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FORECASTING FOREIGN EXCHANGE RESERVES USING BAYESIAN MODEL AVERAGING-NAÏVE BAYES

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Foreign exchange reserves are used by governments to balance international payments and make stable the exchange rate. Numerous works have developed models to predict foreign exchange reserves; however, the existing models have limitations and the literature demands more research on the subject given that the accuracy of the models is still poor, and they have only been used for emerging countries. This paper presents a new prediction model of foreign exchange reserves for both emerging countries and developed countries, applying a method of Bayesian model averaging-Naïve Bayes, which shows better precision results than the individual classifier. Our model has a great potential impact on the adequacy of macroeconomic policy against the risks derived from balance of payment crises providing tools that help to achieve financial stability on a global level.

Keywords: Foreign exchange reserves; balance of payment; Bayesian model averaging; Naïve Bayes; forecasting.

JEL Classification: F3, C63, C11, E5

1. Introduction

Foreign exchange reserves play an important role in any country since they are one of the tools available to their central banks to provide liquidity coverage and face future contingencies and sudden changes in capital flows (Lanteri, 2013). The repeated appearance of systemic financial crises and the integration of emerging economies with those developed through the process of globalization have led to analyzing the liquidity and payment capacity of the countries, and to considering the maintenance of international reserves as a protection mechanism against the balance of payments crises and the consequences of

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external shocks (Frankel and Saravelos, 2012). In this sense, De Gregorio (2011) showed that in situations of sudden changes in capital flows, the evidence would tend to confirm that having a high level of reserves, even when not used, serves as an important deterrent against speculation. For this reason, international reserves have two simultaneous roles, on one hand, to try to affect the exchange rate, to avoid an overvaluation of the currency, and on the other hand, to provide liquidity insurance in the face of possible future contingencies. However, as Rodrik (2006) and Yeyati (2008) have pointed out that reserve accumulation tends to be costly. The return that the government has to pay in excess of the return on liquid foreign assets to fund the purchase of reserves represents the social cost of self-insurance.

Since the early 2000s, foreign reserve accumulation in emerging countries has been one of the controversial recent topics in the field of international macroeconomics (Bhattacharya *et al.*, 2019). Emerging market economies collected reserves at an annual rate of $250 billion (or 3.5% of their annual combined GDP). This was almost five times higher than the level seen in the early 1990s. As a ratio to GDP, such accumulation has been specifically speedy in China, Korea, India, Malaysia, Russia and Taiwan. In Latin America and Central Europe, reserve accumulation has been moderate, rising as a percentage of GDP only in Argentina, the Czech Republic, Mexico and Venezuela over the past 5 years. Many oil-exporting Middle Eastern economies have also seen an enormous expansion in their reserves (Mohanty and Turner, 2006). In this regard, numerous studies have attempted to explain the reasons why countries accumulate international reserves. For example, Aizenman and Lee (2007) detailed two causes: preventive and commercial. In the first case, countries may prefer to maintain reserves (liquidity in foreign currency), in order to face emergency situations or liquidity difficulties. The accumulation of reserves would respond to a precautionary measure, which would seek to minimize the costs of balance of payments crises and the effects of sudden changes in capital movements. The second reason would be the concern about the country's position in international trade since the accumulation of reserves could signal the concern of governments to preserve the competitiveness of their exports due to a possible appreciation of the exchange rate. Following the aforementioned hypotheses, during the last two decades, and especially since the Asian financial crisis, China has accumulated large amounts of foreign currency reserves in order to protect itself from sudden stops of capital flows and financial crises in general, and with the ultimate goal of promoting their own political survival (Seghezza *et al.*, 2017).

In recent literature, some models of prediction of international reserves stand out (Jung and Pyun, 2018; Espinosa, 2016; Gupta *et al.*, 2014). These models have shown that knowing the factors that explain the behavior of international reserves is of great interest to predict the future functioning of the economy. However, there is no unanimity of criteria regarding the predictor variables and, in addition, although the explanatory capacity of these models is significant, they still have certain limitations related to their levels of precision and their exclusive focus on groups of emerging countries. For this reason, the literature demands a new reserve prediction model in which theories with a greater power of validation on the warning factors are needed, where the opening of the financial markets is not the only factor that directly determines the accumulation of reserves (Jung and Pyun, 2018). Likewise, Espinosa (2016) proposed as future research issue to deepen in the estimation of forecasts using Bayesian models, which could be a valid alternative for the prediction of international reserves. Further, the global crisis and it consequences in Europe have demonstrated that capital account risk can strike advanced economies too, putting into question the typical acceptance that they need little reserves. These developed countries can have very disruptive effects on macroeconomic performance as seen during the global financial crisis (IMF, 2011; Bhattacharya *et al.*, 2019). Therefore, there is evidence of the need to create models that develop prediction of international reserves in advance economies.

In order to contribute to the robustness of reserve prediction models, in this study, a new global model for the prediction of foreign exchange reserves has been developed. This model distinguishes itself for the capacity to predict in all countries, also achieving levels of accuracy of more than 93%. This model has been constructed from a sample of 102 countries, including both emerging and developed, and applying the Bayesian model averaging-Naïve Bayes (BMA-NB) classifier, which shows excellent precision results compared to other methods applied in the previous literature (Jung and Pyun, 2018; Espinosa, 2016; Gupta *et al.*, 2014).

We make at least three further contributions to the literature. First, we consider new explanatory variables for predicting international reserves, testing the importance of these variables which have not been considered so far. It has important implications for policymakers, who can help to maintain the adequate foreign exchange reserves in the country and avoid the potential associated costs. Second, we improve the prediction accuracy with respect to that obtained in previous studies with a different and innovative methodology (BMA-NB), not applied in preceding research in this field. Third, our study has made predictions of international reserves globally, and so not restricted to emerging countries, being interesting for those responsible for the economic policies of any country in the world.

This study is structured as follows: Section 2 provides a literature review of empirical research on foreign exchange reserves. Section 3 sets out the methodology used. Section 4 provides details of the data and the variables used in the research. Finally, Section 5 analyses the results obtained. The article concludes by stating the conclusions of the study and its implications.

