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Abstract

This paper assesses a number of early warning (EWS) models of financial crises with the aim of proposing an optimal 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 forecasts from individual models allowing for time varying weights. Taking Egypt as a case study and focusing only on currency crises, our findings show that combining forecasts (DMA- and EW-based EWS) models which account for model 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 Classifications: E44, F31, F47, G01

1. Introduction

Financial crises are recurrent phenomena which come in different shapes and forms. This includes currency crises, sudden stop crises, debt crises, and banking crises. Financial crises can cause severe economic damage not only to their country of origin but also across borders. Output declines, chronic poverty, 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 now after the crisis and the world economy is yet to recover from its impacts. A recent study by 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 accurately. Such indicators or early warning systems (EWSs) are to provide a monitoring system with the purpose of detecting financial crises at early stage. Although they are essential in almost every country, the importance of EWSs becomes even more paramount in developing countries which lack competencies and far from utilizing their full capacity. Well functioned EWSs could help developing countries in their quest to further integrate in the world economy while avoiding huge costs of financial crises. Thus, the ability to identify adequate EWSs should be an integral part of their economic agenda. In addition, EWSs can also suggest suitable policy interventions that could prevent severe crises or at least minimize their negative impacts.

Many central banks and international organizations (such as the IMF) have developed EWS models which are aimed at anticipating the timing of a financial crisis and ensuring the safety of the financial system (Bussière and Fratzscher, 2006). In this regard, several indicators have been used for this purpose. 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 matured 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 to the the ability to identify most efficient systems among competitive model.

Against this backdrop, the current paper aims to assess a number of EWS models of financial crises with the aim of proposing 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 can be grouped 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. These models shall be succinctly reviewed in the ensuing section.

A major shortcoming in the above approaches of modeling EWSs is the absence of explicit modeling of uncertainty embedded in the adopted theory model. Raftery (1995) finds that confidence levels are inflated when uncertainty surrounding a theory's validity has been taken into consideration. Moreover, existing approaches do not offer clear selection criteria of robust EWSs.

To address these shortcomings, 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 allows for time variant weights to be attached to different models. By doing so, we hope to 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 batter than other competing models. We thus contribute to the existing literature in at least two ways. First, we assess alternative approaches for designing EWSs with decision-maker's 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 of financial cries is to precisely distinguish between 'usual' fluctuations and what can be considered as a crisis. Currency crises, for example, and associated sharp depreciations are usually attributed to speculative attacks which force monetary authorities taking several measures to defend the value of the currency. These preemptive measures include selling international currency reserves, sharply increasing interest rates on domestic currency, and possibly erecting more restrictive capital controls. Identifying a proper definition of the crisis of interest is usually followed by examining the main causes of this crisis. Using a large set of indicators, one needs then to decide on which statistical technique would be most appropriate when designing an EWS. In this review of the literature, 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.

There are many theoretical models attempt to explain the causes of currency crises. Early models which 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 large 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). A third group of theoretical models are motivated by the 19997 Asian crisis show how balance sheets mismatches and fluctuations in exchange rates can bring about currency crises. The paper by Chang and Velasco (1999) is an example of these models. They show that vulnerabilities stemming from large outstanding debts dominated in foreign currency can lead to a banking-currency twin crisis.

At the empirical front, 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) provide a good 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 a 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 predicting currency crises such as high ratio of money supply (M2) to international currency reserves and large current-account deficit.

In addition to discrete dependent variable models, the literature on EWS models use 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 certain threshold value. In this family of models, a key challenge arises from the difficulty in setting the 'right' threshold. While very low threshold values would can help avoiding 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. To address this issue, Lin et al. (2008) specify two different threshold values for each indicator:

mild and drastic threshold values. Yet, the issue remains unresolved as the choice of the threshold levels are rather 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 dynamic choice of the threshold value does really 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 a multiple indicator multiple cause (MIMC)approach. A more recent approach can found in the study by Savona and Vezzoli (2015) who propose a new algorithm for regression tree models to obtain predicted probabilities for each country. Furthermore, Markov switching models have been also used to craft EWS models. Abiad (2003) is an example of the research that employs Markov switching models.

These EWS models does not explicitly model uncertainties in the adopted theory model. 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 then combining between different forecasts in order to improve the captured predictions for currency crises.

As highlighted earlier, the majority of currency crisis models are based on a binary dependent variable which takes the value of one or zero. 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 policy makers to overcome existing disturbances in the foreign exchange market.

The estimated probabilities of a currency crisis in different models depend on a constant and other explanatory variables, which can be presented 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 by using the following form:

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

The marginal effect of each explanatory variable can be calculated using the partial derivative for the associated variable.

The Markov switching (MS) regression model is intensively used in economics after the study of Hamilton (1989). It became a common approach for modeling time series data which suffers from structural changes (i.e., breaks) as is the case with most of macroeconomic data. Switching regression models are based on the idea that although a given model is linear in each regime based on a specific state for real data, it is nonlinear in all regimes.

