :

$$y_t \Big| z_t \sim NDist\left(\mu_{zt}, \sigma^2_{zt}\right) \tag{3}$$

Therefore, the underlying relationship and estimates differ in terms of the mean μ_{z_t} and the variance σ^2_{zt} based on the regime i or the latent state variable z_t. The conditional density function can be formed as:

$$y_t \Big| z_t = \frac{1}{\sqrt{2\pi}\sigma_{zt}} exp\left(\frac{-(y_t - \mu_{zt})^2}{2\sigma^2_{zt}}\right) \tag{4}$$

The estimated probability for each regime p_{it} depends on the value of z_t and the set of explanatory variables under consideration. In this regard, we follow Hamilton (1989) and Diebold et al. (1994)

in employing an expectation and maximization (EM) algorithm to generate time-varying probabilities for each regime.

An MS-based EWS would then give an alarm when estimated probabilities lie outside a predetermined threshold value of normal limits. Correct alarms are those alarms which occur before the incidence of a currency crisis, while false alarms are those which are not preceded by a crisis. Demirgüç-Kunt and Detragiache (2000) argue that the risk of not issuing signals before the occurrence of an actual crisis is similar to type I error in statistics, while the risk of issuing a false signal without the incidence of a crisis is similar to a type II error. The probabilities of both types of error at a specific threshold value can be calculated based on in-sample data.

Many leading indicators allow for a parsimonious specification as a tool for predicting pressures in the foreign exchange market. These indicators include the ratio of broad money (M2) to the foreign reserve (M2R), the ratio of imports to exports (IMEX), MSCI index, and the real interest rate.

3.1. Forecast combination

Different specifications for the underlying relationship would give different forecasts for the target variable. Suppose there are M models and each model m generates a specific forecast: $\hat{y}_{t+1,1}$, $\hat{y}_{t+2,2}, \ldots, \hat{y}_{t+1,M}$. Those individual predictions might be combined together as one value: $\hat{y}_{t+1} = g(\hat{y}_{t+1,1}, \hat{y}_{t+2,2}, \ldots, \hat{y}_{t+1,M}, W_{m,t+1})$; assuming the prediction error equals $e_{T+1} = y_{t+1} - g(\hat{y}_{t+1,1}, \hat{y}_{t+2,2}, \ldots, \hat{y}_{t+1,M})$. Therefore, the optimal weights for individual forecasts can be estimated through minimizing the following loss forecasting function (L):

$$minL_{w_{m,t+1}} E\left[L\left(e_{T+1}\left(w_{m,t+1}\right)\right)\middle|\hat{y}_{t+1,1}, \hat{y}_{t+1,2}, \ldots, \hat{y}_{t+1,M}\right] \tag{5}$$

and the loss function described above is assumed to be in the form of minimum squared forecast errors (MSFE):

$$minL_{w_{m,t+1}} = \theta(y_{t+1} - \hat{y}_{t+1})^2 \tag{6}$$

for simplification, we set the value of θ to one.

In order to calculate the $w_(m, t+1)$, we employ two different approaches. Firstly, equal weights (EW) method which is the simple average of all available predictions, as $w_{(m,t+1)} = 1/M$, where M is the number of all available forecasts. Although the EW method is the simplest weighting approach, it sometimes performs better when compared to more complicated forecasts.

The second combination approach we employ in this study is the Dynamic Model Averaging (DMA) proposed by Raftery et al. (2010) and adopted for forecasting inflation in Koop and Korobilis (2012). The DMA is a modern approach which is based on time varying weights. Let M is the number of available models and m is one of these models where $m \in \{1, 2, \ldots, M\}$. In addition, suppose that X_t^z is all information available till a point in time z. Then, the estimate weights are a function in available information, $w_{t/m,z} = pr(M_t = m/X_t^z)$.