2. Literature Review

The previous literature that has addressed the study of international reserves has followed three main lines of research. On one hand, the analysis of the optimal level of international reserves that countries must maintain (Bhattacharya *et al.*, 2019; Gevorkyan and Khemraj, 2019; Shi and Nie, 2017; Lanteri, 2013; Calvo *et al.*, 2012; Mwase, 2012; De Gregorio, 2011; Sula, 2011; Jeanne and Rancière, 2008; Soto *et al.*, 2004). On the other hand, those works that have studied the reasons why countries accumulate international reserves and the implications derived from this fact (Seghezza *et al.*, 2017; Pina, 2015; Delatte and Fouquau, 2012; Vujanovic, 2011; Bastourre *et al.*, 2009; Aizenman and Lee, 2007; Mohanty and Turner, 2006). Finally, those empirical studies have developed prediction models of international reserves (Jung and Pyun, 2018; Espinosa, 2016; Gupta *et al.*, 2014; Li and Yang, 2012).

The level of international reserves that a country must maintain has been a subject of wide discussion over the last years, there being no single criterion in the literature that provides in a clear way what is the optimal level. There are three reasons why an economy requires reserves. In the first place, reserves allow us to reduce the problems of international illiquidity (Calvo *et al.*, 2012). Second, reserves are necessary in case the monetary authority decides to make interventions in the currency market (Gevorkyan and Khemraj, 2019). And lastly, reserves are an indicator that rating agencies assess at the time of assessing a country's sovereign debt (Pina, 2015). However, maintaining reserves represents a high cost for the institutions of a country (Yeyati, 2008; Rodrik, 2006; Soto *et al.*, 2004). Therefore, it is essential to determine the optimum level of reserves that a country should maintain. In this regard, Bhattacharya *et al.* (2019) investigated the determinants of the demand for reserves and possible similarities and differences in the motives for holding of reserves across emerging markets, advanced economies and low-income countries. Using various econometric specifications, they defined that precautionary aims (proposes maintaining reserves to face liquidity difficulties) have achieved in importance for advanced economies and low-income countries since the global financial crisis, while for emerging economies it has been the opposite. Mercantilist motives (suggests that reserves are hoarded to defend export competitiveness) are significant only for emerging countries. Mwase (2012) developed an operational metric for estimating reserves in emerging markets and small islands and considered that there is a positive relationship between short-term debt and reserves, reflecting insurance against deleveraging and rollover risk. Sula (2011) found in a quantile regression that precautionary motives matter more for countries with a low stock of reserves relative to GDP. For its part, De Gregorio (2011) showed that there are different methodologies. One option could be to observe a series of indicators constructed from quotients between reserves and certain macroeconomic variables, and another, to maintain a level of reserves that minimizes its maintenance cost subject to reducing the probability of a crisis. Jeanne and Rancière (2008) investigated a model to establish an optimal level of international reserves in emerging countries. They conclude a formula for the optimal level of reserves and exhibit that credible calibrations can explain reserves of the order of magnitude observed in many emerging market countries. Likewise, Calvo *et al.* (2012) explored the optimal stock of international reserves through a statistical model in which reserves reduce the probability of a sudden stop and its consequent costs.

On the other hand, and regarding the determination of the optimal composition of foreign exchange reserves, Shi and Nie (2017) valued the latent currency composition of China's foreign exchange reserves and reported that this country has started to pay more attention to the emerging international currency. Recently, the study of Gevorkyan and Khemraj (2019) analyzed the composition of international reserves under a central bank's exchange rate policy target and concluded that a central bank could demand a percentage of gold in international reserves, especially when the country prefers to increase international reserves for precautionary reasons.

Several works have studied the reasons why countries accumulate international reserves. Delatte and Fouquau (2012) investigated in a single time-varying relationship if the precautionary benefits continued dominant after 2000 or if mercantilist aims replaced the precautionary motives. They concluded that the acceleration of holding reserves in the emerging markets was driven by management of the real exchange rate. However, the precautionary motive for maintaining reserves is yet an important driver but it does not clarify the acceleration. Bastourre *et al.* (2009) concluded that the main reason to demand reserves is a precaution and they confirmed that the only traditional variable that stays significant is the trade openness, while neither trade and financial volatility nor opportunity cost is relevant. They also verified that although countries with flexible exchange rate regime have higher ratios of reserves to GDP, the flexible exchange rate regime helps explain the accumulation of reserves.

For its part, among the works that have developed prediction models, highlighted are those that made an analysis to predict the size of international reserves for China, finding as a result a possible future growth of the currencies, being the biggest foreign exchange reserves country (Li and Yang, 2012). Arya *et al.* (2010) built different models to forecast international reserves in India, with the peculiarity of the use of quarterly data between 1997 and 2008. They applied univariate and multivariate techniques such as double exponential smoothing by Brown's method, Holt's exponential smoothing, ARIMA models and multiple regression. In their work, they concluded that the ARIMA model is the best technique for the forecast of three and four quarters forward. More recently, the work of Gupta *et al.* (2014) also focused on forecasting China's foreign exchange reserves. In their study, they considered variables that measure trade flows and some financial and risk factors. They found that the models dynamic model averaging (DMA) and dynamic model selection (DMS) were the ones that had the best forecast results, the latter offering the best overall performance, above several linear models and the Bayesian model averaging (BMA). In addition, they concluded that the variables to be considered relevant for predicting international reserves were nominal exchange rate, money supply, net export, oil price and US economic policy uncertainty index. They obtained accuracy close to 68%. For its part, Espinosa (2016) it made a forecast of net international reserves in Colombia. In this study, six different quantitative methodologies were presented for the construction of international reserves growth models. Quarterly data were used with information from the national accounts of the Central Bank, government agencies and the IMF for the period 2000–2014. Their most important conclusions refer to the fact that the VARX model integrated into levels is the best approximation regarding the forecasting capacity, with accuracy of around 72%. Finally, Jung and Pyun (2018) analyzed the validity of the variables (both traditional and recently proposed) to determine the level of international reserves through a dynamic panel model in 51 emerging countries throughout 1990–2011, obtaining accuracy of 79%. They concluded that not only traditional variables, such as short-term debt to GDP ratios or trade openness, have significant effects on the accumulation of reserves, but also would some new financial variables such as M2/GDP and foreign capital inflows through over-the-counter markets.

From the above, we observe that the previous literature has addressed the prediction of reserves in emerging countries, so the evidence is limited for developed countries. Likewise, the existing models in the literature review present certain limitations related to their levels of accuracy. Therefore, our aim is to develop a new model for the prediction of foreign exchange reserves in all countries with a level of accuracy higher than the obtained previously (Jung and Pyun, 2018; Espinosa, 2016; Gupta *et al.*, 2014) and applying the BMA-NB classifier, an innovative methodology not used in the prior research area.

