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An optimal early warning system for currency crises under model uncertainty

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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 dynamic model averaging (DMA), and equal weighting (EW) 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 (DMA- and EW-based EWS) to account for uncertainty perform better than other competing models in both in-sample and out-of-sample forecasts.

Keywords: Financial Crises, Currency Crises, Early Warning, Uncertainty, Egypt
JEL codes: E44, F31, F47, G01

1. Introduction

Financial crises are recurrent phenomena which come in different shapes and forms. Currency crises, sudden stop 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,

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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 nearly 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 do not utilize their full capacity. 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 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. Therefore, there is a need to formulate indicators that suit the nature of developing economies. Furthermore, there is a need 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 by utilizing the dynamic model averaging (DMA), and equal weighting (EW) 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 DMA and EW 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 DMA- and EW-based EWS models perform better than other competing models. Thus, we 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 DMA and EW approaches to obtain more robust signals for currency crises in developing countries. More specifically, we show how the DMA- and EW-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 main causes of the crisis. Using a large set of indicators, one needs then to decide which statistical technique would be most appropriate when designing an EWS. Here we focus on empirically motivated definitions and EWSs of currency crises. Following the seminal work of Girton and Roper (1977), Eichengreen et al. (1994, 1995) developed an exchange market pressure (EMP) index, which is a weighted average of changes of the exchange rate, interest rate, and currency reserves.

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 turns 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 crisis.

There is a large body of literature investigating possible early warning indicators of financial crises in general and currency crises in particular (see Rose and Spiegel (2012) for a survey). Frankel and Saravelos (2012) provides a summary of both theoretical and empirical studies on financial crises. The authors highlight at least 83 different approaches for EWS. The multitude of candidate theories and approaches highlight the associated model uncertainty.

Recent research on developing EWS models of currency crises received special attention following the Mexican and Asian crises. These models attempt to identify some indicators and use 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, for example, Kumar et al. (2003). 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 discrete dependent variable models, the literature on EWS models uses a 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 thresholds would minimize the incidence of false alarms but with higher risks of missing a crisis. 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.

Other methods of constructing an EWS model include Rose and Spiegel (2012) who use multiple indicators multiple causes (MIMC) approaches. Savona and Vezzoli (2015) propose a new algorithm for regression tree models to obtain predicted probabilities for each country. Furthermore, Markov switching models have been used to craft EWS models. Abiad (2003) is an example of the research that employs Markov switching models.

These EWS models do not explicitly account for uncertainty. To fill in this gap in the literature, we aim to identify an optimal EWS under model uncertainty. For this purpose, we employ the DMA and EW approaches which combine forecasts from different EWS models.

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.

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

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:

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

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 :

$$y_t|z_t \sim NDist(\mu_{zt}, \sigma^2_{zt}) \quad (3)$$

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:

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

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):

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

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 employs monthly data for the nominal exchange rate, foreign reserves minus gold, MSCI index, total exports in dollars, total imports in dollars, consumer price index, the nominal interest rate for three months deposits, broad money (M2) and domestic credit.

Regarding the measuring of foreign currency pressure, we depend on the fact that monetary authority usually protects their national currency either by increasing domestic interest rates on domestic currency or reducing foreign reserves in order to face huge fluctuations in the foreign exchange market. Accordingly, generating the index of foreign exchange pressures (FEP) depends on the generated index of speculative stress which merges between different aspects of the foreign market and the crisis is defined when this index outreach a specific threshold of this index. Indeed, by following the approach of Eichengreen et al. (1995), the FEP index can be accounted for as:

