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A TEST

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by Tuomas A. Peltonen[2]

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Abstract

This paper analyzes the predictability of emerging market currency crises by comparing the often used probit model to a new method, namely a multi-layer perceptron artificial neural network (ANN) model. According to the results, both models were able to signal currency crises reasonably well in-sample, but the forecasting power of these models out-of-sample was found to be rather poor. Only in the case of Russian (1998) crisis were both models able to signal the crisis well in advance. The results reinforced the view that developing a stable model that can predict or even explain currency crises is a challenging task.

JEL classification: F31, E44, C25, C23, C45
Keywords: Currency crises, emerging markets, artificial neural networks

Non-technical summary

This paper investigates the predictability of emerging market currency crises by comparing two non-linear models. In particular, the paper discusses the capacity of a probit model and a multi-layer perceptron artificial neural network (ANN) model to predict currency crises with a sample of commonly used emerging market countries and crisis indicators. The main contribution of the paper is that it introduces a new method for currency crisis prediction, namely the ANN model. Similar types of ANN models have been successfully used in other fields of economics and finance to detect binary outcomes, such as firm bankruptcies. In addition, currency crises determinants and their stability are evaluated using different subsamples to see whether currency crises of 1980s and 1990s were caused by the same factors. Finally, the impact of a *de facto* exchange rate regime on the probability of currency crises is evaluated using the data from Reinhart and Rogoff (2004).

The main result of the study is that both the probit and the ANN model were able to correctly signal crises reasonably well in-sample, and that the ANN model slightly outperformed the probit model. In contrast to the findings in the earlier literature on currency crises, the ability of the models to predict currency crises out-of-sample was found to be weak. Only in the case of the Russian crisis (1998) were both models able to signal its occurrence well in advance. In addition, certain economic factors were found to be related to the emerging market currency crises. These factors are the contagion effect, the prevailing *de facto* exchange rate regime, the current account and government budget deficits, as well as real GDP growth. Furthermore, it appears that economic fundamentals were able to statistically better explain the onset of currency crises in the subsample of the 1980s than in the subsample of the 1990s, where other variables, such as the contagion effect, were statistically significant. This confirms earlier findings in the literature that the contagion effect versus economic fundamentals might have played a greater role in the onset of the currency crises in the 1990s, in contrast to the crises of the 1980s. Furthermore, our findings confirmed the results of Rogoff *et al.* (2003) and Ghosh *et al.* (2002) that emerging markets with more rigid exchange rate regimes were less prone to currency crises during the last two decades. Finally, the results reinforced the view that developing a stable model capable of predicting currency crises can be a challenging task.

1 Introduction

According to Bordo *et al.* (2001), the frequency of financial crises has doubled since the collapse of the Bretton Woods system in 1973, but there is little evidence that crises have become more severe in terms of output losses and durations. Furthermore, both the IMF (1998) and Bordo *et al.* (2001) report that low-income economies have experienced more banking and currency crises than advanced economies during this time. Similar conclusions are drawn in Ghosh *et al.* (2002), who also find that currency crises are more prevalent under *de jure* floating exchange rate regimes. Likewise, Rogoff *et al.* (2003) find that, especially in emerging markets, currency crises have occurred during the last three decades more often under *de facto* less rigid exchange rate arrangements, such as the managed floating exchange rate regime. In contrast, they find that twin crises (both banking and currency crises) occurred more often under *de facto* pegged exchange rate arrangements.

The unfortunate feature of currency crises, and more generally, financial crises is that they can be very costly. These costs include fiscal and quasi-fiscal costs, misallocation and an underutilization of resources, losses in real output and changes in distribution of wealth. Bordo *et al.* (2001) estimate that the downturns following financial crises have lasted on average 2-3 years and cost 5-10 per cent of GDP. However, Ghosh *et al.* (2002) report that costs of currency and banking crises have varied depending on the exchange rate regime.[1] This motivates the study as it is important to investigate the causes of past currency crises and ways of detecting countries vulnerable to crises.

In the spirit of Berg and Pattillo (1999),[2] who investigated the predictability of emerging markets currency crises by comparing a 'signal' approach proposed by Kaminsky *et al.* (1998) and a probit model, this paper analyzes the predictability of emerging market currency crises comparing two different models. More specifically, the paper discusses the capacity of often used probit/logit models to predict currency crises with a sample of commonly used emerging market countries and crisis indicators. Furthermore, the main contribution of the paper is that it introduces a new method for currency crisis prediction, namely a multi-layer perceptron artificial neural network (ANN) model. Similar types of ANN models have successfully been used in other fields of economics and finance to detect binary outcomes, such as firm bankruptcies.[3] In addition, currency crises determinants and their stability are evaluated using different subsamples to see whether currency crises of 1980s and 1990s were caused by the same factors.[4] Finally, the impact of a *de facto* exchange rate regime on the probability of currency crises is evaluated using the data from Reinhart and Rogoff (2004).[5]

[1] Ghosh et al. (2002) found that, in their sample, per capita GDP growth rate under floating exchange rate regime was faster after currency crises than before them. However, under fixed or intermediate exchange rate regimes, crises caused substantial declines in per capita GDP growth rates.

[2] See also Edison (2003).

[3] See e.g. a survey by Wong and Selvi (1998).

[4] One should note that in many of the analyzed economies, the capital accounts were liberalized at the early 1990s.

[5] Also Rogoff et al. (2003) evaluated this using the same data, however their approach was different as they only tabulated the occurance of currency crises under different *de facto* exchange regimes without conditioning the probability of currency crises on other factors like in this study.

According to currency crisis theories, economic fundamentals affect the probability of currency crises. However, whether the exact timing of a currency crisis is predictable is another issue. According to the first generation models of currency crisis,[6] the exact timing of currency crisis is linearly determined by, and therefore, predictable with economic fundamentals. In contrast, in the second generation models of currency crisis,[7] economic fundamentals also affect the probability of crisis, but the relationships can be non-linear. Furthermore, other factors than economic fundamentals, such as 'herding behaviour' and other types of investor behaviour, can affect the probability of crisis. Therefore, it may not be possible to predict the exact timing of crisis solely by economic fundamentals. However, the possible non-linear relationship between economic fundamentals and currency crises motives the use of non-linear methods, such as probit/logit or ANN models for empirical analyses of currency crisis. Thus, it also motivates the study to analyze whether the more advanced ANN model could outperform the standard probit model in currency crisis prediction.

However, there is an important issue of endogeneity linked to the currency crises. Consider that economic agents follow an economic indicator that is expected to be linked to currency crises. Thus, crises can either be prevented due to policy changes or, in contrast, they can erupt due to 'self-fulfilling prophecies'. Furthermore, not all currency crises are caused by the same factors, and other issues, such as political factors, can also play a role in the onset of currency crises. Another problem related to currency crisis prediction, especially in emerging markets, is linked to the availability of timely and accurate information about economic fundamentals and other relevant factors, as well as indicators that contain information about investors' expectations about future economic conditions. Despite these issues, many earlier studies have claimed to be successful in predicting currency crises using economic fundamentals, which will also be the focus of this study.

The main result of the study is that both the probit and the ANN model were able to correctly signal crises reasonably well in-sample, and that the ANN model slightly outperformed the probit model. In contrast to the findings in the earlier currency crises literature, the ability of the models to predict currency crises out-of-sample was found to be weak. Only in the case of the Russian (1998) crisis were both models were able to signal its occurrence well in advance. In addition, certain economic factors were found to be related to the emerging market currency crises. These factors are the contagion effect, the prevailing *de facto* exchange rate regime, the current account and government budget deficits, as well as real GDP growth. Furthermore, it appears that economic fundamentals were able to statistically better explain the onset of currency crises in the subsample of the 1980s than in the subsample of the 1990s, where other variables, such as the contagion effect, were statistically significant. This confirms the earlier findings in the literature that the contagion effect versus economic fundamentals might have played a greater role in the onset of the currency crises in the 1990s, in contrast to the crises of the 1980s. This result is possibly linked to the fact that many of the analyzed emerging market economies liberalized their capital accounts in the beginning of the 1990s, which possibly made them more vulnerable to international capital flows than they were in

[6] See Krugman (1979).
[7] See Obstfeld (1986, 1995).

the 1980s. Furthermore, our findings confirmed the results of Rogoff *et al.* (2003) and Ghosh *et al.* (2002) that emerging markets with more rigid exchange rate regimes were less prone to currency crises during the last two decades. Finally, the results reinforced the view that developing a stable model capable of predicting or even explaining currency crises can be a challenging task.