3. Methodology

3.1. *Naïve Bayes classifiers*

Suppose we have N independent random variables and identically distributed (i.i.d.) observations, $D = \{(y_i, x_i)\}(1 \le i \le N)$ where $y_i \in \{1, \ldots, C\}$ is the category for observation i and $x_i = (x_{i,1}, \ldots, x_{i,K})$ is the vector of K features for observation i. In a probabilistic framework for classification, determining a new feature vector x_{N+1} (also denotes x), the target is to predict the highest probability category y_{N+1} (also denotes y) based on the observations (Mitchell, 2010). That is, for each y, we estimate the following equation:

$$P(y|x, D) \propto P(y, x, D) = \prod_{i=1}^{N+1} P(y_i, x_i). \tag{1}$$

where the first proportionality is because D and x are fixed, and the $\prod_{i=1}^{N+1}$ is subject to our i.i.d. supposition for D and the point that we can take up $(y, x) = (y_{N+1}, x_{N+1})$ into the product by changing the range of i to include $N+1$ (Fung *et al.*, 2011). The independence assumption of Naïve Bayes (NB) sets that all features $x_{i,k}(1 \le k \le K)$ are independent given the category y_i. If we suppose that $P(y_i)$ and $P(x_{i,k}|y_i)$ are establish to their maximum likelihood estimates given D, we get the following result for NB in Equation (2).

$$\begin{aligned} \underset{y}{\operatorname{argmax}}\, P(y|x, D) &= \underset{y}{\operatorname{argmax}} \prod_{i=1}^{N+1} P(y_i) \prod_{k=1}^{K} P(x_{i,k}|y_i) \\ &= \underset{y_{N+1}}{\operatorname{argmax}}\, P(y_{N+1}) \prod_{k=1}^{K} P(x_{N+1,k}|y_{N+1}). \end{aligned} \tag{2}$$

Once BMA-NB is derived, we will check that it is impossible to draw the $\prod_{i=1}^{N+1}$ since latent feature selection variables will depend on D.

3.2. *BMA*

In this case, we dispose of different models $m \in \{1 \ldots M\}$, each one detailed in a different way to produce the feature probabilities $P(x_i|y_i, m)$, allowing to define a prediction for a classification model m created as it appears in the following equation:

$$P(y, x|m, D) = P(y, x|m, D)P(y\,|D). \tag{3}$$

While we could choose a sole model m according to previous criteria, an optimal way to combine all models to generate a lower variance prediction than any one model is to apply BMA (Hoeting *et al.* 1999) and estimate a weighted average over all models as shown in the following equation:

$$P(y, x|D) = \sum_{m} P(x|m, y, D)P(y|D)P(m|D). \tag{4}$$

Here, we can observe $P(m|D)$ as the weight of model m and observe that it provides a convex combination of model predictions, since by definition: $\sum_m P(m|D) = 1$. BMA has the property that in the asymptotic limit of data D, as $|D| \to \infty$, $P(m|D) \to 1$ for the best model m meaning that asymptotically, BMA can be observed as efficient model selection (Pham and Olafsson, 2019; Wu *et al.*, 2015). To estimate $P(m|D)$, we can use Bayes rule to obtain the following equation:

$$P(m|D) \propto P(D|m)P(m) = P(m)\prod_{i=1}^{N} P(y_i, x_i|m) = P(m)\prod_{i=1}^{N} P(y_i)P(x_i|m, y_i). \tag{5}$$

Substituting Equation (5) into Equation (4), we arrive at the final simple form expressed in Equation (6), where we again absorb $P(x|m, y_{N+1}, D)$ into the renamed $N+1$st factor of $\prod_{i=1}^{N+1}$.

$$P(y, x|D) \propto \sum_m P(m) \prod_{i=1}^{N+1} P(y_i)P(x_i|m, y_i). \tag{6}$$

3.3. *BMA-N*

Suppose a combination of the previous parts on BMA and NB whether we allow for each model m to match to a different subset of features (Wu *et al.*, 2015). Given K features, there are 2^K feature subsets in the powerset of features producing an exponential number of models m to add up in Equation (6). Nevertheless, if we presume feature selections are independent, we can factorize our representation of m. So, we can utilize $f_k \in \{0, 1\} \times (1 \le k \le K)$ to represent if feature $x_{i,k}$ for each observation i is used or not.

Regarding the model class m to be $f = (f_1, \ldots, f_K)$, we can now combine the NB factorization of Equation (2) and BMA from Equation (6) into the BMA-NB model represented in Equation (7), the joint probability marginalized over the latent model class f and reducing associative and reverse distributive laws (Dean and Raftery, 2010).

$$\begin{aligned} P(y|x, D) &= \sum_f \left[\prod_{k=1}^{K} P(f_k)\right] \prod_{i=1}^{N+1} P(y_i) \prod_{k=1}^{K} P(x_{i,k}|f_k, y_i) \\ &= \sum_{f_1}\sum_{f_2}\cdots\sum_{f_k} \left[\prod_{i=1}^{N+1} P(y_i)\right] \prod_{k=1}^{K} P(f_k) \prod_{i=1}^{N+1} P(x_{i,k}|f_k, y_i) \\ &= \left[\prod_{i=1}^{N+1} P(y_i)\right] \prod_{k=1}^{K} \sum_{f_k} P(f_k) \prod_{i=1}^{N+1} P(x_{i,k}|f_k, y_i). \end{aligned} \tag{7}$$

Before continuing, we need to define what model prior $P(f_k)$ and feature distribution $P(x_{i,k}|f_k, y_i)$ we have as target to use for BMA-NB. For $P(f_k)$, we apply the simple unnormalized prior expressed in Equation (8).

$$P(f_k) = \begin{cases} \dfrac{1}{\beta} & \text{if } f_k = 1 \\ 1 & \text{if } f_k = 0 \end{cases}, \tag{8}$$

where β is a positive constant. In a generative model such as NB, the feature used is defined as it appears in Equation (9).

$$P(x_{i,k}|f_k, y_i) = \begin{cases} P(x_{i,k}|y_i) & \text{if } f_k = 1 \\ P(x_{i,k}) & \text{if } f_k = 0 \end{cases}. \tag{9}$$

Therefore, if $f_k = 0$, $P(x_{i,k}|f_k, y_i)$ becomes a constant that can be ignored in the arg $\max_y$ of Equation (2) of NB. Joining the pieces and adding up over $f_k \in (0, 1)$, we finish the derivation from Equation (8), obtaining the final equation (10) that defines BMA-NB (Wu *et al.*, 2015).