More specifically, the DMA method is based on a recursive algorithm and 'forgetting factor' approach for capturing the predictive likelihood for individual forecasts, which can be formally presented as follows.

$$w_{t/m} = \frac{w_{t/t-1,m} p_m(X_t/X_{t-1})}{\sum_{m=1}^{M} w_{t/t-1,m} p_m(X_t/X_{t-1})} \tag{7}$$

Where p_m is the predictive density for model m assuming some known initial values w_0 for each model.

4. Dataset

This study aims to identify an optimal early warning system for currency crises in Egypt under model uncertainty. For this purpose, we collect a monthly dataset that covers the period from February 1995 to July 2018, with December 2012 denoting the end of our in-sample period and January 2013 denoting the start of the out-of-sample period. Our choice of at which point to split our dataset between in-sample and out-of-sample periods allows for including several calm and crisis episodes in both sub-samples. Table 1 summarises the variables included in our dataset. All data are extracted from the monthly database of IFS by the IMF.

We use the ratio of change in exports to change in imports (EXIM) as a proxy for the country's competitiveness and the change in the demand for domestic credit (CD) as a proxy for domestic monetary conditions. Moreover, we collect data on the real exchange rate (RER), which reflects the country's competitiveness at the international level and also gives an indication whether the domestic currency is under(over) valued. We also include the change in the MSCI index to capture the state of the Egyptian stock market and investors confidence. To measure the extent to which liabilities on the domestic banking sector is covered by foreign reserves, we include the change in the ratio of broad money to the foreign reserve minus gold (MRS). Finally, to proxy for the world economy supply-side and monetary conditions, we collect data for oil crude price (OP) and the US interest rate (USIR). The choice of these variables is also motivated by previous research on currency crises, which is reviewed in Section 2, as well as data availability.

In addition to the variables discussed above (see Table 1 for a summary), we need a measure for foreign exchange pressure. To defend the national currency against undesirable huge value swings, monetary authorities usually increase interest rates on the domestic currency and exhaust their foreign reserves. Thus, to identify the incidence of a currency crisis, we would need to construct a measure of foreign currency pressure which takes into account changes in the nominal exchange rate, foreign reserves, and changes in the domestic interest rate. Following Eichengreen et al. (1995), we construct a foreign exchange pressure (*FEP*) index as follows:

$$FEP_t = \delta\Delta ER_t - \zeta\Delta FR_t + \gamma\Delta IR_t \tag{8}$$

where *ER* is the nominal exchange rate defined as the number of Egyptian pounds needed to buy one US dollar[1], *FR* is foreign exchange reserves minus gold[2], *IR* is the interest rate, and the coefficients ζ and γ are the weighted average computed as the inverse of the standard deviation $(\frac{1}{\sigma_i})$ of each associated variable.

Higher values of the *FEP* index denote higher stress levels in the foreign currency market which implies an increase in the number of domestic currency units needed to get one US dollar, loss of the dominated foreign reserves or a rise in the level of the domestic interest rate. The incidence of a currency crises takes place when the value of the *FEP* index goes beyond a certain threshold usually defined in terms of the standard deviation of the *FEP* index. Empirical research has been subjective when choosing a threshold for the *FEP* index to denote a currency crisis episode. Such threshold is typically between one and three standard deviations of the crisis indicator (i.e., the *FEP* index). This study sets a threshold of a one

[1] We use the nominal exchange rate rather than the real effective exchange rate because the nominal value of the currency reflects the pressure on the currency regardless of the price level or any other factors.

[2] We exclude the value of gold reserves to reflect the amount of foreign reserve available to monetary authorities regardless of any fluctuations in the price of gold.

Table 1
Variables in the dataset.

Short Name	Variable
EXIM	Ratio of change in exports to change in imports
CD	Change in demand of domestic credit
RER	Real exchange rate
MSCI	stock market index
MRS	Change in the ratio of broad money to foreign reserve minus gold
OP	Change in the price of crude oil
USIR	US interest rate
FEP	Foreign exchange pressure index (see Eq. (8))

standard deviation of the *FEP* index to denote the incidence of a currency crisis in Egypt. Fig. 1 depicts the *FEP* index and Table 2 presents the descriptive statistics for all variables included in our dataset.