The study is organized in the following way. Section Two briefly summarizes the related literature. Section Three discusses methodological issues, while section Four presents the empirical framework. Section Five presents the results and, finally, section Six concludes.

2 A brief review of the literature

Before the financial crises of the 1990s, it was commonly held that currency crises could be, to some extent, predictable with variables derived from the first generation models of currency crisis stemming from Krugman (1979).[8] Authors such as Blanco and Garber (1986), Cumby and van Wijnbergen (1989), Edwards (1989) and Goldberg (1994) explored the Latin American currency crises of the 1980s, for example the devaluations in Mexico (1982, 1986) and Argentina (1981). They found that variables such as current account and government budget balances, credit growth, foreign reserves, inflation, and real exchange rates were related to currency crises.

In the early 1990s, there were several financial and currency crises, e.g. the EMS crisis of 1992-93, which could not be explained using the arguments from first generation models of currency crisis. This led to the development of second generation models of currency crisis originating from Obstfeld (1986, 1995).[9] Furthermore, it again raised the question whether currency crises could be predicted with economic fundamentals. To tackle the problem, Eichengreen *et al.* (1995), Sachs *et al.* (1995) and Kaminsky *et al.* (1996), among others, introduced models with a broader set of explanatory variables. Kaminsky *et al.* (1996) summarized the results of a large number of earlier studies and found that the following variables had the greatest predictive power of currency crises: inflation, GDP growth, exports, real exchange rate misalignment, money growth, reserves, credit growth, credit to the public sector, fiscal deficit and M2 to reserves ratio. In addition, current account, short-term debt to reserves ratio, stock market growth, lending boom (credit to private sector to GDP) and the world interest rate were found to be related to currency crises.

The Asian crises of 1997-98 motivated the development of third generation currency crises models with financial issues from both banks' and firms' side being the key elements. Concepts such as the 'over-borrowing syndrome', 'crony capitalism', and 'moral hazard lending' became known from papers such as McKinnon and Pill (1996), Chang and Velasco (1998), Krugman (1999), Aghion *et al.* (2001, 2004) and Burnside *et al.* (2004). In addition to economic fundamentals related to currency crises, models explaining the propagation of crises, i.e. contagion effects have been studied extensively, see e.g. Forbes and Rigobon (2002).

In the empirical works on currency crisis, the binary crisis variable is usually related to the explanatory variables or 'leading indicators' in different ways.

[8] Agenor et al. (1991) review these models.
[9] Flood and Marion (1998) review this literature.

Firstly, the most often used method is a binary choice model, like the probit/logit model. Examples of these studies are e.g. Eichengreen *et al.* (1995, 1996) and Frankel and Rose (1996). Recently, Berg and Pattillo (1999), Komulainen and Lukkarila (2003) and Kumar *et al.* (2003) have also analyzed the predictability of emerging market currency crises using probit/logit models, whereas Bussière and Fratzscher (2002) used a more sophisticated multinomial logit model. All these studies conclude that certain economic fundamentals (from the variables mentioned earlier) can explain currency crises, and the crises of the 1980s and the 1990s would have been, at least to some extent, predictable. Secondly, the other method is to consider the predictive power of the variables one at a time (univariate) so that a variable is considered to be a good leading indicator if it gives a correct signal of crisis before the incident. This 'signal' approach, or 'early warning indicator system', was introduced by Kaminsky *et al.* (1996, 1998), and further developed by Edison (2003) and Kaminsky (2003). Finally, other recent approaches analyzing currency crises have been Fisher's linear discriminant analysis by Burkart and Coudert (2002), a duration model analysis by Tudela (2004), and an analysis using ANN models by Frank and Schmied (2003).[10] In addition, Scott (2000) explored contagion effects applying an ANN model to Asian crisis countries.

3 Methodological issues

3.1 Definition of the crisis

In this study, currency crises are defined using the concept of 'exchange market pressure' by Girton and Roper (1977). This way of defining crises has an advantage over the alternative definitions of currency crisis, which rely only on extreme currency movements, because both 'successful' and 'unsuccessful' speculative attacks can be considered.[11] In addition, the 'exchange market pressure' definition of crises has the appeal that it can be used to analyze speculative attacks under both fixed and flexible exchange rate regimes.

Following earlier studies,[12] the exchange market pressure in a country i at time t can be measured as:

$$EMP_{i,t} = [\alpha\%\Delta e_{i,t} - \beta\%\Delta r_{i,t}] \tag{1}$$

where $e_{i,t}$ denotes the price of a U.S. Dollar in the country i's currency at the time t; $r_{i,t}$ denotes the foreign reserves (excluding gold) of country i at the time t and α and β are the weights that equalize the variances of these two components.

[10] A study by Franck and Schmied (2003) uses a very similar type of ANN model to predict Russian (1998) and Brazilian (1999) crises. However, their analysis is more event study type and does not compare the results to an alternative statistical model like this study.

[11] The 'successful' speculative attack means occassions where the currency in consideration depreciates/appreciates strongly. The 'unsuccessful' speculative attacks means occassions, where the central bank has been able to defend the currency (i.e. the currency has not been devalued/revalued) by intervening in the foreign exchange markets.

[12] Sometimes the exchange market pressure index also includes a term consisting of short interest rate differential to the US. This term is, however, omitted here due to data problems, as in many emerging market economies a representative market determined money market interest rate is available only from the mid-1990s onwards.

The first term, $\alpha\%\Delta e_{i,t}$, measures the percentage change of the price of a U.S. Dollar in the country i's currency at the time t; in another words, it measures the devaluation (or revaluation) rate of the nominal exchange rate of the country i. The second term, $\beta\%\Delta r_{i,t}$, measures the percentage change in the level of the country i's foreign reserves. It has a negative sign because a decrease in the foreign reserves is assumed to reflect foreign currency outflows (weakening pressure of the local currency i) that the central bank attempts to limit by intervening (buying the local currency) in the foreign exchange market. Therefore, a positive value of the exchange market pressure index measures the depreciation pressure of the currency i, while a negative value of the index measures the appreciation pressure of the currency i.

A currency crisis is defined as an extreme value of the exchange market pressure index:

$$Crisis_{i,t} = 1, \text{ if } EMP_{i,t} > \mu_{EMPi} + 2.0\sigma_{EMPi} \quad (2)$$

$$Crisis_{i,t} = 0, \text{ otherwise} \quad (3)$$

where μ_{EMPi} and σ_{EMPi} are the sample mean and the standard deviation of the exchange market pressure index for each country i. Furthermore, currency crises occurring within three months were considered as one crisis. This method of detecting speculative attacks and currency crises is widely used in the empirical works although it has faced some criticism, mostly because of its *ad hoc* nature and due to the lack of a direct role of market expectations. To test the robustness of the results, alternative crisis definitions were also constructed. This is explained in more detail in section 5.4.

3.2 The data

The dataset consists of 24 commonly used emerging market countries,[13] namely: Argentina, Brazil, Chile, Colombia, Czech Republic, Ecuador, Egypt, Hungary, India, Indonesia, Israel, Korea, Malaysia, Mexico, Morocco, Peru, Philippines, Poland, Russia, Slovakia, South Africa, Thailand, Turkey, and Venezuela. The time span of the monthly dataset was 12/1980 – 12/2001. However, in most cases, the data was not available for the whole time period and the actual dataset that was used in estimations was unbalanced and had a maximum of 3706 observations. The dataset already ends by 12/2001, because the data for the *de facto* currency regime classification by Reinhart and Rogoff (2004) was not available for later periods. Furthermore, as Reinhart and Rogoff (2004) show, there is a significant difference between the IMF's *de jure* classification and the *de facto* classification of exchange rate regimes, especially in the hyper-inflationary periods of 1980s. Therefore, it was considered important to include the *de facto* exchange rate regime into the analysis with the cost of losing some of the latest observations.[14] Other data sources were: the IMF International Financial Statistics 2/2005, J.P. Morgan (for real effective exchange rates), and

[13] The coverage of countries in the Morgan Stanley Capital International (MSCI) Emerging Markets (EM) index is nearly identical to the sample of countries that is used in this study. In addition to the countries in the sample, the EM index also includes China, Jordan, Pakistan, and Taiwan. However, it does not include Ecuador and Slovakia.

[14] This is clearly a drawback as e.g. the floating of Venezuela's crawling peg regime in January 2002 and Argentina's currency board system in February 2002 cannot be investigated.

Global Financial Data Inc. (for stock market indices). The choice of the independent variables was based on theoretical models of currency crisis, which aim to measure domestic and external conditions[15] of the economy. In addition, all used variables have also been found to be related to currency crises in the earlier empirical literature reviewed in section 3.2. Table 1 summarizes the independent variables and more information about the data can be found in the Appendix.