$$P(y|x, D) = \left[\prod_{i=1}^{N+1} P(y_i)\right] \prod_{k=1}^{K} \left[\prod_{i=1}^{N+1} P(x_{i,k}) + \frac{1}{\beta} \prod_{i=1}^{N+1} P(x_{i,k}|f_k, y_i)\right]. \tag{10}$$

3.4. *Research steps*

Empirical research for forecasting foreign exchange reserves needs to follow five steps: creating sample, data pre-processing, construction of model, accuracy assessment, and classification and forecasting, as shown in Figure 1. First, the step of creating a sample is based on obtaining the data from relevant sources, such as information publicly disclosed by international economic bodies. The attributes of the data set include attributes of the external sector, domestic macroeconomic factors, the banking sector and financial markets. The step data pre-processing consists of the discretization of attributes of continuous values, generalization of data and analysis of attribute relativity, and elimination of outliers. For its part, the step construction of a model is based on learning inductively from the data pre-processed by the algorithm BMA-NB exposed in Section 2, and selecting the most significant independent variables. To do this, and randomly, the sample is divided into three sets of mutually exclusive data: training data set (70%), validation data set (10%) and testing data set (20%). In this process, we used the cross-validation method with 10-fold and 500 iterations to estimate error ratios (Tsamardinos *et al.* 2018). The first data set is used for model training, that is, for parameter estimation. The second set is used to evaluate BMA-NB during training and to detect an over-training of it. If the error for the validation grows during a certain number of training times, the training is stopped. Finally, the third data set (testing) is used to evaluate the prediction accuracy of the model during the accuracy assessment step. In a complementary way, classification and forecasting step examine the robustness of the model and its ability to predict foreign exchange reserves worldwide.

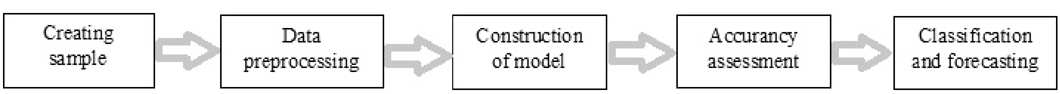

Figure 1. Flowchart of the Research

4. Sample, Data and Variables

The sample period selected is from 1980 to 2018 for a sample of 102 countries (71 emerging countries and 31 developed countries; see Appendices A–C), which has made it possible to build three prediction models of foreign exchange reserves. For the classification of the countries and to obtain the information of the dependent and independent variables, data from the IMF's International Financial Statistics (IFS) and the World Bank have been used.

The dependent variable used in this study is foreign exchange reserves, which include special drawing rights, reserves of IMF members and accumulation of currencies under the control of the monetary authorities. Gold reserves are excluded. On the other hand, we used 26 independent variables as possible predictors of international reserves (Table 1). These variables have been used throughout previous literature (Sula, 2011; IMF, 2011; Mwase, 2012; Gupta *et al.*, 2014; Jung and Pyun, 2018; Laeven and Valencia, 2018; Gruss and Kebhaj, 2019).

Table 1. Independent Variables

Code	Description	Source
NEER	Nominal Effective Exchange Rate (%)	Gupta *et al.* (2014)
INT	Interest Rate (%)	Gupta *et al.* (2014)
ISPREAD	Within Interest Rate Spread (%)	Gupta *et al.* (2014)
INTDIFF	Short-term Interest Rate Differential USA (%)	Sula (2011)
M1	Money Supply (2015 = 100)	Sula (2011)
IP	Industrial Production (% of GDP)	Gupta *et al.* (2014)
X	Export (% of GDP)	Gupta *et al.* (2014)
X-M	Net Export (% of GDP)	Gupta *et al.* (2014)
OP	Oil Price Indice	Gruss and Kebhaj (2019)
CP	Copper Price Indice	Gruss and Kebhaj (2019)
CPUI	Economic Policy Uncertainty (CurrentPriceGDP)	Gupta *et al.* (2014)
UPUI	US Economic Policy Uncertainty (CurrentPriceGDP)	Gupta *et al.* (2014)
KCFSI	Kansas City Fed's Financial Stress Index	Gupta *et al.* (2014)
POP	Population	Jung and Pyun (2018)
GDPCAP	GDP PerCapita	Jung and Pyun (2018)
TGDP	Trade/GDP (%)	Jung and Pyun (2018)
TOT	Terms of Trade (constant LCU)	Jung and Pyun (2018)
M2/GDP	M2/GDP (%)	IMF (2011)
EXDEBT	External Debt to GDP (%)	IMF (2011)
LaggegREGDP	Lagged Rerves/GDP (Current USA$)	Jung and Pyun (2018)
CFGDP	Capital Flows/GDP	IMF (2011)
Soft PEG	Soft Peg (Dummy Variable)[1]	Mwase (2012)
PEG	Peg (Dummy Variable)[2]	Mwase (2012)
CUCRISIS	Currency Crisis (Dummy Variable)[3]	Laeven and Valencia (2018)

Table 1. (*Continued*)

Code	Description	Source
BANKCRISIS	Banking Crisis (Dummy Variable)[3]	Laeven and Valencia (2018)
DEBTCRISIS	Debt Crisis (Dummy Variable)[3]	Laeven and Valencia (2018)

Notes: [1]A soft peg currency describes the type of exchange rate regime applied to a currency to keep its value stable against a reserve currency or a basket of currencies. It is denoted with 1 when the country applies this exchange rate regime for the year under consideration, or otherwise. [2]A peg currency describes the type of exchange rate regime in which a currency's value is fixed against either the value of another country's currency. It is denoted with 1 when the country applies this exchange rate regime for the year under consideration, or otherwise. [3]The dummies variables of currency, banking and debt crisis are defined as 1 for the years of crisis and 0 otherwise, according to the data of the base of Laeven and Valencia (2018).