The MS modeling approach for predicting currency pressures has several desirable properties. Firstly, there is no need for defining episodes for currency crises. Alternatively, forecast probability is defined and estimated simultaneously. Therefore, the problem of defining a currency crisis in an arbitrary way is no longer a cause of concern. 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 incorporates 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 is changing based on the value of the latent variable z_t :

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

Therefore, the underlying relationship and therefore 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:

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

The estimated probability for each regime p_{it} depends on the value of z_t and the set 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.

A 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 type II. The probabilities of both types of error at a specific threshold value can be calculated based on in-sample data.

A number of leading indicators allow for a parsimonious specification which can be utilized 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 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 to $e_{T+1} = y_{t+1} - g(\hat{y}_{t+1,1}, \hat{y}_{t+2,2}, \ldots, \hat{y}_{t+1,M})$. 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):

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

Where θ is set to one for simplification.

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 initial values w_0 which are known for each individual model.

4. Dataset

This study employs monthly data for nominal exchange rate, foreign reserve minus gold, MSCI index, total exports in dollars, total imports in dollars, consumer price index, 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 the amount of foreign reserves dominated by the monetary authority 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 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, 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 refers to increasing the stress in the foreign currency market might can be 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 domestic interest rate. Thus, as it is mentioned before, the critical level of currency is defined when the value of

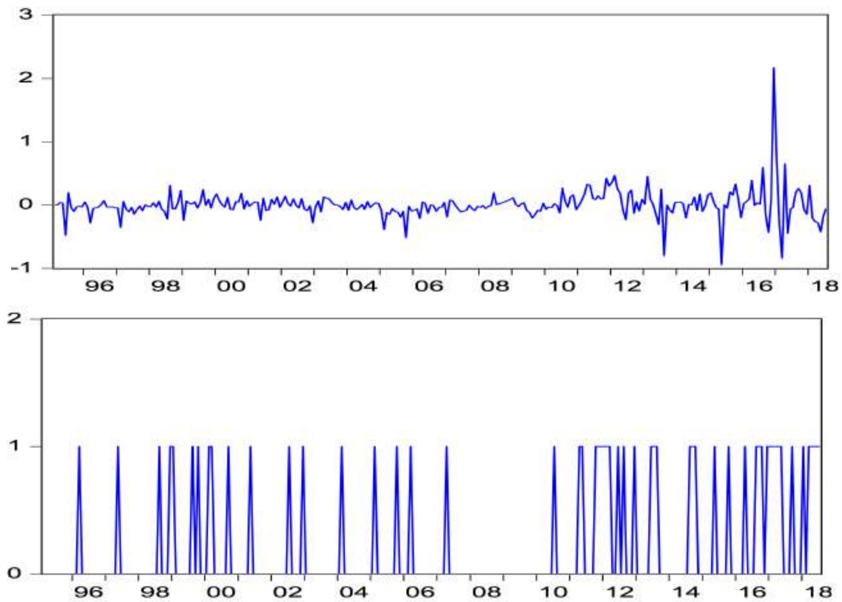
FEP goes beyond a certain threshold which is defined as FEPSD of FEP (The selecting the standard deviation of foreign exchange index to determine the critical threshold is based on subjective judgement in crisis empirical studies and it comes between one to three of the calculated standard deviation). Figure 1 depicts the FEP index and the crisis dummy variable for foreign exchange crisis.

5. Empirical Results

5.1 Estimation

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

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



The study depends on the general to the specific approach, as we start with all included variables and removing the less significant variables. Table 2 depicts the estimates results for different individual models. In regard of Probit, Logit and Gombit models, we can find that the leading indicators that have significant effect are the ratio of broad money to international reserve, change in domestic credit and change in broad money. This in addition to both external included variables: changes in oil price and changes in US interest rate.

For switching regression model, we find the most proper form is two regimes form. In the first regime we can see the change in ratio of broad money to the foreign reserve, exports to imports ratio, changes in US interest rate, and with the constant. While, for the second regime we see

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).

the ratio of broad money to foreign reserve and change in MSCI have a significant index on the index. In addition, the calculated values for the two type errors from different models are presented in Figures from A.3 to A.6 in the appendix.

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 in-sample forecast, we can see that logit model performs better than other individual models with RAFSE equal to 0.25864 then Probit model with RAFSE equal to 0.26094. However, both forecast combination methods give better prediction than all individual models. Indeed, equal weighting combination scheme gives the best forecast; with RAFSE equal to 0.23731, over DMA and other individual models. For out-sample forecast, we can observe that extreme model performs better than other individual models with RAFSE equal to 0.49270 then Probit model with RAFSE equal to 0.49836. However, also as in the case of in-sample forecast, both forecast combination methods performs better than all individual models in terms of prediction. In addition, equal weighting combination method act as the best in terms of prediction; with RAFSE equal to 0.44795, over DMA and other individual models.

Table 2: Estimates of different individual models

	Probit	Logit	Extreme	MS Regime 1	MS 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).