Independent variables	Formula
Ratio of government budget balance to GDP	IFS line 80 / IFS line 99B
Ratio of current account to GDP	IFS line 78ALD / (IFS line 99B / IFS line AE)
Measure of under or overvaluation of Real Effective Exchange Rate	(REER - HP trend of REER with a parameter of 14400) / REER
Real interest rate	IFS line 60L - IFS line 64.X
Annualized growth rate of real GDP	Annualized growth rate[IFS line 99B / IFS line 99BIP]
Annualized growth rate of real domestic credit	Annualized growth rate[IFS line 32 / IFS line 99BIP]
Annualized growth rate of ratio of broad money to foreign reserves	Annualized growth rate[((IFS line 34 + IFS line 35) / IFS line AE) / IFS line 1L.D]
Annualized growth rate of stock market	Annualized growth rate[Composite stock index]
Dummy for contagion	A currency crisis within 3 months in the same region
Dummy for hyperinflation	Annual CPI inflation > 40%
Dummy for *de facto* pegged FX regime	See Reinhart and Rogoff, 2004
Dummy for *de facto* crawling ped FX regime	See Reinhart and Rogoff, 2004
Dummy for *de facto* managed float FX regime	See Reinhart and Rogoff, 2004
Dummy for *de facto* floating FX regime	See Reinhart and Rogoff, 2004
Dummy for *de facto* freely falling FX regime	See Reinhart and Rogoff, 2004
Dummy variables for area	
Linear and quadratic time trends	

Table 1: The independent variables.

On this occasion, it is useful to discuss the data-related issues a bit more in detail. Firstly, as has been the case in many recent papers investigating the determinants and/or predictability of the emerging markets currency crisis, the frequency of data was chosen to be monthly. This raises an issue, as variables such as the GDP, current account or government budget balance, are only available for emerging markets in annual frequency for long enough time periods. Therefore, a common feature of many earlier papers has been that annual or quarterly variables have been interpolated either linearly or using spline techniques. In this study, the GDP, current account and government budget balance variables were linearly interpolated into monthly series. While using interpolated series, some econometrical issues might arise. However, economically, the greatest difficulty of using interpolated series is that by doing so one uses information about future economic conditions that was not available to economic agents at the time. In contrast, it can be argued that economic agents often use forecasts of the key economic variables when they make their investment decisions simply because the actual information is not available. This issue has been dealt with in earlier papers by lagging the interpolated variables. In this study, the independent variables were lagged by a month[16] to alleviate this problem. Another problem related to the timing of the variables is that if the independent variables were contemporaneous to the crisis variable, it would

[15] In addition, foreign debt variables (both total and short-term debt as a ratio of foreign reserves and the GDP) were tested. These variables were not, however, taken into the final models as the foreign debt data from BIS-IMF-OECD-World Bank starts only from 6/1990, which would have shorten the sample considerably.

[16] All the models were estimated also using the independent variables lagged by 3 months. See section 5.4 for more information.

be difficult to evaluate the relationship between economic fundamentals and the currency crisis.[17]

Secondly, an important issue that has often been neglected in many earlier studies is related to the time series properties of the variables, as both the discrete choice models and the ANN models[18] require stationary variables. Although many authors in the field have constructed their independent variables as ratios to GDP, deviations from a trend or as growth rates, there are econometrical problems linked to hyperinflation periods and transition phases. For example, the often used variables such as inflation, the ratio of M2 to foreign reserves, nominal interest rate or the interest rate differential to the US, are highly unlikely to be stationary throughout 1980-2004 in economies with hyperinflationary periods or transition phases from command to market economies. In some cases, however, the question is not whether the series contains a unit root; instead, the question is how the structural shifts should be taken into account.

In this study, both standard univariate (augmented Dickey and Fuller (1981) and Phillips and Perron (1981) tests) and panel (Levin *et al.* 2002 and Im *et al.*, 2003) unit root tests were applied. In all the univariate unit root tests, the null hypothesis of a unit root was rejected at a minimum of 10 per cent level of significance in 17 countries in the case of the variable government budget balance, in 21 countries in the case of the variable current account to GDP, and in 22 countries in the case of real interest rate. However, both panel unit root tests rejected the null hypothesis that all series are non-stationary against an alternative that all series are stationary at a minimum of 10 per cent level of significance in the case of these three variables. In the case of the other variables, both panel unit root tests rejected the null hypothesis at a minimum of 5 per cent level of significance. Therefore, the variables used in the regressions were considered to be stationary or trend stationary.

The hyperinflationary periods were identified with a dummy variable that received value one for the months in which the annual inflation rate exceeded 40 per cent. This definition is consistent with the freely falling exchange rate regime classification by Reinhart and Rogoff (2004). In contrast to many earlier studies, the inflation rate was not used as an explanatory variable, as it was expected to be integrated of order 1 in most cases. In addition, variables such as the interest rate, domestic credit and the GDP were expressed as real series. Some studies exclude hyperinflationary periods from their sample. This would, however, limit the sample considerably and also cause some sample selection issues if the hyperinflationary periods and *de facto* freely falling exchange rate regimes were left out of study. In contrast to some earlier studies, variables, such as (lagged) changes in foreign reserves or changes in exchange rate were left out due to obvious collinearity problems as crises themselves were defined using these variables. Finally, a dummy variable was generated to proxy for contagion effects. Namely, this dummy was set to unity when another country in the same area had experienced a currency crisis within the last three months.

[17] It is important to emphasize that this paper does not aim to investigate the causal relationships between economic fundamentals and currency crises and therefore the abovementioned relationships should not be interpreted as causal relationships.

[18] Some ANN models can be used with non-stationary time series.

4 Empirical frameworks

4.1 Probit model

Consider the binary choice model with a panel data ($i = 1, ..., N; t = 1, ..., T$). The unobservable response variable y^*_{it} can be written in the latent form as follows:

$$y^*_{it} = x_{it}\beta + u_{it} = x_{it}\beta + \alpha_i + \nu_{it}, \tag{4}$$

where the error term u_{it} is disaggregated to the unobserved effect α_i and the general error term ν_{it}. The observed binary variable y_{it} is defined by

$$y_{it} = 1, \text{ if } y^*_i \geq 0 \tag{5}$$
$$y_{it} = 0, \text{ otherwise} \tag{6}$$

In the probit model case, the cumulative distribution is a standard normal:

$$\Pr(y_{it} = 1|x_i, \alpha_i) = \Pr(y_{it} = 1|x_{it}, \alpha_i) = \Phi(x_{it}\beta + \alpha_i) \tag{7}$$

The first equality states that x_{it} is assumed to be strictly exogenous conditional on α_i. Another standard assumption is that the outcomes $y_{it} = y_{i1}, ..., y_{iT}$ are independent conditional on (x_i, α_i). Thus, the density of y_{it} conditional on (x_i, α_i) can be derived:

$$f(y_1, ..., y_T|x_i, \alpha_i; \beta) = \prod_{t=1}^{T} f(y_t|x_{it}, \alpha_i; \beta), \tag{8}$$

where

$$f(y_t|x_t, \alpha; \beta) = \Phi(x_t\beta + \alpha)^{y_t} \left[1 - \Phi(x_t\beta + \alpha)^{1-y_t}\right] \tag{9}$$

Finally, in a random effects panel framework, the unobserved effect α_i conditional on x_i is expected to be normally distributed with:

$$\alpha_i|x_i \sim N(0, \sigma^2_\alpha) \tag{10}$$

However, the assumption of independency of outcomes (i.e. crisis and tranquil periods) is limiting and it can be relaxed by using the formula:

$$\Pr(y_{it} = 1|x_i) = \Pr(y_{it} = 1|x_{it}) = \Phi(x_{it}\beta_\alpha) \tag{11}$$

where $\beta_\alpha = \beta/\left(1 + \sigma^2_\alpha\right)^{1/2}$ is estimated from pooled probit of y_{it} on x_{it} using Huber/White robust standard errors, meaning that the coefficients are average partial effects. Another observation is that most of the independent variables are transformed into growth rates, meaning that if the unobservable effect (country specific effect) is expected to be time invariant, it will be removed through these variable transformations. Indeed, the likelihood ratio test of $\alpha_i = 0$ after a random effects probit model could not have been rejected at conventional levels of significance. This confirmed the chosen approach of estimating the model using pooled panel. Finally, it should be emphasized that the probit (as well as the ANN) models were estimated using lagged independent variables, i.e. the probability of crisis at time t was predicted using information at $t-1$: $\Pr(y_{it} = 1|x_{it-1})$ for the reasons mentioned above.