5. Results

5.1. *Descriptive statistics*

Tables 2–4 show a statistical summary of the independent variables for emerging countries, developed countries and for the total sample (global). The average values of the variables

Table 2. Emerging Summary Statistics

Variables	Obs.	Mean	S.D.	Min.	Max.
NEER	2.698	1,403.035	5,136.860	0.800	32,124.710
INT	2.698	7.407	11.146	−65.516	93.915
INSPREAD	2.698	11.967	77.157	−6.913	2,334.963
INTDIFF	2.698	4,127.188	2,984.265	−0.329	14,756.667
M1	2.698	33.512	37.614	0.000	156.000
IP	2.698	28.922	9.173	3.720	104.637
X	2.698	35.337	22.568	3.396	165.253
X-M	2.698	38.877	22.446	4.631	160.610
OP	2.698	72.120	19.653	43.560	98.069
CP	2.698	1.639	1.063	0.615	4.004
CPUI	2.698	110.501	35.665	62.003	189.665
UPUI	2.698	111.328	26.882	67.136	157.977
KCFSI	2.698	−0.006	0.841	−0.847	2.773
POP	2.698	76,390,865.452	213,776,024.563	144,155.000	1,386,395,000.000
GDPCAP	2.698	4,987.295	7,293.010	94.271	94,004.390
TGDP	2.698	73.617	43.862	9.136	325.998
TOT	2.698	1,753,620, 499,271.970	21,391,574,756, 360.400	−151,522,244, 481,926.000	376,561,685, 960,052.000
M2/GDP	2.698	54.195	32.750	6.666	208.458
EXDEBTGDP	2.698	51.655	34.949	2.576	384.012
LAREGDP	2.698	0.135	0.113	0.003	0.954
CFGDP	2.698	426,355, 025.203	22,014,111, 761.450	−100, 598, 529, 768.205	442,464,337, 234.814

Table 2. (*Continued*)

Variables	Obs.	Mean	S.D.	Min.	Max.
Soft PEG	2.698	0.386	0.437	0.000	1.000
PEG	2.698	0.292	0.391	0.000	1.000
CUCRISIS	2.698	0.071	0.150	0.000	1.000
BANKCRISIS	2.698	0.122	0.258	0.000	1.000
DEBTCRISIS	2.698	0.085	0.223	0.000	1.000

Table 3. Developed Summary Statistics

Variables	Obs.	Mean	S.D.	Min.	Max.
NEER	1.178	15.100	41.545	0.920	185.670
INT	1.178	4.625	6.338	−70.428	92.224
INSPREAD	1.178	3.671	1.864	−3.190	10.217
INTDIFF	1.178	1,138.883	1,344.043	−0.784	6,279.167
M1	1.178	42.095	34.690	0.000	136.571
IP	1.178	27.144	16.627	6.717	213.690
X	1.178	45.951	34.408	6.976	230.016
X-M	1.178	43.522	30.755	6.936	221.010
OP	1.178	72.128	19.681	43.560	98.069
CP	1.178	1.638	1.063	0.615	4.004
CPUI	1.178	110.463	35.663	62.003	189.665
UPUI	1.178	111.311	26.884	67.136	157.977
KCFSI	1.178	−0.006	0.841	−0.847	2.773
POP	1.178	30,279,540.828	55,001,183.644	223,775.000	325,719,178.000
GDPCAP	1.178	28,446.719	19,852.689	1,148.494	119,225.380
TGDP	1.178	89.392	64.538	16.014	442.620
TOT	1.178	290,235,401, 242.043	219,925,627, 8874.900	−8, 305, 196, 324, 415.270	18,408,504, 571,447.400
M2/GDP	1.178	89.477	60.638	18.431	376.524
EXDEBTGDP	1.178	73.146	33.382	3.928	119.416
LAREGDP	1.178	0.081	0.099	0.001	1.131
CFGDP	1.178	−6, 315, 248, 455.513	84,391,878, 569.215	−809, 143,000, 000.000	323,910,329, 454.027
Soft PEG	1.178	0.352	0.418	0.000	1.000
PEG	1.178	0.210	0.382	0.000	1.000
CUCRISIS	1.178	0.057	0.144	0.000	1.000
BANKCRISIS	1.178	0.102	0.245	0.000	1.000
DEBTCRISIS	1.178	0.068	0.204	0.000	1.000

Table 4. Global Summary Statistics

Variables	Obs.	Mean	S.D.	Min	Max.
NEER	6.536	1,136.012	4,546.725	0.420	46,069.120
INT	6.536	6.890	22.955	−97.616	789.799
INSPREAD	6.536	13.461	264.165	−1,027.885	14,526.860
INTDIFF	6.536	2,516.102	2,588.813	−0.784	14,756.667
M1	6.536	38.378	36.353	0.000	156.000
IP	6.536	27.674	13.301	1.882	213.690
X	6.536	37.949	27.909	0.005	231.194
X-M	6.536	43.221	26.566	0.016	236.392
OP	6.536	72.126	19.631	43.560	98.069
CP	6.536	1.639	1.063	0.615	4.004
CPUI	6.536	110.511	35.653	62.003	189.665
UPUI	6.536	111.335	26.879	67.136	157.977
KCFSI	6.536	−0.006	0.841	−0.847	2.773
POP	6.536	36,353, 646.716	129,938, 451.212	12,194.000	1,386,395, 000.000
GDPCAP	6.536	9,100.442	14,841.228	94.271	119,225.380
TGDP	6.536	81.251	52.261	0.021	442.620
TOT	6.536	−3,025,373, 883,709.950	53,239,357, 188,811.100	−1,374,105,267, 873,750.000	376,561,685, 960,052.000
M2/GDP	6.536	51.190	39.671	2.822	376.524
EXDEBTGDP	6.536	65.902	83.869	0.239	1,380.767
LAREGDP	6.536	0.144	0.177	0.000	3.020
CFGDP	6.536	−570,031, 716.505	38,773,172, 206.601	−809,143,000, 000.000	442,464,337, 234.814
Soft PEG	6.536	0.368	0.422	0.000	1.000
PEG	6.536	0.257	0.394	0.000	1.000
CUCRISIS	6.536	0.062	0.147	0.000	1.000
BANKCRISIS	6.536	0.115	0.253	0.000	1.000
DEBTCRISIS	6.536	0.074	0.216	0.000	1.000

of emerging countries are generally higher than those of developed countries. For example, the average of Industrial Production (IP) in emerging countries is 28.92%, while in developed countries it is 27.14%. This suggests that most industrialized countries are no longer the most developed. If we analyze the average GDP per capita (GDPCAP) in developed countries (28,446.72), which is higher than in emerging countries (4,987.29), because although the economies of emerging countries are in full economic development and, therefore, grow faster than the developed world. The average population of emerging countries is much higher than the average of developed countries, as can be seen also in the variable Population (POP).