5. Empirical results

5.1. Estimation

We first check whether collinearity exists amongst the variables in our dataset. The correlation matrix presented in Table 3 shows week correlation coefficients (the highest is 0.24) which suggests that multicollinearity is not a cause of concern. We also examine the integration properties of the series using the Augmented Dickey-Fuller (ADF) unit root test. Table 4 shows that the null hypothesis of a unit root is rejected for the *FEP* index and the ratio of exports to imports (EXIM) at a significance level of 5%, while other variables are stationary at first-difference.

The study adopts the general-to-specific approach, as we start with all included variables and remove less significant variables. Table 5 presents the results for different individual models. In regard of Probit, Logit and Gombit models, we find that the leading indicators that have significant effects are the ratio of broad money to international reserve (MRS), change in demand of domestic credit (CD). We also find that global conditions represented change in the price of crude oil (OP) and the US interest rate (USIR) are important determinants of currency crises in Egypt.

For the switching regression model, we find that the most appropriate form is two regimes form. In the first regime, we can see the change in the ratio of broad money to the foreign reserve (MRS), exports to imports ratio (EXIM), and changes in US interest rate (USIR) are statistically significant. Regarding the other regime, we find the ratio of broad money to foreign reserve (MRS) and changes in the MSCI index have statistically significant impacts on the *FEP* index. Fig. A1, in the appendix, presents the calculated values for the two type errors from different models.

5.2. Evaluating forecasts

In order to assess the predictive power for different models, the paper utilizes the Average of Forecast Squared Errors (AFSE) and

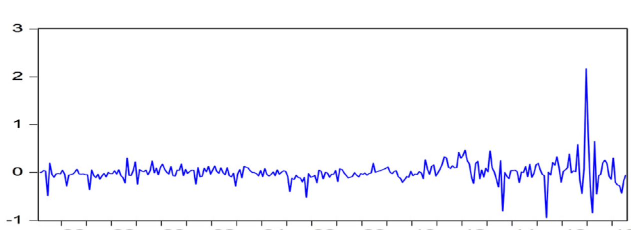


Fig. 1. Foreign exchange rate pressure (*FEP*) index.

Squared Root of Average of Forecast Squared Errors (RAFSE). Fig. 2 depicts probabilities forecasts of different models and Table 6 presents evaluation of different individual models and combination schemes. For the in-sample forecast, we can see that the logit model performs better than other individual models with RAFSE equal to 0.25864 and in the Probit model with RAFSE equal to 0.26094; both forecast combination methods give superior predictions than all individual models. Indeed, the equal weighting combination scheme gives the best forecast; with RAFSE equal to 0.23731, over DMA and other individual models. For the out-sample forecast, we observe that the extreme model performs better than other individual models with RAFSE equal to 0.49270 and the Probit model with RAFSE equal to 0.49836. Similar to the in-sample forecast, both forecast combination methods perform better than all individual models in terms of prediction. Besides, equal weighting combination methods act as the best in terms of prediction; with RAFSE equal to 0.44795, over DMA and other individual models.

Our second approach to evaluate the predictions of different models uses the ratio of the correct predictions. First, we set up a value for above which the system should warn with signals, and there are several approaches for selecting this value. While some of these approaches depend on the estimated models' outputs, others utilize real data. We prefer using the real data approach because being dependent on the output of estimated models might give biased results if the model suffers from uncertainties. We use the percentage of crisis observation to the total number of observation in the sample as the threshold value. The second step is to determine the number of correct predictions for each model and the combination scheme.

Table 7 shows the number of correct predictions for in-sample period. The DMA combination method gives the highest correct percentage at 80%, and the Equal Weighting combination scheme is second at 79%. Table 8 outlines the numbers and the percentages of correct predictions for different individual prediction schemes. The equal weighting combination scheme gives the highest correct ratio with 67% and second is the DMA.