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

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

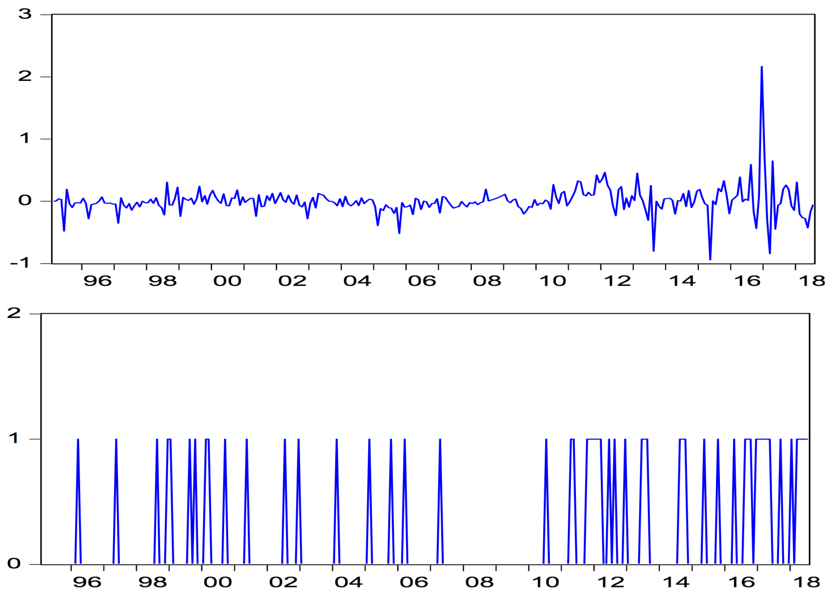
Increasing the value of the index indicates stress in the foreign currency market induced by increasing the number of domestic currency units needed to get one dollar, loss of the dominated foreign reserves or raising the level of the domestic interest rate.
A particular currency is at a critical level when the value of FEP goes beyond a certain threshold defined by its standard deviation. The selected critical threshold is a subjective judgment in empirical studies, and it is usually between one to three standard deviations. Figure 1 depicts the FEP index and the crisis dummy variable for the foreign exchange crisis.

5. Empirical Results

5.1. Estimation

We examine the integration properties of the series using the Augmented Dickey-Fuller (ADF) unit root test (Dickey and Fuller, 1981). Table 1 shows that the null hypothesis of a unit root is rejected for the index, the crisis dummy variable, the ratio of exports to imports (EXIM), and the annual change in inflation at a significance level of 5%, while other variables are stationary at level. All data are captured from the monthly database of IFS by the IMF.

Figure 1: Foreign exchange rate pressure index and crisis dummy for Egypt



The study adopts the general-to-specific approach, as we start with all included variables and remove less significant variables. Table 2 depicts 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, change in domestic credit and change in broad money. This is in addition to both external variables: changes in oil price and changes in US interest rate.

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, exports to imports ratio, changes in US interest rate, and with the constant. For the other regime, we see the ratio of broad money to foreign reserve and change in MSCI have a significant impact on the index. Fig. A.3 to A.6, in the appendix,

Table 1: Unit root test results

Var.	Level	1st Diff.	Var.	Level	1st Diff.
Index	-6.70***		EX (Exports)	0.81	-8.17***
	(0.000)			(0.99)	(0.000)
Y	-8.35****		RER	-2.21	-12.68***
	(0.000)			(0.47)	(0.000)
M2RS	-0.79	-15.04***	RR	-2.24	-8.41***
	(0.82)	(0.000)		(0.46)	(0.000)
EXIM	-16.20***		RS	-1.20	-8.22
	(0.000)			(0.908)	(0.000)
MSCI	-1.09	-13.85***	S	-2.03	-23.19***
	(0.72)	(0.000)		(0.275)	(0.000)
DC	1.26	-14.23***	USINF	-3.05**	
	(0.998)	(0.000)		(0.032)	
Dr	-1.44	-8.42***	USIR	-1.93	-8.35***
	(0.56)	(0.000)		(0.317)	(0.000)
OP	-1.73	-12.81***			
	(0.41)	(0.00)			

Notes: The ratio of broad money to foreign reserves (M2RS), Domestic credit (DC), Exports to Imports ratio (EXIM), Broad money (M2), MSCI index, Consumer price index (CPI), US interest rate (USIR), US inflation rate (USINF).

present 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 Squared Root of Average of Forecast Squared Errors (RAFSE). Figure 2 depicts probabilities forecasts of different models and Table 3 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