Table 5. Results of Estimated Models

	Classification (%)		RMSE		Model Selection			
Sample	Training	Validation	Training	Validation	AIC	BIC	ROC Curve	Significant Variables
Emerging	96.42	94.74	0.17	0.20	84.26	91.23	0.95	LAREGDP, M2/GDP, INTDIFF, CFGDP, X, TGDP, CUCRISIS
Developed	97.11	95.89	0.15	0.19	78.18	88.64	0.96	LAREGDP, GDPCAP, EXDEBTGDP, INSPREAD, IP
Global	94.31	93.28	0.19	0.22	171.73	203.05	0.94	LAREGDP, M2/GDP, INTDIFF, EXDEBTGDP, TGDP, CFGDP, UPUI, SoftPEG

Note: RSME: Root of the Mean Square Error; AIC: Akaike Information Criteria; BIC: Bayesian Information Criteria.

5.2. *Empirical results*

Table 5 and Figures 2 and 3 show the level of accuracy, the root mean square error (RMSE), the criteria for selecting models, the value of the ROC curve and the significant variables of each of the developed models. In all three models, the level of accuracy always exceeds 93.28% and both RMSE levels and ROC curve values are adequate. The model

Figure 2. Results of Accuracy Evaluation

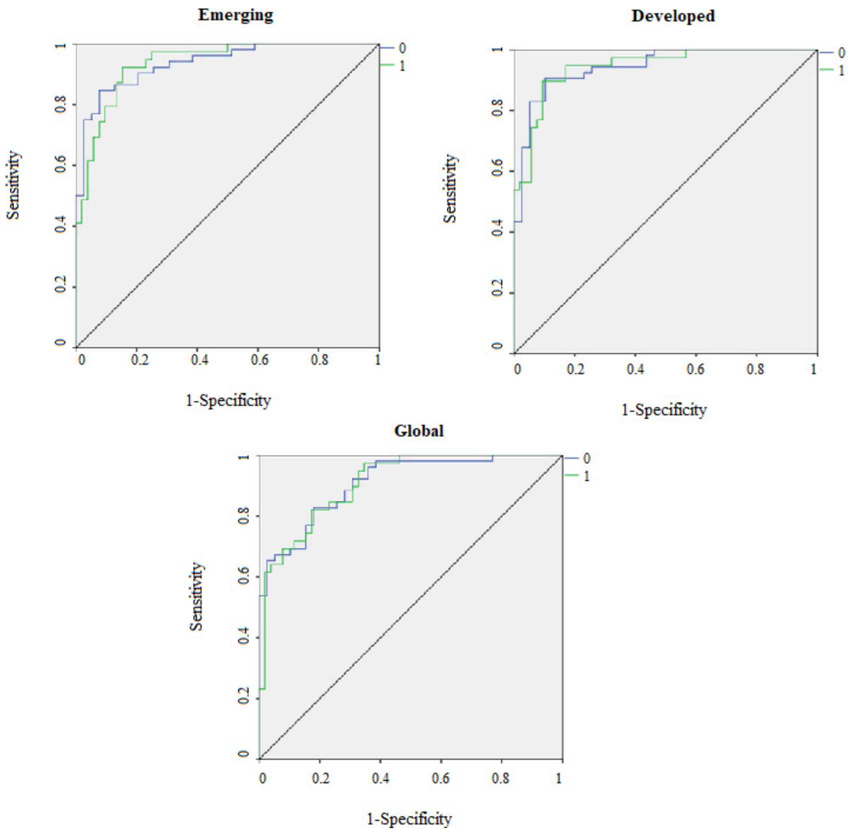

Figure 3. ROC Curves of Estimated Models

with the highest accuracy is that of developed countries with 95.89%, followed by the model of emerging countries with 94.74%. Taken together, these results provide a level of accuracy far superior to that of previous studies. Thus, in the study of Gupta *et al.* (2014), an accuracy of around 68% is revealed; in the case of Espinosa (2016), it is close to 72%, and in the study of Jung and Pyun (2018), it approaches 79%. Also, the values shown by the AIC and BIC information criteria indicate that model for developed economies is the most appropriate for the prediction of reserves since it has obtained the lowest values, but the three models improve the results of these criteria compared to the work of Bhattacharya *et al.* (2019) and Gupta *et al.* (2014).

Using the data reserved for the testing of the models, Table 6 and Figure 4 show the accuracy and error capacity results. The range of precision for the three models is 91.87–93.56%, being in the model of developed countries where the percentage of accuracy is higher (93.56%). These results show that high precision and great stability of the models have been achieved (see Appendix D).

On the other hand, Figure 5 shows additional information on the significant variables. The LAREGDP variable has been significant in the three models (emerging, developed and global). The variables M2/GDP, INTDIFF, CFGDO, TGDP and EXDEBTGDP have been repeated in two models, the first four in the models of emerging and global countries, and

Table 6. Results of Estimated Models in Testing Data

Sample	Classification (%)	RMSE
Emerging	92.68	0.28
Developed	93.56	0.26
Global	91.87	0.31

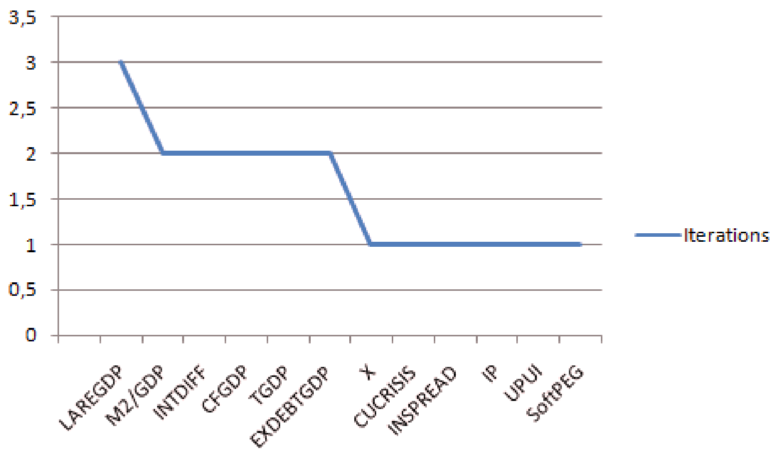

Figure 4. RMSE Score in Testing Data for 500 Iterations

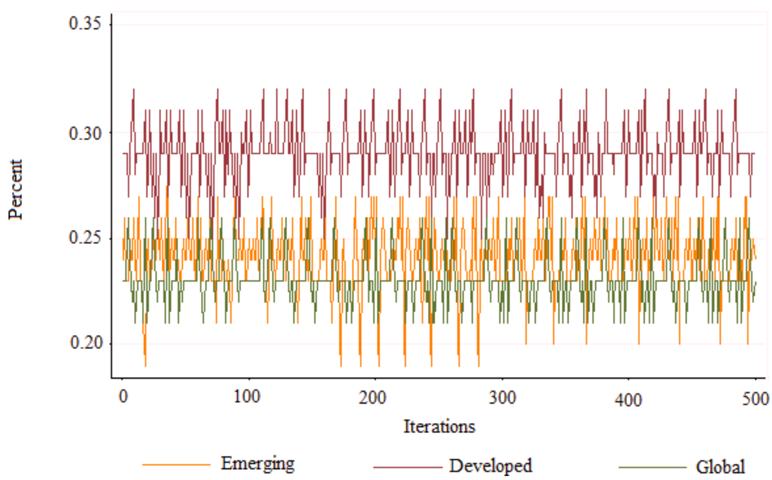

Figure 5. Number of Repetitions of the Significant Variables

the last, EXDEBTGDP in the models of developed and global countries. Finally, the variables that have been reiterated in a single model have been X and CUCRISIS in the model of emerging countries, INSPREAD and IP in the model of developed countries, and UPUI and SoftPEG in the global model.