Here we check whether our results are robust when the selected critical level of the threshold variable is changed from one standard deviation to be two standard deviations. Table 9 presents forecast evaluations of different individual models and combination schemes under the new threshold level. For the in-sample forecast, we see that the logit model performs better than other individual models with a RAFSE equal to 0.25885 and the Probit model with RAFSE equal to 0.260962. However, both forecast combination methods give better predictions than all individual models. The DMA combination scheme gives the best forecast; with RAFSE equal to 0.19262, and outperforms the qual weighting combination and other individual models.

For the out-sample forecast, the switching regression model performs better than other individual models with RAFSE equal to 0.3863337 and then the Extreme model with RAFSE equal to

Table 2
Descriptive statistics.

Var.	*FEP*	EXIM	MSCI	MRS	CD	OP	RER	USIR
Mean	0.003	−0.097	0.008	0.0004	0.011	0.005	0.028	−0.014
Median	−0.006	0.269	0.006	0.0004	0.012	0.014	−0.015	0.000
Max.	2.165	50.588	0.351	0.005	0.454	0.214	10.571	0.450
Min.	−0.943	−43.456	−0.395	−0.009	−0.598	−0.332	−3.943	−0.860
Std. Dev.	0.223	5.887	0.092	0.001	0.055	0.084	0.789	0.172
Skewness	2.829	−0.739	0.064	−1.972	−5.002	−0.707	9.297	−1.778
Kurtosis	35.513	39.465	4.832	15.168	87.278	4.437	124.366	8.599

See Table 1 for variable definition.

0.50872. However, as with the in-sample results, the forecast combination method performs better than all individual models in terms of prediction. Indeed, the DMA combination method is the best in terms of prediction; with RAFSE equal to 0.324022.

6. Conclusion

This paper aims to propose an optimal early warning system for currency crises. Taking Egypt as a case study, we first assess the predictive power of various individual models, including Probit, Logit, Extreme values, and Switching regression models. We then show that combining all available forecasts using the equal weighting (EW) and dynamic model averaging (DMA) methods would improve the prediction power.

Unlike existing literature assessing early warning systems of currency crises which suggest one model or another, our findings show that forecast combinations outperform individual models over both in-sample and out-sample forecast. For example, when predicting currency crises, while Berg and Pattillo (1999), Comelli (2014) find discrete outcome models outperform other models, Ari and Cergibozan (2018) find that the Markov-switching approach to be superior. For Egypt, El-Shazly (2011) find that the extreme value model provides good predictive power for exchange rate crises. On the contrary to these studies, we suggest combining (averaging) forecasts from competing models, which we show to outperform all individual models.

For future research, assessing the application of different combination (averaging) scheme methods to predict other types of financial crises, such as banking crises, is recommended. Also, estimating and combining density forecasts rather than point forecast is a good point for future studies.

Table 3
Correlation matrix.

	MRS	CD	EXIM	MSCI	OP	USIR	RER
MRS	1.000	0.174	0.029	0.191	0.054	0.031	0.129
CD	0.174	1.000	0.146	0.040	0.001	0.019	0.090
EXIM	0.029	0.146	1.000	0.024	0.051	0.004	0.006
MSCI	0.191	0.040	0.024	1.000	0.240	0.142	0.165
OP	0.054	0.001	0.051	0.240	1.000	0.126	0.084
USIR	0.031	0.019	0.004	0.142	0.126	1.000	−0.015
RER	0.129	0.090	0.006	0.165	0.084	−0.015	1.000

See Table 1 for variable definitions.

Table 4
Unit root test results.

Var.	Level	1st Diff.	Var.	Level	1st Diff.
FEP	−6.70***		MSCI	−1.09	−13.85***
	(0.000)			(0.72)	(0.000)
MRS	−0.79	−15.04***	OP	−1.73	−12.81***
	(0.82)	(0.000)		(0.41)	(0.00)
CD	1.26	−14.23***	USIR	−1.93	−8.35***
	(0.998)	(0.000)		(0.317)	(0.000)
EXIM	−16.20***		RER	−2.21	−12.68***
	(0.000)			(0.47)	(0.000)

See Table 1 for variable definitions.