4.2 General about artificial neural networks

Artificial neural networks (ANN)[19] are multivariate nonlinear nonparametric statistical methods,[20] which have been used since the late 1980s in finance applications and lately in many different economics research contexts, as in forecasting exchange rates, inflation and GDP growth. One of the definitions of ANN is

> ... a neural network is a system composed of many simple processing elements operating in parallel whose function is determined by network structure, connection strengths, and the processing performed at computing elements or nodes. DARPA (1988, 60).

Several distinguishing features of ANNs make them valuable for function approximation, forecasting, pattern recognition and classification tasks. Firstly, ANNs are distribution-free methods. Secondly, ANNs are suitable for problems where the (economic) relationships are not known from the theory or they are difficult to specify. An ANN model is normally composed of several layers of computing elements called nodes (or neurons). Each node receives an input signal from other nodes or external inputs and then, after processing the signals locally through a transfer function, it outputs a transformed signal to the other nodes or gives the final result. The ANN models are characterized by the network architecture: the structure and number of layers, the number of nodes in each layer, how the layers are connected, and how the network is trained.

Many of the above features make the ANN models also subject to criticism. Firstly, the ability and flexibility of ANN models to fit well to the data often raises concerns of 'overfitting'. Secondly, as for many nonlinear models, there exists no 'closed form' solutions for the ANN model, which makes it difficult to interpret the coefficients in the way it is done with linear models. Thirdly, in many cases the optimization algorithms of complex non-linear functions are subject of finding locally optimal solutions instead of globally optimal solutions. Therefore, the ANN models are sometimes called as 'black box' methods despite their sound statistical background.

This study utilizes the most often used ANN model called multi-layer perceptron (MLP), where all the nodes and layers are arranged in a feed-forward manner (see figure 1). The first layer is called the input layer, where the information is received in the ANN. Usually the input layer consists of as many input nodes as there are independent variables. The last layer is called the output layer where the ANN produces its solution.[21] In between, there are one or more hidden layers, which make the ANN models distinctive from other statistical models. Finally, all nodes in the adjoining layers are connected by acyclic arcs from lower to higher layers. Commonly, in the classification studies, one hidden layer structure is used referring to the study of Hornik *et al.* (1989), which shows that an ANN model with a single hidden layer can approximate any continuous function to any desired accuracy. In some cases, however, a two-hidden layer

[19] See Haykin (1999) for a comprehensive theoretical presentation of ANNs. In addition, McNelis (2005) provides an excellent book of ANN applications.

[20] See White (1989) for more details.

[21] The output values from these type of ANNs are the estimates of the Bayesian posterior probabilities.

structure may provide better results, but with the cost of increased number of parameters to be estimated.

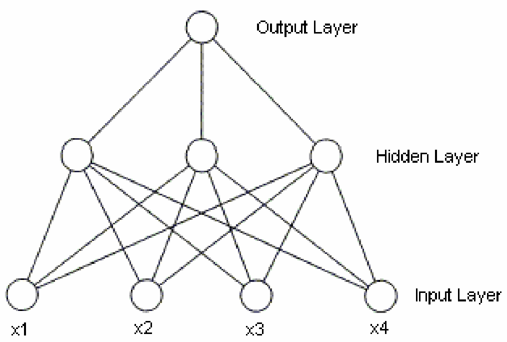

Figure 1: Multilayer-Perceptron ANN.

Like any statistical model, the parameters (arc weights) of the ANN model need to be estimated before it can be used for forecasting purposes. The process of determining these weights is called training. In most of the classification problems, the used training process is supervised where the target response (currency crises in our case) is known *a priori*. The aim of training is to minimize the differences between the ANN output values and the known target values using some loss function e.g. mean square error. The most commonly used training method is the backpropagation (BP) algorithm popularized by Rumelhart *et al.* (1986). After the ANN is trained, its forecasting ability can be tested on another sample. This out-of-sample forecasting is called simulation in the ANN literature.

4.3 ANN model specification

Consider a feed-forward multilayer perceptron ANN model with one hidden layer:[22]

$$\Pr(y_t = 1|x_{ht}) = \Lambda\left(\alpha_0 + \sum_{j=1}^{J}\alpha_j \Lambda\left(\beta_0 + \sum_{h=1}^{H}\beta_{hj}x_{ht-1}\right)\right) = F(x_{ht}, \theta), \quad (12)$$

where $\Pr(y_t = 1|x_t)$ is the probability of a binary outcome $y_t = 1$ conditional on the information set x_t at time t. There are $(h = 1, ..., H)$ input variables x_{ht}, each with a time dimension $(t = 1, ..., T)$, and there are $(j = 1, ..., J)$ nodes α_j in the hidden layer. $\Lambda(a) = \frac{1}{1+\exp(-a)}$ are log-sigmoid transfer functions in both output and hidden layers. α_j and β_{hj} are the network weights and α_0 and β_0 are the network biases. Finally, x_{ht} denotes a matrix of inputs $(H \times T)$, while θ denotes the vector of network weights $\theta = (\alpha_0, \alpha_1, ..., \alpha_J, \beta_0, \beta_{11}, ...\beta_{JH})'$

The most widely used training method for ANN models is the error backpropagation (BP) algorithm, which is a recursive gradient descent method,

[22] See Schumacher et al. (1996) for further details on the comparison of the artificial neural networks and logistic regression.

where the network weights θ are chosen to minimize a loss function, typically the sum of squared errors:

$$\min_{\theta} L = \frac{1}{T}\sum_{t=1}^{T} \left(y_t - \widehat{y}_t\right)^2 , \tag{13}$$

where y_t is the target output, $\widehat{y}_t$ is the estimated output value $\widehat{y}_t = F(x_{ht}, \theta)$ with sample size T. The loss function is iterated until its minimum[23] is achieved. The iterative step of the algorithm takes θ to $\theta + \Delta\theta$, which is calculated as:

$$\Delta\theta = -\pi \nabla F\left(x_{ht}, \theta\right)\left(y_t - F\left(x_{ht}, \theta\right)\right) \tag{14}$$

where π is the learning rate and $\nabla F\left(X_{ht}, \theta\right)$ is the gradient of $F\left(X_{ht}, \theta\right)$ with respect to the weight vector θ.

The standard backpropagation algorithm is often too slow for practical problems. Therefore, a notable faster variation of the BP algorithm, namely the Levenberg-Marquardt (LM) algorithm, was used.[24] The main difference between the standard BP algorithm and the LM algorithm is that the LM algorithm uses an approximation of the Hessian matrix. Otherwise, the network structure was the following: First, the choice of the number of nodes in the hidden layer was based on Hannan-Quinn (HQ criteria)[25] when the model was estimated using a different number of nodes (from 2 to 10). The model was chosen to be as parsimonious as possible to avoid 'overfitting' the model to the data, which would have meant a loss of generalization ability of the model. Therefore, the number of nodes in the hidden layer was set to two ($j = 2$). Second, the learning rate was kept at its default rate of 0.1 ($\pi = 0.1$). Theoretically, a too large learning rate would lead to unstable learning, but a too small learning rate would lengthen the estimation time. Third, the models also contained input delays in order to take into account the sequential time order of the input vectors, i.e. the ANN models were constructed as dynamic models. However, the models were trained in a 'batch mode' with all the input vectors presented to the network before the weights and biases were adjusted.[26] Finally, in order to compare the forecast capability of the ANN models to the probit models, the same independent variables ($h = 19$) and the binary crisis indicator were used in both cases.

[23] The well-known problems of the backpropagation algorithm are its slowness in convergence and its inability to escape from local minima.

[24] In this study, the estimations were repeated several times in order to ensure the convergence of the optimization algoritm. However, ANN model trained with a genetic algoritm could avoid possible problems related to local minima of the loss function minimization. This is left for future study.

[25] Another way of choosing the ANN model is suggested by Anders and Korn (1999). Their 'bottom-up' strategy starts with a simple network infrastructure and adds hidden nodes one at a time to the ANN model until cross validation errors of the more complex model become larger than with the simpler model.

[26] Adaptive learning machine could be constructed for currency crises purposes. This is left for future studies.