The results obtained show that for emerging countries, the significant variables for predicting international reserves are LAREGDP, M2/GDP, INTDIFF, CFGDP, X, TGDP and CUCRISIS. In comparison with previous studies, the variables NEER, M1, X-M, OP and UPUI were significant in the work of Gupta *et al.* (2014). The study of Jung and Pyun (2018) concluded that both the traditional economic variables (short-term debt to GDP ratios or trade openness) and financial variables (M2/GDP and CFGDP) have significant effects on the accumulation of reserves. All the above confirms that our research has validated new significant variables (LAREGDP, INTDIFF, X, TGDP and CUCRISIS), detecting a new set of relevant variables different from what was shown in previous studies. Lagged reserves are positively related to the level of reserves because they are an amount of reserves required in the Federal reserve bank, based on the value of all outstanding deposits in the bank's demand deposit accounts from two weeks prior. INTDIF represents the opportunity cost of reserves, and a higher interest rate differential is associated with a higher opportunity cost of reserves, having a negative relation to the reserves. One interpretation of this result is that there exists an inverted-U shape relationship between the size of reserves and their opportunity cost. The influence of the opportunity cost of reserves increases as nations accumulate reserves. Once the level of reserves exceeds a threshold, opportunity cost loses its effect as an important determinant (Sula, 2011). For its part, X and TGDP have a positive relation to the international reserves because higher degrees of openness are expected to increase the demand for reserves. CUCRISIS is a dummy variable indicating a currency crisis. During crises, nations may try to defend their currency by selling large amounts of reserves, so the relation is negative.

For its part, the results for developed countries show that LAREGDP, GDPCAP, EXDEBTGDP, INSPREAD and IP are the most significant variables to predict foreign exchange reserves. Therefore, developed countries should be on alert regarding the behavior of these variables, because for example, a high value in EXDEBTGDP would show a negative effect on international reserves. However, a high value in GDPCAP and IP would have a positive effect. Given that there are no previous studies that develop predictions expressly for developed countries, the results of this research represent a novel contribution to the foreign exchange reserves literature.

After observing the results of the global models, it is deduced that the most significant variables to predict foreign exchange reserves are LAREGDP, M2/GDP, INTDIFF, EXDEBTGDP, UPUI and softPEG. There are also no previous studies on prediction of international reserves globally to be able to compare with our results. However, we can understand that our research provides new significant variables to make predictions in any country. These variables are LAREGDP, INTDIFF, X, TGDP, CUCRISIS, EXDEBTGDP, INSPREAD, IP, UPUI and SoftPEG. M2/GDP is positively associated with reserves as they have been used to capture the risks from potential currency mismatches and drains arising from bank deposit runs to currency holdings, and capital flight can put pressure on central bank reserve holdings (Mwase, 2012). Also, a positive correlation between reserves and INSPREAD exists, as high liquidity reserve requirements act as an implicit financial tax by keeping interest rates high (Bhattacharya *et al.*, 2019). For its part, SoftPEG describes the type of exchange rate regime applied to a currency to keep its value stable against a reserve currency or a basket of currencies. Currencies with a soft peg are halfway between those with a fixed or hard pegged exchange rate and those with a floating exchange rate. The demand for reserves is likely to be higher for intermediate exchange rate regimes since these regimes are shown to be more prone to currency crisis and they may hold reserves mainly for precautionary reasons (Sula, 2011).

Finally, regarding the computing power used for our estimations, we use a two four-core Intel Core I7-6500U and the code is made from MATLAB package (R2016b version). The algorithm takes a total time to estimate the results of 28.34 s for the emerging countries model, 24.45 s for the developed countries model and 33.72 s for the global model.

6. Conclusions

In this study, new prediction models of foreign exchange reserves have been constructed for emerging and developed countries, and for a global sample of countries. For this purpose, BMA-NB has been applied as an innovative methodology not used in previous research in this area. Specifically, the objective has been to improve the prediction accuracy with respect to that obtained previously with a different methodology and expanding the sample size to all countries around the world. This research has shown that the results obtained significantly surpass those already achieved by the previous literature until now, achieving a precision range between 93.28% and 95.89%. It has also detected new relevant variables to be considered in the prediction models of foreign exchange reserves, which has allowed high stability of the models.

In contrast to previous research, this study has made predictions of international reserves not limited to emerging countries but globally. The results achieved to detect significant different variables in emerging countries and in developed countries, as well as globally, providing an essential contribution to the field of international finance. Therefore, the conclusions obtained may be relevant for those responsible for the economic policies of any country in the world, since our study suggests new significant explanatory variables for political agents to predict international reserves. In addition, this research has contributed to a new international reserves prediction model developed through BMA-NB. This new model can be taken as a reference for the approach of macroeconomic policy in making better decisions.

In short, this study provides a great opportunity to contribute to the field of international finance, since the results obtained have important implications for the future decisions of political agents, which through these new financial and economic predictors can help to maintain the adequate foreign exchange reserves as an instrument of protection against the balance of payments crisis, as well as, can be liquidity insurance in order to avoid an overvaluation of the currency in your country.

Future lines of research in this field could develop prediction models taking into account political factors that evaluate the possible influence of the management and effectiveness of economic policy in the prediction of international reserves.

Appendix A. Global Countries Sample

Table A.1.