Table 5
Estimates of different individual models.

	Probit	Logit	Extreme	MS	
				Regime 1	Regime 2
C	−9.25***	−19.16**	−6.92 ***	−0.16***	−0.05***
	(0.003)	(0.001)	(0.002)	(0.000)	(0.000)
MRS	13.90 **	29.73***	10.76**	15.70***	9.90***
	(0.010)	(0.002)	(0.010)	(0.000)	(0.000)
D(CD)	28.64**	51.66**	24.87**		
	(0.03)	(0.03)	(0.031)		
EXIM	−0.06*	−0.11*	−0.05*	0.01*	0.00
	(0.02)	(0.023)	(0.012)		
D(MSCI)	−2.98**	−5.97**	−2.53*	−1.31***	
	(0.02)	(0.026)	(0.071)	(0.000)	
D(OP)	4.08**	8.31*	3.74**	−0.00	−0.002
	(0.04)	(0.08)	(0.037)	(0.601)	(0.126)
D(USIR)	1.66*	3.29**	1.54	0.29***	−0.05
				(0.056)	(0.11)
D(RER)				−0.02***	0.16***
				(0.750)	(0.005)
LOG(SIGMA)					−2.21***
					(0.000)
Transition Matrix Parameters			P11-C	1.70***	(0.000)
			P21-C	−2.64***	(0.000)

See Table 1 for variable definitions. The 'D' letter in front of a variable short name denotes a first-differenced series.

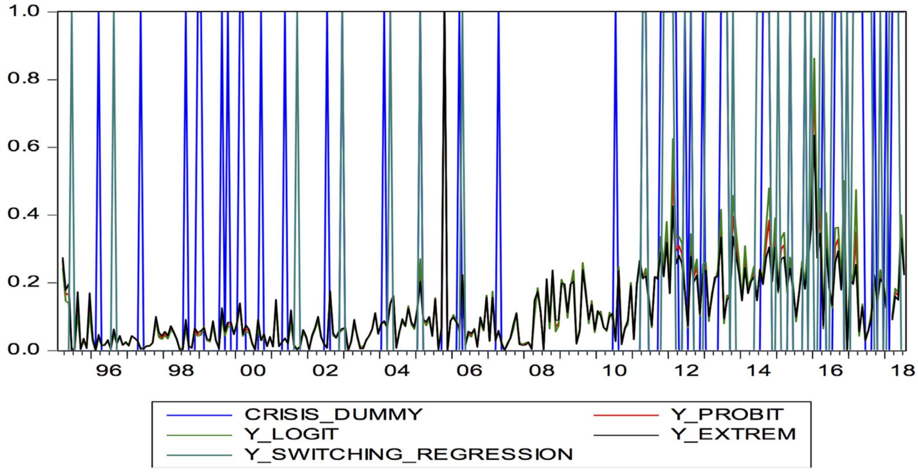


Fig. 2. In-sample and out-sample forecasts for different models.

Table 6
Forecast evaluation for different models and combination schemes.

	In-sample Forecast		Out-sample	
	ASFE	RASFE	ASFE	RASFE
Probit	0.06809 (4)	0.26094 (4)	0.24836 (4)	0.49836 (4)
Logit	0.06689 (3)	0.25864 (3)	0.25420 (5)	0.50418 (5)
Extreme	0.06934 (5)	0.26333 (5)	0.24275 (3)	0.49270 (3)
Switching Reg.	0.07009 (6)	0.26475 (6)	0.35820 (6)	0.59850 (6)
Equal weight Comb.	0.05631 (1)	0.23731(1)	0.20066 (1)	0.44795 (1)
DMA Comb.	0.05995 (2)	0.24485 (2)	0.21605 (2)	0.46482 (2)

Table 7
In-sample percentage of correct prediction for different models and combination.