5 Empirical results

5.1 Factors affecting to currency crisis

Factors affecting the probability of an emerging market currency crisis were estimated using a probit model with robust standard errors. As mentioned above, the data used was a pooled panel with independent variables lagged by one month.[27] Table 5 in the Appendix presents the marginal effects (slope coefficients) of the economic factors and exchange rate regimes, as well as contagion and area dummies on the probability of currency crisis. All the variables were expressed in natural logarithms with the exception of the real interest rate and the dummy variables allowing the slope coefficients to be interpreted as elasticities. There are four columns in the table: columns 1-3 present the estimates for models that were used for in-sample predictions, while column 4 shows the estimates for the model that was used for the out-of-sample predictions. Column 1 shows the results for the whole sample of 12/1980 - 12/2001, while columns 2 and 3 show the results for the subsamples of 12/1980 - 12/1989 and 1/1990 - 12/2001, respectively. Finally, the model in column 4 was estimated using the sample of 12/1980 - 12/1996. The models were estimated using different subsamples[28] to see whether different factors affected the probability of currency crises in the 1980s and 1990s, and to evaluate the stability of the models. This is because, the liberalization of capital accounts in many of the analyzed countries in the early 1990s is expected to have an impact on the crisis dynamics, as countries have became more exposed to international capital flows.

As can be seen from table 2, the signs of the estimated slopes are in line with currency crisis theories. The economically most significant factors increasing the probability of currency crises are the proxy for contagion effect, the prevailing *de facto* exchange rate regime, an increase in the current account and government budget deficits, a decrease in the real GDP growth rate, as well as regional factors. According to the results for the whole sample (column 1), the proxy for contagion effect is found to have the largest marginal effect.[29] Namely, a currency crisis in the same region within three months is estimated to increase the monthly probability of currency crisis by around 15 per cent. Economically, this effect is significant. In addition, *de facto* rigid (pegged, crawling peg, and to a lesser extent, managed float) exchange rate regimes are associated with a lower probability of currency crises. More specifically, the monthly probability of a currency crisis is estimated to decrease by around 2-4 per cent when a country operates under a rigid exchange rate regime. This result is in line with earlier studies, such as Rogoff *et al.* (2003) and Ghosh *et al.* (2002).

Turning to other economic factors linked to currency crises, a one per cent increase in the level of current account and government budget balance (both to the GDP) is estimated to decrease the monthly probability of currency crisis by around 0.19 per cent and 0.13 per cent, respectively. This means that a one percentage point increase of both ratios from their sample mean values (-2.1 to -1.1 per cent and -2.7 to -1.7 per cent, respectively) would decrease the monthly

[27] All models were estimated also using independent variables lagged by 3 months. The results remained broadly unchanged and are available on request.

[28] The subsamples for 1980s and 1990s have different number of observations due to missing observations.

[29] The dummy for contagion effect is statistically significant only with the independent variables lagged by one month.

probability of a currency crisis by around 9.1 and 4.8 per cents, respectively. Similarly, a one per cent increase in the growth rate of real GDP decreases the probability of a currency crisis around 0.07 per cent. This means that if the annual growth rate of real GDP increases by one percentage point from its sample mean of 4.1 per cent to 5.1 per cent, the monthly probability of currency crisis would decrease by around 1.7 per cent. Furthermore, Asian countries seem to be statistically more prone to currency crises, while, in contrast, European countries seem to be less so. Finally, the marginal effects of the real interest rate and the growth rate of the ratio of broad money to foreign reserves are statistically significant, but economically very small.

The following observations can be made from the results when the subsamples were used (columns 2 and 3). Firstly, it appears that economic fundamentals[30] could statistically better explain the onset of currency crises in the subsample of the 1980s than in subsample of the 1990s.[31] Specifically, more variables from the traditional currency crisis theories seem to be statistically significant in column 2, while in column 3 other variables, such as dummy variables for contagion effect and exchange rate regimes, are statistically significant.[32] In addition, the model for the 1980s subsample has higher goodness-of-fit measures, such as the Pseudo R-square. This confirms earlier findings in the literature that the contagion effect versus economic fundamentals might have played a larger role in the onset of the currency crises in the 1990s. In addition, this also indicates that the liberalization of capital accounts in many of the analyzed countries in the early 1990s has possibly made them more vulnerable to international capital flows than they were in the 1980s. Furthermore, a regional dummy variable for Asia has a positive and statistically significant marginal effect in the sample of the 1990s, while a regional dummy variable for Latin America has a negative and statistically significant marginal effect in the sample of the 1980s. Finally, the slope coefficients of the model in column 4 are in line with the findings from the other subsamples.

To sum up, the analysis shows that certain economic variables were associated with the currency crises of the 1980s and the 1990s, and can have statistically and economically significant impact on the probability of currency crises. It seems that in the 1980s economic fundamentals derived from the currency crisis theories were capable of explaining the onset of the currency crises. In contrast, in the 1990s, other factors, such as the contagion effect and the *de facto* currency regimes, seem to have played a larger role in the occurrence of currency crises. This reinforces the view that developing a stable model that could predict or even explain currency crises can be challenging.

5.2 Issues related to crisis prediction

The ability of models to predict currency crises was evaluated using cross-tabulations of correct classifications, as well as different goodness-of-fit measures, such as Brier's Quadratic Probability Score (QPS), the Receiver Operat-

[30] Also hyperinflation dummy was found to be statistically and economically significant for the 1980s subsample.

[31] It should be noted that in both subsamples, the share of crisis periods was roughly the same: 3.66 percent in the 1980s subsample and 3.72 percent in the 1990s subsample.

[32] When the model was estimated using the subsample of the 1990s and using the independent variables lagged one period (column 3), the marginal effect of currency crisis in the region was estimated to be 0.18 (18 percent).

ing Characteristic (ROC) and Cramer's Gamma. In addition, the in-sample and out-of-sample predicted probabilities for the countries were plotted to illustrate the ability of the models to predict crisis.

Certain issues are related to the evaluation of the predictive ability of the models. First, in the binary choice models, the choice of the probability threshold is critical. As Greene (2000, 833) states, the usual threshold value of 50 per cent may not be a good value if the binary outcomes in the sample are unevenly distributed, as it may lead to a severe understatement of the prediction ability of the model. In the sample used in this study, the share of crisis and tranquil periods were around 3 per cent and 97 per cent, respectively.[33] Therefore, the ability of the model to predict currency crises was evaluated using four different threshold values: 0.50, 0.25, 0.15 and 0.10. Secondly, as mentioned in the introduction, the costs of currency crises can be substantial, and therefore, the costs of giving wrong signals of crises and tranquil periods are asymmetric. Furthermore, as mentioned earlier, according to the second generation of currency crisis, worsening economic fundamentals can expose countries to currency crises although the exact timing of currency crises might be difficult to determine. Therefore, the predictive ability of the models were evaluated separately for two cases. On the one hand, the model was considered to have successfully predicted the crisis if the predicted probability was above the set threshold value at exactly the timing of the crisis. On the other hand, the model was considered to successfully signal the crisis if the predicted probability was above the set threshold within 3 months ($t-3$) before the actual crisis period. Many earlier studies use these 'crisis windows' of 12 or 24 months to 'improve' the predictability of the models. In addition, in some studies, the sample size has been reduced only to cover certain crisis windows. In this study these measures were not applied, as the main purpose of the study was to objectively evaluate whether the estimated models could predict currency crises.

Finally, as both the probit and the ANN model are estimated using the independent variables lagged by one month, in each time, the predicted probability of crisis is a one-month ahead forecasts. However, as in the case of in-sample estimations, the information set is larger than the economic agents had at each time, and therefore, the true predictive power of the models was evaluated using the out-of-sample forecasts.

5.3 Predicting currency crises

The results of the in-sample and out-of-sample forecasts are presented in the Appendix in sections 7.4 and 7.5, while the goodness-of-fit measures are presented in section 7.6. The obtained results are benchmarked to earlier studies in section 7.7. Finally, the graphs of one month ahead predicted probabilities are shown in section 7.8.

The following observations can be made from the in-sample forecasts (tables 6-9). Firstly, the signals of the currency crises are stronger from the ANN model than from the probit model, meaning that predicted probability levels in the crisis periods are higher in the ANN model than in probit model. Therefore, the choice of the threshold value is less relevant in the case of ANN models, while

[33] Bordo et al. (2001) found roughly similar frequency of currency crises in their sample of 1973-1997.

in the probit case, the choice of the threshold is critical. For example, using the threshold value of 0.50, the probit model would have predicted only 5 crises (3.7 per cent of the crises), while the ANN model would have predicted 47 crises (34.6 per cent of the crises). Lowering the threshold value to 0.10 increases the share of predicted crises with the probit model to nearly 48 per cent, while in the case of the ANN model the share of the crises predicted is around 45 per cent between the thresholds of 0.25 and 0.10.