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

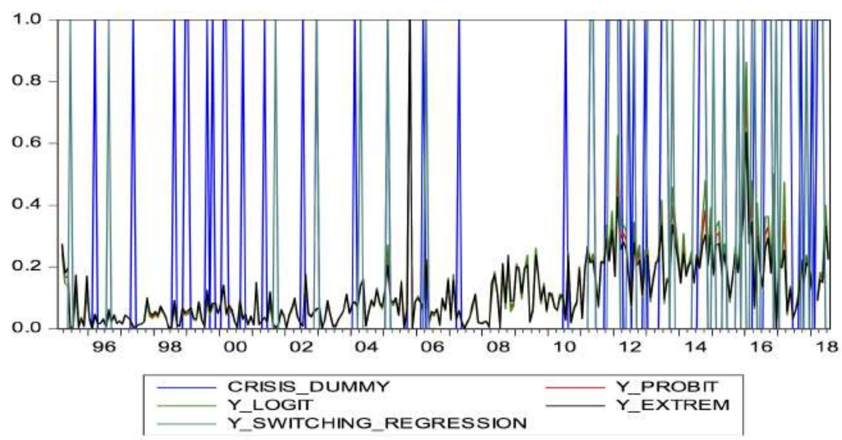


Table 3: Forecast Evaluation for Different Models and Combination Schemes

	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)

The second approach we follow in order to evaluate the predictions of different models is the ratio of the correct predictions. Therefore, the first step is to set up a value for which above a system should warn with signals. There as a number of approaches for selecting this value. Some of these approaches depend on the estimated models outputs and others are based on the real data. We prefer using the real data because depending on the outputs of estimated models might give biased results as the selecting model itself suffers from some uncertainties. We will depend on 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 combination scheme.

Table 4 shows the number of correct predictions for In-sample period. We can see that DMA combination method gives the highest correct percentage by 80% and then the Equal Weighting combination scheme gives with around 79%. Table 5 outlines the numbers and the percentages of correct predictions for different individual prediction schemes. We can notice that Equal weighting combination scheme gives the highest correct ratio with 67% and then 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

In this section we are going to check how our results are robust when the selected critical level if the threshold variable are changed to be two standard deviation instead of one standard deviation.

Table 6 presents forecast evaluation of different individual models and combination schemes under the new threshold level. Regarding in-sample forecast, we can see that logit model performs better than other individual models with RAFSE equal to 0.25885 then Probit model with RAFSE equal to 0.260962. However, both forecast combination methods give better prediction than all individual models. Indeed, DMA combination scheme gives the best forecast; with RAFSE equal to 0.19262, over Equal weighting combination and other individual models.

Moreover, regarding out-sample forecast, we can see that Switching Regression model performs better than other individual models with RAFSE equal to 0.3863337 then Extreme model with RAFSE equal to 0.50872. However, also as in the case of in-sample forecast, forecast combination method performs better than all individual models in terms of prediction. Indeed, DMA combination method acts as 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 build the optimal model for predicting currency crisis 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 between all available forecasts by using the DMA and EW methods in order to improve the prediction power. Our key findings show that forecasts combination performs better than each individual mode over both in-sample and out-sample forecasts.

For future research, applying combination scheme methods in different kinds of financial crises such as banking crises is recommended. Also, estimating and combining density forecasts rather than point forecast is a worthy point for future studies.

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AppendixA.

Figure A.3: Two error probabilities - Probit model

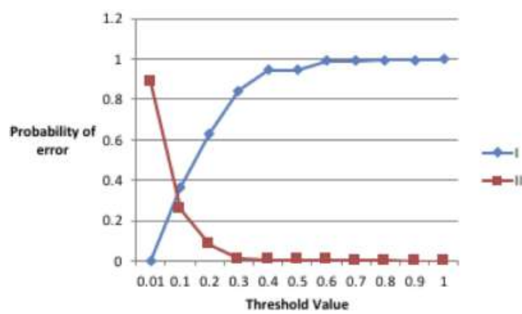

Figure A.4: Two error probabilities - Logit model

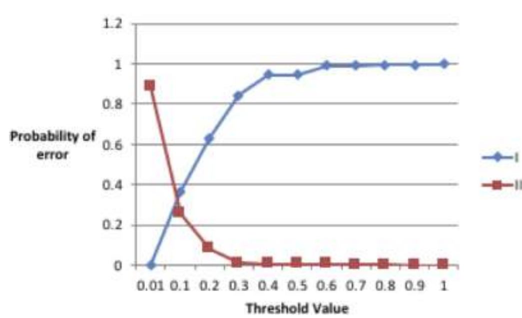

Figure A.5: Two error probabilities - Extreme model

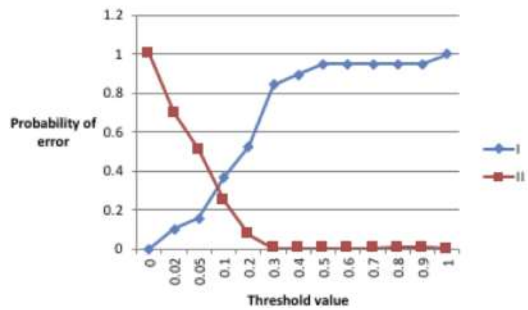

Figure A.6: Two error probabilities - Switching model