Table 2: 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)
M2RS	13.90 **	29.73***	10.76**	15.70***	9.90***
	(0.010)	(0.002)	(0.010)	(0.000)	(0.000)
D(DC)	28.64**	51.66**	24.87**		
	(0.03)	(0.03)	(0.031)		
EXIM	-0.06*	-0.11*	-0.05*	0.01*	0.00
	(0.051)	(0.037)	(0.05)	(0.051)	(0.31)
D(M2)	-51.12**	-52.01**	-54.14**		
	(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
	(0.091)	(0.021)	(0.101)	(0.002)	(0.16)
D(RR)				-0.07*	0.01
				(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)

Notes: The ratio of broad money to foreign reserves (M2RS), Domestic credit (DC), Exports to Imports ratio (EXIM), Broad money (M2), MSCI index, Consumer price index (CPI), US interest rate (USIR), US inflation rate (USINF).

act as the best in terms of prediction; with RAFSE equal to 0.44795, over DMA and other individual models.

Figure 2: In-sample and out-sample forecasts for different models

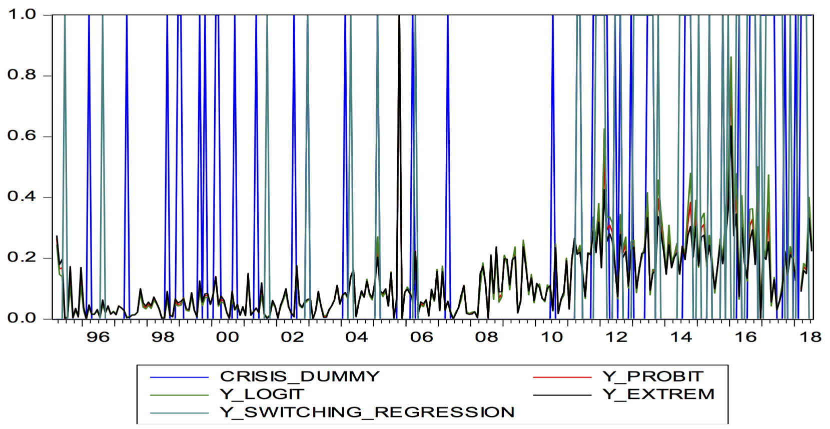


Table 3: Forecast Evaluation for Different Models and Combination Schemes

	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)

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 4 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 5 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.

Table 4: 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 5: 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)	

6. Robustness Checks

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 6 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 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.

Table 6: 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)

7. Conclusion

The paper aim is to propose an optimal model for predicting currency crises through two main steps. Firstly, we assess different individual models in terms of predicting the currency risk (Probit, Logit, Extreme values, and Switching regression model). Secondly, we combine all available forecasts by using the DMA and EW methods in order to improve the prediction power. Our findings show that forecast combinations perform better than individual models over both in-sample and out-sample forecasts.

For future research, applying combination scheme methods for different 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.

References

Abiad, M. A. (2003), *Early warning systems: A survey and a regime-switching approach*, number 3-32, International Monetary Fund.

Bussière, M. and Fratzscher, M. (2006), 'Towards a new early warning system of financial crises', *journal of International Money and Finance* **25**(6), 953–973.

Casu, B., Clare, A. and 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. and Velasco, A. (1999), 'Liquidity crises in emerging markets: theory and policy', *NBER macroeconomics Annual* **14**, 11–58.

Demirgüç-Kunt, A. and Detragiache, E. (2000), 'Monitoring banking sector fragility: a multivariate logit approach', *The World Bank Economic Review* **14**(2), 287–307.

Diebold, F. X., Lee, J.-H. and Weinbach, G. C. (1994), 'Regime switching with time-varying transition probabilities', *Business Cycles: Durations, Dynamics, and Forecasting* **1**, 144–165.

Edwards, S. and 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. and Wyplosz, C. (1994), Speculative attacks on pegged exchange rates: an empirical exploration with special reference to the european monetary system, Technical report, National Bureau of economic research.

Eichengreen, B., Rose, A. K., Wyplosz, C., Dumas, B. and Weber, A. (1995), 'Exchange market mayhem: the antecedents and aftermath of speculative attacks', *Economic policy* pp. 249–312.