Secondly, the signals of the currency crises are more accurate from the ANN model than from the probit model. This can be seen from the fact that when the threshold value is set lower in, the specificity of the model (the ability of the model to detect tranquil periods) decreases meaning the probit model gives more wrong signals of the crises than the ANN model.

Thirdly, when the signals of crisis are evaluated within a window of $t-3$ to t (tables 8 and 9), it can be seen that part of the 'wrong signals' of the probit model are actually correct signals of the forthcoming crises as the number of predicted crises increases with the probit model. As mentioned earlier, the signals from the ANN model are more accurate and therefore the share of the predicted crises as well as the tranquil periods remains stable.

Fourthly, as noted earlier, the models fit the sample of 1980s (model 2) better than the whole sample (model 1) or the sample of 1990s (model 3) and therefore the share of predicted crises, as well as the other goodness-of-fit measures are the highest with the model 2.

Finally, the goodness-of-fit measures point out that the ANN model fits the data slightly better. All in all, as the in-sample predictions show, both the probit and the ANN model correctly signalled (one month ahead) 4 to 52 per cent of the crises periods depending on the choice of the threshold, meaning that the models fitted the data quite well. This observation is confirmed when the graphs of the predicted probabilities are analyzed (section 7.8, the upper figures). Both the probit and the ANN model seem to correctly signal the Latin American crises at the turn of the 1990s, as well as the Asian crises of 1997 and the Russian crises of 1998. However, the true ability of the models to predict crises need to be evaluated using out-of-sample forecasts and the results from the in-sample forecasts can be thought of only as a measure of goodness-of-fit of the models.

The results from out-of-sample forecasts are shown in tables 10 and 11. Both the probit and the ANN model were estimated using the sample of 12/1980 - 12/1996 and the out-of-sample forecasts were calculated using the sample of 1/1997 - 12/2001. The out-of-sample forecasts were calculated using simple static models, meaning that the coefficients were not re-estimated recursively after each time period. The choice of using a static model to forecast has the drawback that it ignores the latest available information, as the coefficients are not updated after each time period. However, the static models allow us to better evaluate the ability of the model to generalize with different datasets than the recursive model. In addition, the static model also partly alleviates the problem that the interpolation of some variables might cause, namely that the statistician and the economic agent have different information sets available.

Turning to the results, the out-of-sample data contains 56 crises periods[34]

[34]The mean probability of currency crises in the out-of-sample data was slightly higher than in the in-sample subsets of the data, namely 4.38 percent.

of which the models were able to predict a maximum of 4 periods using the lowest threshold value of 0.10. In addition, the other goodness-of-fit measures also point out that the out-of-sample forecasts are not particularly strong. Especially, the Pearson's chi-squared test for the hypothesis that the predicted and actual outcomes (crisis and tranquil periods) are independent could not be rejected in most cases of the out-of-sample predictions, while it was rejected in all cases of the in-sample predictions. However, when the graphs of the out-of-sample forecasts are evaluated, it can be noted that both the probit and the ANN models correctly forecasted the Russian crisis of 1998 out-of-sample. Furthermore, the ANN model was capable of signalling, to some extent, the onset of speculative attacks in Slovakia in 1999 and in Turkey in 2001.

Tables 13 and 14 are constructed to compare the results to some selected earlier papers. Obviously, the comparison of results between different papers is not straightforward as the estimation samples, countries included, the threshold values as well as the crisis windows differ. However, it has become a standard to benchmark the obtained results to the 'signal approach' developed by Kaminsky et al. (1998), as well as to a standard probit model. Both of these models have been estimated by Berg and Pattillo (1999), whose results will be used to benchmark the obtained results. Furthermore, the in-sample fit is also analyzed in contrast to an innovative multinominal logit model by Bussière and Fratzscher (2002), while the out-of-sample forecasting potential is compared to a recent panel probit model by Komulainen and Lukkarila (2003). One should note that only a limited number of earlier studies have reported thoroughly their in- and out-of-sample results, which limits the deep comparison of results to the earlier literature. Furthermore, in most cases the out-of-sample forecasts are limited to case studies, such as in Frank and Schmied (2003) or Scott (2000).

As can be seen from the tables 13 and 14, the obtained results in the in-sample predictions were in line with the earlier papers, while the out-of-sample predictions were found to be much weaker than earlier found in the literature. The relatively strong in-sample performance indicates that the estimated models were correctly specified. Furthermore, as will be discussed in the next section, the results are robust to various modifications of the models. Therefore, the most likely reason for the diverging out-of-sample results from the earlier studies is that the models were required to predict crises truly out-of-sample without using information that was potentially not available to economic agents at the time. In addition, the models were classified as being able to predict crises correctly only if the predicted crisis probabilities were above the set threshold value within a maximum time window of $t-3$ to t. This time window is significantly narrower than in most studies which often use a time window of $t-12$ to t. The use of very wide crisis windows can be questionable on statistical grounds despite they might be economically appealing. In addition, some earlier studies have trimmed the samples to include only a certain number of tranquil period observations around crises in order to rebalance the share of crises in the sample to ease the estimation procedure. Finally, some earlier studies have also adjusted the crisis thresholds, in order to maximize the number of crises predicted. All these factors can explain why the obtained out-of-sample results were weaker than in the earlier literature.

To sum up, early warning indicator models can be useful to identify underlying economic problems associated with currency crises and they can be used explain occurred currency crises *ex post*. However, due to the endogeneity of currency crisis and evolving economic and financial structures in the global economy, finding a stable model to predict currency crises out-of-sample can be a challenging task.

5.4 Robustness of results

The robustness of the results were tested in various ways. Firstly, the currency crises were defined using a different threshold for exchange market pressure index, namely $1.5\sigma_{EMPi}$ instead of $2.0\sigma_{EMPi}$. Secondly, all the separate crises periods were considered as different crises in contrast to the used method that crises within three months were considered as one crisis. Thirdly, all models were estimated using the independent variables lagged by three months instead of the base line models with one month lagged independent variables. Fourthly, the probit models were estimated using random effects specification. Fifthly, the ANN models were estimated using different numbers of nodes in the hidden layer. Finally, all models were estimated using three different subsamples as reported above. All in all, the basic results remained unchanged throughout these robustness tests. It was noted that the biggest problem with the ANN model was that the training algorithm could sometimes not find the global minimum of the loss function, which is a well-known problem of backpropagation algorithms. However, the training of the ANN model with a global search method, such as genetic algorithms, is left for future studies.

6 Conclusion

The purpose of this study was to examine the predictability of the emerging market currency crises of the last two decades with two models, namely a often used probit model and a multi-layer perceptron Artificial Neural Network model. This paper is one of the first applications of the artificial neural networks in the currency crisis literature context. Furthermore, factors affecting currency crises were evaluated with a special focus on the economic fundamentals derived from the currency crises theories, as well as on *de facto* exchange rate regime and contagion effects. According to the results, both the probit and the ANN models were able to signal in-sample correctly around 45 per cent of the emerging market currency crises of the 1980s and 1990s. In addition, it was found that economic fundamentals could statistically better explain the onset of currency crises in the subsample of the 1980s than in subsample of the 1990s, where other variables, such as the contagion effect, were found to be statistically significant. This verifies the earlier findings in the literature that the contagion effect versus economic fundamentals might have a larger role in the onset of the currency crises in the 1990s than in the 1980s. Furthermore, our findings confirmed the results of Rogoff *et al.* (2003) and Ghosh *et al.* (2002) that emerging markets with more rigid exchange rate regimes were less prone to currency crises during the last two decades. In contrast to the findings in the earlier currency crises literature, the ability of the models to signal currency crises out-of-sample was found to be weak. In particular, of the currency crises of late 1990s, only the Russian 1998 crisis could have been predicted out-of-sample. It also reinforces the view that developing a stable model that can predict currency crises is a challenging task.

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7 Appendix

7.1 Data sources and transformations

Table 2 shows the data sources and sample period of the variables that were used to construct the crisis indicator and the independent variables. In the table, IFS refers to the IMF International Financial Statistics 2/2005, JPMorgan refers to JPMorgan's Real Effective Exchange Rate (REER) accessed at www.morganmarkets.com. Finally, GFD refers to Global Financial Data Inc., which database was accessed at www.globalfindata.com.