Predicted	Probit		Logit		Extreme		Switching Reg.		Equal Weight. Comb.		DMA	
Actual	D = 0	D = 1	D = 0	D = 1	D = 0	D = 1	D = 0	D = 1	D = 0	D = 1	D = 0	D = 1
D = 0	158	8	158	8	157	8	186	9	180	5	186	5
D = 1	56	11	56	11	57	11	28	10	34	14	28	14
Total	214	19	214	19	214	19	214	19	214	19	214	19
Correct	158	11	158	11	157	11	186	10	180	14	186	14
%correct	0.738	0.578	0.738	0.578	0.734	0.579	0.869	0.526	0.841	0.737	0.869	0.737
Average prob.	0.6586(6)		0.6586(5)		0.6562(4)		0.6977(3)		0.788982 (2)		0.803 (1)	

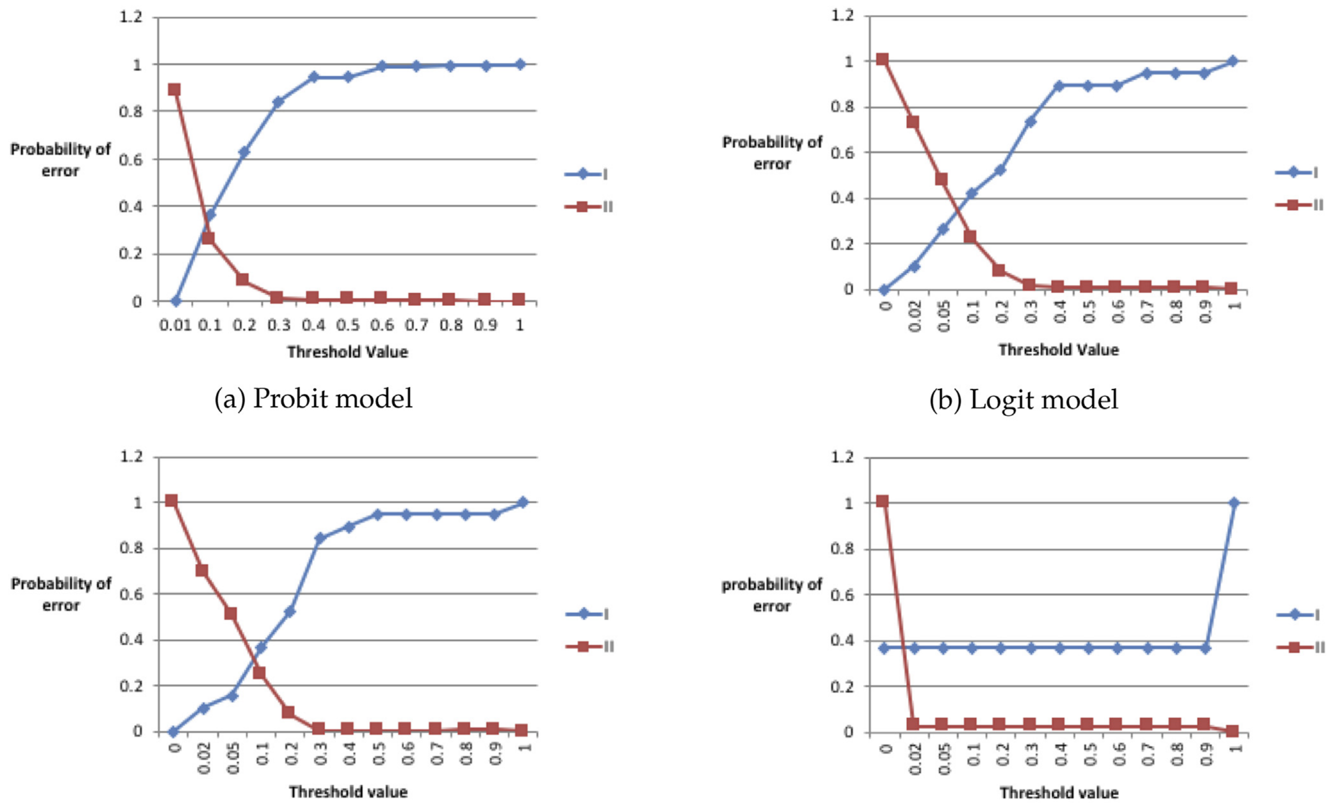
Table 8
Out-sample percentage of correct prediction for different models and combination.