Afghanistan	Dominican Republic	Kuwait	Palau
Angola	Ecuador	Lao PDR	Papua New Guinea
Albania	Egypt, Arab Rep.	Lebanon	Poland
Algeria	Eritrea	Liberia	Puerto Rico
Argentina	Spain	Libya	Portugal
Armenia	Estonia	St. Lucia	Paraguay
Antigua and Barbuda	Ethiopia	Sri Lanka	Qatar
Australia	Finland	Lesotho	Romania
Austria	Fiji	Lithuania	Russian Federation
Azerbaijan	France	Luxembourg	Rwanda
Burundi	Micronesia, Fed. Sts.	Latvia	Saudi Arabia
Belgium	Gabon	Macao SAR, China	Sudan
Benin	United Kingdom	Morocco	Senegal
Burkina Faso	Georgia	Monaco	Singapore
Bangladesh	Ghana	Moldova	Sierra Leone
Bulgaria	Guinea	Madagascar	El Salvador
Bahrain	Greece	Mexico	Serbia
Bosnia and Herzegovina	Grenada	Macedonia, FYR	Slovak Republic
Belarus	Guatemala	Mali	Slovenia
Belize	Guam	Malta	Sweden
Bermuda	Guyana	Myanmar	Syrian Arab Republic
Bolivia	Hong Kong SAR	Montenegro	Thailand
Brazil	Honduras	Mongolia	Tajikistan
Barbados	Croatia	Mozambique	Tonga
Brunei Darussalam	Haiti	Mauritania	Tunisia
Bhutan	Hungary	Mauritius	Turkey
Botswana	Indonesia	Malawi	Tuvalu
Central African Republic	India	Malaysia	Tanzania
Canada	Ireland	Namibia	Uganda
Switzerland	Iran, Islamic Rep.	Niger	Ukraine
Chile	Iraq	Nigeria	Uruguay
China	Iceland	Nicaragua	United States
Cameroon	Israel	Netherlands	Uzbekistan
Congo, Dem. Rep.	Italy	Norway	Venezuela, RB
Colombia	Jamaica	Nepal	Vietnam
Cabo Verde	Jordan	Nauru	Vanuatu
Costa Rica	Japan	New Zealand	Samoa
Cuba	Kazakhstan	Oman	Kosovo
Cyprus	Kenya	Pakistan	Yemen, Rep.
Czech Republic	Kyrgyz Republic	Panama	South Africa
Germany	Cambodia	Peru	Zambia
Denmark	Korea, Rep.	Philippines	Zimbabwe

Appendix B. Emerging Countries Sample

Table B.1.

Albania	Estonia	Mexico
Antigua and Barbuda	French Polynesia	Moldova
Argentina	Georgia	Morocco
Armenia	Grenada	Nigeria
Bahrain	Guatemala	Pakistan
Bangladesh	Guyana	Panama
Barbados	Haiti	Paraguay
Belarus	Honduras	Peru
Belize	Hungary	Philippines
Bermuda	India	Poland
Bhutan	Indonesia	Romania
Bolivia	Israel	Russian Federation
Brazil	Jamaica	Slovenia
Brunei Darussalam	Jordan	South Africa
Cabo Verde	Kenya	Sri Lanka
China	Korea, Rep.	St. Lucia
Colombia	Latvia	Tanzania
Costa Rica	Lithuania	Thailand
Croatia	Macedonia, FYR	Tunisia
Cuba	Madagascar	Turkey
Dominican Republic	Malaysia	Uruguay
Ecuador	Maldives	Venezuela, RB
Egypt, Arab Rep.	Malta	Vietnam
El Salvador	Mauritius	

Appendix C. Developed Countries Sample

Table C.1.

Australia	Germany	New Zealand
Austria	Greece	Norway
Belgium	Hong Kong SAR	Portugal
Bulgaria	Iceland	Qatar
Canada	Ireland	Slovak Republic
Chile	Italy	Spain
Cyprus	Japan	Sweden
Czech Republic	Luxembourg	Switzerland
Denmark	Macao SAR, China	United Kingdom
Finland	Netherlands	United States
France		

Appendix D. Accuracy in Testing Sample for 500 Iterations

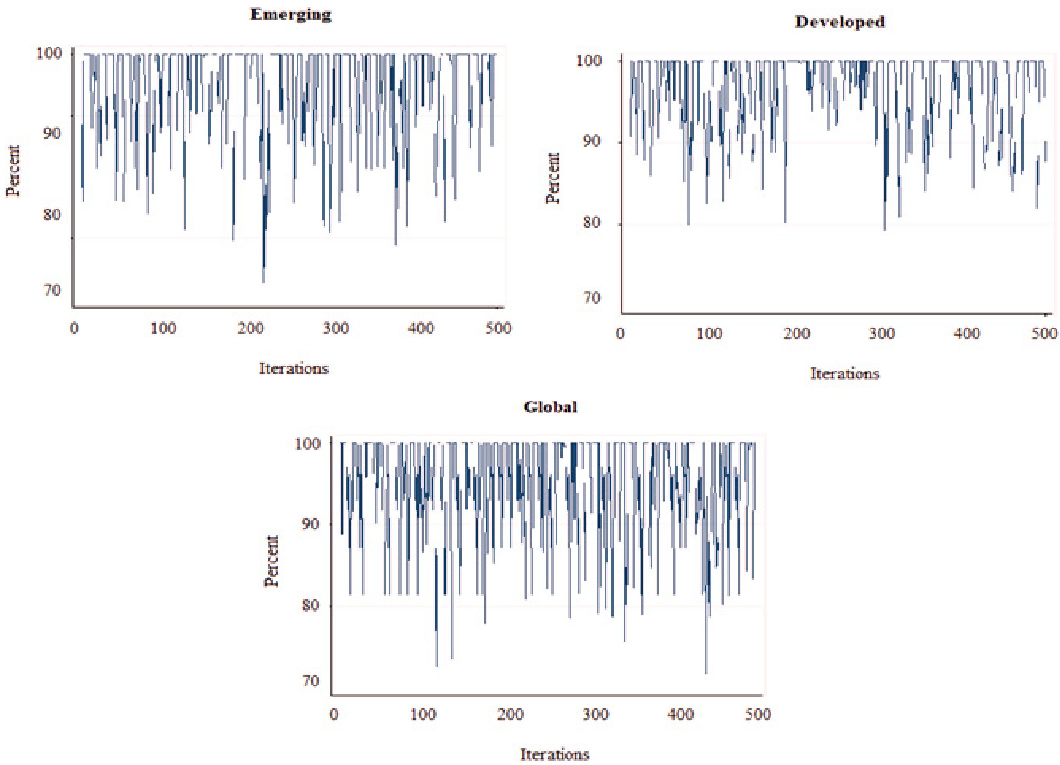

Figure D.1.

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