Variables for crisis index	Source	Frequency, period
Exchange rate national currency per U.S. dollar	IMF IFS line AE	Monthly, 1980:1 - 2001:12
Total reserves minus gold	IMF IFS line 1L.D	Monthly, 1980:1 - 2001:12

Variables for independent variables	Source	Frequency, period
Gross Domestic Product	IMF IFS line 99B	Annual, 1980 - 2001
GDP deflator	IMF IFS line 99BIP	Annual, 1980 - 2001
Current Account	IMF IFS line 78ALD	Annual, 1980 - 2001
Government budget balance	IMF IFS line 80	Annual, 1980 - 2001
Domestic credit	IMF IFS line 32	Monthly, 1980:1 - 2001:12
Money	IMF IFS line 34	Monthly, 1980:1 - 2001:12
Quasi-money	IMF IFS lines 35	Monthly, 1980:1 - 2001:12
Consumer Prices	IMF IFS line 64	Monthly, 1980:1 - 2001:12
Changes in consumer prices	IMF IFS line 64.X	Monthly, 1980:1 - 2001:12
Real Effective Exchange Rate (REER)	IMF IFS line REC / JPMorgan	Monthly, 1980:1 - 2001:12
Composite stock index	GFD / IMF IFS line 62	Monthly, 1980:1 - 2001:12
Deposit rate	IMF IFS line 60L	Monthly, 1980:1 - 2001:12
Exchange rate regime (*de facto*)	Reinhart and Rogoff (2004)	Monthly, 1980:1 - 2001:12

Table 2: Data sources and frequencies.

The following data conversions were made. Firstly, the annual data observations: the GDP, the GDP deflator, current account and government budget balance were linearly interpolated into monthly frequency. Secondly, JPMorgan REER was used in the following cases: Argentina, Egypt, India, Indonesia, Korea, Mexico, Peru, Thailand, and Turkey. In all other cases, the data from IFS was used. In addition, some observations (numbers in parenthesis) of REER were linearly interpolated in the following countries: Morocco (4 obs.), Poland (1 obs.), and Venezuela (5 obs.). The measure of under or overvaluation of REER was calculated subtracting from REER the trend, which was calculated using the Hodrick-Prescott filter with a parameter of 14400. Thirdly, stock market indices were taken from Global Financial Data Inc. with the exception of Brazil, in which case, data from IFS was used. In Morocco 6 observations were linearly interpolated. Fourthly, in case of Hungary, Money, Quasi-Money and Domestic credit were available on quarterly basis 12/1987 - 12/1997 and therefore the missing observations (49 obs. per variable) for this period were linearly interpolated. Fifthly, the real interest rate was calculated using deposit rate subtracted by consumer price inflation. In the case of India, money market rate was used instead. Finally, GDP deflator was missing for Russia and therefore the CPI was used to deflate the Russian GDP.

7.2 Descriptive statistics

Table 3 shows the descriptive statistics of the variables in levels. In the models, all variables were expressed in natural logarithms with the exception of real interest rate and the dummy variables. Furthermore, real GDP, real domestic credit, ratio of broad money to foreign reserves and stock market composite index were expressed as annualized growth rates. Table 4 presents the countries, the number of observations, the number of crises and tranquil periods and the share of crises of the total number of crises in each country.

Variable	Obs	Mean	Std. Dev.	Min	Max
Crisis indicator	3706	0.0366972	0.1880428	0	1
Ratio of government budget balance to GDP	3706	-0.0273134	0.0365802	-0.2608266	0.0525756
Ratio of current account to GDP	3706	-0.0208352	0.0463155	-0.2093936	0.1829959
Measure of under or overvaluation of REER	3706	0.0005456	0.0686768	-0.5418338	0.7379388
Real interest rate	3706	0.082609	14.45685	-163.7298	504.7866
Real GDP	3706	4.65E+13	2.12E+14	1.45E+08	1.25E+15
Real domestic credit	3706	1.46E+13	7.46E+13	1.196855	8.29E+14
Ratio of broad money to foreign reserves	3706	6.496915	10.01548	0.8051434	134.3178
Stock market composite index	3706	2351.651	9322.714	1.36E-10	336200.8
Dummy for hyperinflation	3706	0.1681058	0.3740107	0	1
Dummy for contagion	3706	0.0099838	0.0994324	0	1
Dummy for *de facto* pegged FX regime	3706	0.1573125	0.3641442	0	1
Dummy for *de facto* crawling ped FX regime	3706	0.3354021	0.4721945	0	1
Dummy for *de facto* managed float FX regime	3706	0.2884512	0.4531032	0	1
Dummy for *de facto* floating FX regime	3706	0.0348084	0.183319	0	1
Dummy for *de facto* freely falling FX regime	3706	0.1643281	0.3706231	0	1
Dummy for Latin America	3706	0.3472747	0.4761682	0	1
Dummy for Europe	3706	0.1511063	0.3582008	0	1
Dummy for Asia	3706	0.361306	0.4804438	0	1
Dummy for Africa	3706	0.140313	0.3473584	0	1

Table 3: Descriptive statistics of original variables.

Country	Frequency	Crises	Tranquil	Crises %
Argentina	192	8	184	4.17
Brazil	194	14	180	7.22
Chile	240	3	237	1.25
Colombia	130	6	124	4.62
Czech Republic	95	3	92	3.16
Ecuador	93	8	85	8.60
Egypt	95	0	95	0.00
Hungary	76	0	76	0.00
India	244	5	239	2.05
Indonesia	220	6	214	2.73
Israel	216	15	201	6.94
Korea	204	3	201	1.47
Malaysia	178	9	169	5.06
Mexico	58	0	58	0.00
Morocco	91	2	89	2.20
Peru	167	6	161	3.59
Philippines	242	17	225	7.02
Poland	90	1	89	1.11
Russia	72	1	71	1.39
Slovakia	60	1	59	1.67
South Africa	118	3	115	2.54
Thailand	251	10	241	3.98
Turkey	167	6	161	3.59
Venezuela	213	9	204	4.23
Total	3706	136	3570	3.67

Table 4: List of countries and frequencies of crises and tranquil periods.

7.3 Factors affecting to currency crisis

Dependent variable: binary currency crisis indicator	Models for in-sample predictions			Out-of-sample predictions
Independent variables (t-1), marginal effects:	1	2	3	4
	12/1980 - 12/2001	12/1980 - 12/1989	1/1990 - 12/2001	12/1980 - 12/1996
Goverment budget balance to GDP	-0.13559**	-0.11911**	0.0750	-0.22254***
	[0.05705]	[0.05597]	[0.11174]	[0.06392]
Current account to GDP	-0.18799***	-0.19525***	-0.0853	-0.0643
	[0.06154]	[0.08788]	[0.07842]	[0.08246]
Over/undervaluation of REER	0.0333	0.07626**	0.0051	0.07319**
	[0.02383]	[0.04032]	[0.02839]	[0.03684]
Real interest rate	0.00031**	0.00052*	0.00034***	0.00024**
	[0.00013]	[0.00032]	[0.00012]	[0.00012]
Growth rate of real GDP	-0.07459**	-0.10466**	-0.07843**	-0.1036
	[0.03271]	[0.05197]	[0.03358]	[0.07167]
Growth rate of real domestic credit	0.0019	0.0019	0.0026	0.0011
	[0.00159]	[0.00210]	[0.00189]	[0.00169]
Growth rate of broad money to foreign reserves	0.00368**	0.0028	0.0020	0.00419*
	[0.00167]	[0.00194]	[0.00246]	[0.00214]
Growth rate of stock market	0.0000	-0.0005	-0.0003	0.0022
	[0.00033]	[0.00209]	[0.00038]	[0.00190]
Hyperinflation	0.0102	0.03445***	-0.0055	0.03051**
	[0.00932]	[0.02026]	[0.00828]	[0.01703]
Contagion	0.15015***		0.18352***	0.1128**
	[0.07144]		[0.08577]	[0.08680]
Pegged FX regime	-0.0292***	0.0074	-0.03587***	-0.0074
	[0.00400]	[0.01119]	[0.00484]	[0.00997]
Crawling peg FX regime	-0.04378***	-0.0053	-0.04397***	-0.0083
	[0.00691]	[0.00761]	[0.00654]	[0.00962]
Managed floating FX regime	-0.0221***	0.02101*	-0.03487***	0.0074
	[0.00555]	[0.01666]	[0.00732]	[0.01248]
Floating FX regime	-0.0119		-0.0147	
	[0.00641]		[0.00615]	
Latin America	-0.0047	-0.01992***	0.0204	-0.0097
	[0.00725]	[0.00878]	[0.01439]	[0.00780]
Europe	-0.01948***		-0.0020	-0.0141
	[0.00487]		[0.01188]	[0.00696]
Asia	0.02969***	-0.0147	0.05807***	-0.0045
	[0.01096]	[0.01189]	[0.02205]	[0.01040]
Observations	3706	1010	2662	2375
Log-likelihood	-481.09498	-100.74794	-348.60976	-288.77926
Pseudo R2	0.1747	0.3650	0.1759	0.1747
Wald statistics β=0	176.92	114.80	140.09	114.36
P-value	0.0000	0.0000	0.0000	0.0000

Robust standard errors (cluster) in brackets, * significant at 10%; ** significant at 5%; *** significant at 1%, marginal effects are evaluated at the mean of the independent variables. For continuos variables, the reported marginal effects are elasticities, for dummy variables, the marginal effects denote the shift from value 0 to 1. All models included linear and quadratic time trends. Dummy variables for contagion, floating FX regime and European countries for samples 12/1980-12/1989 are dropped due to time invariance, missing observations or collinearity. Similarly, floating FX regime is dropped for the model 4 for the same reasons.