Predicted	Probit		Logit		Extreme		Switching Reg.		Equal Weight. Comb.		DMA	
Actual	D = 0	D = 1	D = 0	D = 1	D = 0	D = 1	D = 0	D = 1	D = 0	D = 1	D = 0	D = 1
D = 0	7	7	7	4	10	10	26	10	47	12	11	17
D = 1	41	12	41	15	38	9	22	9	1	7	37	2
Total	48	19	48	19	48	19	48	19	48	19	48	19
Correct	7	12	7	15	10	10	26	9	47	7	11	17
%correct	0.146	0.632	0.146	0.789	0.208	0.526	0.542	0.474	0.979	0.368	0.229	0.895
	0.3887(5)		0.467(4)		0.3673 (6)		0.507(3)		0.67379 (1)		0.561951(2)	

Table 9
Forecast evaluation for different models (2 standard deviations).

	In-sample Forecast		Out-sample	
	ASFE	RASFE	ASFE	RASFE
Probit	0.068101 (4)	0.260962 (4)	0.2610995 (5)	0.510979 (5)
Logit	0.0670049 (3)	0.2588531(3)	0.262384 (6)	0.512234 (6)
Extreme	0.0726467 (5)	0.2695306 (5)	0.2587996 (4)	0.5087235 (4)
Switching Reg.	0.0747663 (6)	0.2734343 (6)	0.149253 (2)	0.3863337 (2)
Equal weight Comb.	0.0474655 (2)	0.2178658 (2)	0.1591791 (3)	0.398973(3)
DMA Comb.	0.0371025 (1)	0.19262 (1)	0.104990(1)	0.324022(1)

Appendix A



(a) Probit model

(b) Logit model

(c) Extreme Value model

(d) Switching model

Fig. A.1. Two error probabilities.