Flood, R. P. and Garber, P. M. (1984), 'Collapsing exchange-rate regimes: some linear examples', *Journal of international Economics* **17**(1-2), 1–13.

Frankel, J. A. and Rose, A. K. (1996), 'Currency crashes in emerging markets: An empirical treatment', *Journal of international Economics* **41**(3), 351–366.

Frankel, J. and Saravelos, G. (2012), 'Can leading indicators assess country vulnerability? evidence from the 2008–09 global financial crisis', *Journal of International Economics* **87**(2), 216–231.

Ghosh, S. R. and Ghosh, A. R. (2003), 'Structural vulnerabilities and currency crises', *IMF Staff Papers* pp. 481–506.

Girton, L. and Roper, D. (1977), 'A monetary model of exchange market pressure applied to the postwar canadian experience', *The American Economic Review* pp. 537–548.

Goldstein, M., Kaminsky, G. L. and 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: Journal of the Econometric Society* pp. 357–384.

IMF (2018), *World Economic Outlook, October 2018*, International Monetary Fund.

Kaminsky, G., Lizondo, S. and Reinhart, C. M. (1998), 'Leading indicators of currency crises', *Staff Papers* **45**(1), 1–48.

Koop, G. and Korobilis, D. (2012), 'Forecasting inflation using dynamic model averaging', *International Economic Review* **53**(3), 867–886.

Krugman, P. (1979), 'A model of balance-of-payments crises', *Journal of money, credit and banking* **11**(3), 311–325.

Kumar, M., Moorthy, U. and Perraudin, W. (2003), 'Predicting emerging market currency crashes', *Journal of Empirical Finance* **10**(4), 427–454.

Lin, C.-S., Khan, H. A., Chang, R.-Y. and 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?', *Journal of International Money and Finance* **27**(7), 1098–1121.

Raftery, A. E. (1995), 'Bayesian model selection in social research', *Sociological methodology* pp. 111–163.

Raftery, A. E., Kárnỳ, M. and 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. and Spiegel, M. M. (2012), 'Cross-country causes and consequences of the 2008 crisis: early warning', *Japan and the World Economy* **24**(1), 1–16.

Savona, R. and Vezzoli, M. (2015), 'Fitting and forecasting sovereign defaults using multiple risk signals', *Oxford Bulletin of Economics and Statistics* **77**(1), 66–92.

AppendixA.

Figure A.3: Two error probabilities - Probit model

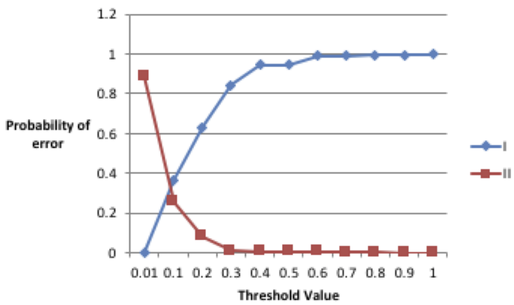


Figure A.4: Two error probabilities - Logit model

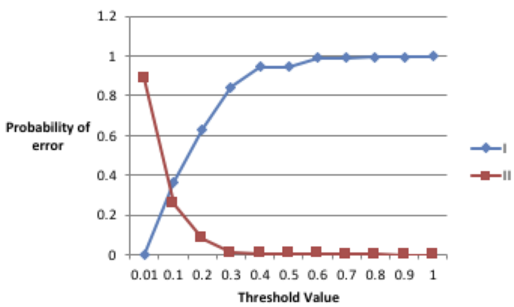


Figure A.5: Two error probabilities - Extreme model

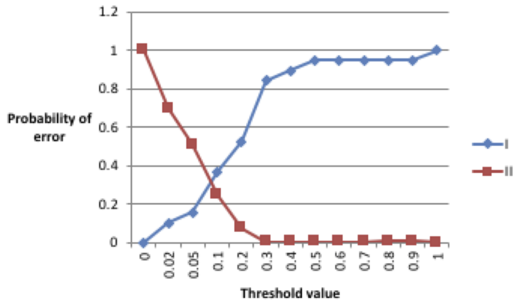


Figure A.6: Two error probabilities - Switching model