References

Abiad, M.A., 2003. Early Warning Systems: A Survey and a Regime-Switching Approach. International Monetary Fund number 3-32.
Adams, J., Metwally, A., 2019. Identifying currency crises indicators: the case of Egypt. Afr. J. Econ. Manag. Stud. 10 (2).
Al-Assaf, G., 2017. An early warning system for currency crisis: a comparative study for the case of Jordan and Egypt. Int. J. Econ. Financ. Issues 7 (3), 43–50.
Ari, A., Cergibozan, R., 2018. Currency crises in Turkey: an empirical assessment. Res. Int. Bus. Finance 46, 281–293.
Berg, A., Borensztein, E., Pattillo, C., 2005. Assessing early warning systems: how have they worked in practice? IMF Staff Pap. 52 (3), 462–502.
Berg, A., Pattillo, C., 1999. Predicting currency crises: the indicators approach and an alternative. J. Int. Money Finance 18 (4), 561–586.
Budsayaplakorn, S., Dibooglu, S., Mathur, I., 2010. Can macroeconomic indicators predict a currency crisis? evidence from selected southeast asian countries. Emerg. Mark. Finance Trade 46 (6), 5–21.
Bussière, M., Fratzscher, M., 2006. Towards a new early warning system of financial crises. J. Int. Money Finance 25 (6), 953–973.
Candelon, B., Dumitrescu, E.-I., Hurlin, C., 2012. How to evaluate an early-warning system: toward a unified statistical framework for assessing financial crises forecasting methods. IMF Econ. Rev. 60 (1), 75–113.
Casu, B., Clare, A., Saleh, N., 2011. Towards a New Model for Early Warning Signals for Systemic Financial Fragility and Near Crises: an Application to Oecd Countries.
Chang, R., Velasco, A., 1999. Liquidity crises in emerging markets: theory and policy. NBER Macroecon. Annu. 14, 11–58.
Comelli, F., 2014. Comparing parametric and non-parametric early warning systems for currency crises in emerging market economies. Rev. Int. Econ. 22 (4), 700–721.
Demirgüç-Kunt, A., Detragiache, E., 2000. Monitoring banking sector fragility: a multivariate logit approach. World Bank Econ. Rev. 14 (2), 287–307.
Diebold, F.X., Lee, J.-H., Weinbach, G.C., 1994. Regime switching with time-varying transition probabilities. Business Cycles: Durations, Dynamics, and Forecasting 1, 144–165.
Edwards, S., Santaella, J., 1993. Devaluation controversies in the developing countries: lessons from the bretton woods era. In: A Retrospective on the Bretton Woods System: Lessons for International Monetary Reform. University of Chicago Press, pp. 405–460.
Eichengreen, B., Rose, A.K., Wyplosz, C., Dumas, B., Weber, A., 1995. Exchange Market Mayhem: the Antecedents and Aftermath of Speculative Attacks. Economic policy, pp. 249–312.
El-Shazly, A., 2006. Early warning of currency crises: an econometric analysis for Egypt. Middle East Bus. Econ. Rev. 18 (1), 34.
El-Shazly, A., 2011. Designing an early warning system for currency crises: an empirical treatment. Appl. Econ. 43 (14), 1817–1828.
Flood, R.P., Garber, P.M., 1984. Collapsing exchange-rate regimes: some linear examples. J. Int. Econ. 17 (1–2), 1–13.
Frankel, J.A., Rose, A.K., 1996. Currency crashes in emerging markets: an empirical treatment. J. Int. Econ. 41 (3), 351–366.
Frankel, J., Saravelos, G., 2012. 'Can leading indicators assess country vulnerability? evidence from the 2008–09 global financial crisis'. J. Int. Econ. 87 (2), 216–231.
Ghosh, S.R., Ghosh, A.R., 2003. Structural vulnerabilities and currency crises. IMF Staff Pap. 481–506.
Goldstein, M., Kaminsky, G.L., Reinhart, C.M., 2000. Assessing Financial Vulnerability: an Early Warning System for Emerging Markets. Peterson Institute.
Hamilton, J.D., 1989. A new approach to the economic analysis of nonstationary time series and the business cycle. Econometrica: J. Econom. Soc. 357–384.
IMF, 2018. World Economic Outlook. International Monetary Fund. October 2018.
Kaminsky, G., Lizondo, S., Reinhart, C.M., 1998. Leading indicators of currency crises. Staff Papers 45 (1), 1–48.
Koop, G., Korobilis, D., 2012. Forecasting inflation using dynamic model averaging. Int. Econ. Rev. 53 (3), 867–886.
Krugman, P., 1979. A model of balance-of-payments crises. J. Money Credit Bank. 11 (3), 311–325.
Kumar, M., Moorthy, U., Perraudin, W., 2003. Predicting emerging market currency crashes. J. Empir. Finance 10 (4), 427–454.
Lin, C.-S., Khan, H.A., Chang, R.-Y., Wang, Y.-C., 2008. A new approach to modeling early warning systems for currency crises: can a machine-learning fuzzy expert system predict the currency crises effectively? J. Int. Money Finance 27 (7), 1098–1121.
Raftery, A.E., 1995. Bayesian model selection in social research. Socio. Methodol. 111–163.

Raftery, A.E., Kárný, M., Ettler, P., 2010. Online prediction under model uncertainty via dynamic model averaging: application to a cold rolling mill. Technometrics 52 (1), 52–66.
Rose, A.K., Spiegel, M.M., 2012. Cross-country causes and consequences of the 2008 crisis: early warning. Jpn. World Econ. 24 (1), 1–16.
Savona, R., Vezzoli, M., 2015. Fitting and forecasting sovereign defaults using multiple risk signals. Oxf. Bull. Econ. Stat. 77 (1), 66–92.