Table 5: Probit model estimates.

7.4 In-sample forecasts of currency crisis probabilities

	Number of crises predicted	Share of predicted crises	Sensitivity Pr(crisis>th) | crisis	Specificity Pr(crisis<th) | tranquil	Share of correctly classfied obs	Pearson Chi square test	P-value	Cramer's V
Model 1								
Threshold (th)								
0.10	65	47.79 %	47.79 %	93.00 %	91.34 %	280.2913	0.000	0.2750
0.15	47	34.56 %	34.56 %	97.12 %	94.82 %	341.1984	0.000	0.3034
0.25	26	19.12 %	19.12 %	99.30 %	96.36 %	327.4237	0.000	0.2972
0.50	5	3.68 %	3.68 %	100.00 %	96.47 %	131.4273	0.000	0.1883
Model 2								
Threshold (th)								
0.10	21	56.76 %	56.76 %	95.79 %	94.36 %	170.7912	0.000	0.4112
0.15	21	56.76 %	56.76 %	97.53 %	96.04 %	246.7961	0.000	0.4943
0.25	18	48.65 %	48.65 %	98.56 %	96.73 %	258.9473	0.000	0.5063
0.50	13	35.14 %	35.14 %	99.69 %	97.33 %	277.3045	0.000	0.5240
Model 3								
Threshold (th)								
0.10	46	46.46 %	46.46 %	92.12 %	90.42 %	167.9580	0.000	0.2512
0.15	34	34.34 %	34.34 %	97.27 %	94.93 %	253.7284	0.000	0.3087
0.25	19	19.19 %	19.19 %	99.53 %	96.54 %	290.3311	0.000	0.3302
0.50	8	8.08 %	8.08 %	99.84 %	96.43 %	133.3936	0.000	0.2239

Model 1 refers to an estimation sample of 12/1980 - 12/2001, model 2 to a sample of 12/1980 - 12/1989 and model 3 to a sample of 1/1990 - 12/2001.

Table 6: Probit model in-sample forecasts, exact timing of crisis predicted correctly.

	Number of crises predicted	Share of predicted crises	Sensitivity Pr(crisis>th) | crisis	Specificity Pr(crisis<th) | tranquil	Share of correctly classfied obs	Pearson Chi square test	P-value	Cramer's V
Model 1								
Threshold (th)								
0.10	62	45.59 %	45.59 %	99.16 %	97.19 %	1100.0000	0.000	0.5407
0.15	62	45.59 %	45.59 %	99.24 %	97.27 %	1100.0000	0.000	0.5506
0.25	61	44.85 %	44.85 %	99.33 %	97.33 %	1100.0000	0.000	0.5549
0.50	47	34.56 %	34.56 %	99.94 %	97.54 %	1200.0000	0.000	0.5679
Model 2								
Threshold (th)								
0.10	28	75.68 %	75.68 %	95.79 %	95.05 %	285.9871	0.000	0.5321
0.15	23	62.16 %	62.16 %	99.69 %	98.32 %	543.7519	0.000	0.7337
0.25	23	62.16 %	62.16 %	99.69 %	98.32 %	543.7519	0.000	0.7337
0.50	23	62.16 %	62.16 %	99.79 %	98.41 %	566.8068	0.000	0.7491
Model 3								
Threshold (th)								
0.10	42	42.42 %	42.42 %	99.10 %	96.99 %	690.0247	0.000	0.5091
0.15	42	42.42 %	42.42 %	99.34 %	97.22 %	767.0198	0.000	0.5368
0.25	42	42.42 %	42.42 %	99.53 %	97.41 %	844.2664	0.000	0.5632
0.50	41	41.41 %	41.41 %	99.61 %	97.45 %	853.6705	0.000	0.5663

Model 1 refers to an estimation sample of 12/1980 - 12/2001, model 2 to a sample of 12/1980 - 12/1989 and model 3 to a sample of 1/1990 - 12/2001.

Table 7: ANN model in-sample forecasts, exact timing of crisis predicted correctly.

	Number of crises predicted	Share of predicted crises	Sensitivity Pr(crisis>th) | crisis	Specificity Pr(crisis<th) | tranquil	Share of correctly classfied obs	Pearson Chi square test	P-value	Cramer's V
Model 1								
Threshold (th)								
0.10	71	52.21 %	47.79 %	94.53 %	88.48 %	1400.0000	0.000	0.4312
0.15	55	40.44 %	34.56 %	98.17 %	90.53 %	1100.0000	0.000	0.384
0.25	30	22.06 %	19.12 %	99.52 %	90.31 %	536.9549	0.000	0.2692
0.50	5	3.68 %	3.68 %	100.00 %	89.94 %	131.4273	0.000	0.1883
Model 2								
Threshold (th)								
0.10	25	67.57 %	56.76 %	97.66 %	90.79 %	517.0086	0.000	0.5059
0.15	22	59.46 %	56.76 %	98.77 %	91.09 %	521.0565	0.000	0.5079
0.25	22	59.46 %	48.65 %	99.33 %	90.79 %	453.4256	0.000	0.4738
0.50	13	35.14 %	35.14 %	99.78 %	90.00 %	309.5407	0.000	0.3915
Model 3								
Threshold (th)								
0.10	48	48.48 %	46.46 %	92.99 %	86.74 %	728.3261	0.000	0.3699
0.15	38	38.38 %	34.34 %	97.96 %	90.27 %	651.1157	0.000	0.3497
0.25	20	20.20 %	19.19 %	99.71 %	90.69 %	428.1128	0.000	0.2836
0.50	9	9.09 %	8.08 %	99.87 %	90.27 %	161.9941	0.000	0.1744

Model 1 refers to an estimation sample of 12/1980 - 12/2001, model 2 to a sample of 12/1980 - 12/1989 and model 3 to a sample of 1/1990 - 12/2001.

Table 8: Probit model in-sample forecasts, timing of crisis predicted within t-3 and t.

	Number of crises predicted	Share of predicted crises	Sensitivity Pr(crisis>th) | crisis	Specificity Pr(crisis<th) | tranquil	Share of correctly classfied obs	Pearson Chi square test	P-value	Cramer's V
Model 1								
Threshold (th)								
0.10	63	46.32 %	45.59 %	99.64 %	91.64 %	1600.0000	0.000	0.4689
0.15	63	46.32 %	45.59 %	99.64 %	91.55 %	1600.0000	0.000	0.4626
0.25	62	45.59 %	44.85 %	99.67 %	91.50 %	1600.0000	0.000	0.4574
0.50	47	34.56 %	34.56 %	100.00 %	91.12 %	1300.0000	0.000	0.4153
Model 2								
Threshold (th)								
0.10	30	81.08 %	75.68 %	96.88 %	90.10 %	522.6972	0.000	0.5087
0.15	23	62.16 %	62.16 %	99.78 %	90.99 %	579.0866	0.000	0.5354
0.25	23	62.16 %	62.16 %	99.78 %	90.99 %	579.0866	0.000	0.5354
0.50	23	62.16 %	62.16 %	99.78 %	90.89 %	566.8212	0.000	0.7491
Model 3								
Threshold (th)								
0.10	43	43.43 %	42.42 %	99.46 %	91.51 %	978.5009	0.000	0.4287
0.15	42	42.42 %	42.42 %	99.62 %	91.58 %	1000.0000	0.000	0.4374
0.25	42	42.42 %	42.42 %	99.79 %	91.70 %	1100.0000	0.000	0.4515
0.50	42	42.42 %	41.41 %	99.79 %	91.58 %	1000.0000	0.000	0.4396

Model 1 refers to an estimation sample of 12/1980 - 12/2001, model 2 to a sample of 12/1980 - 12/1989 and model 3 to a sample of 1/1990 - 12/2001.

Table 9: ANN model in-sample forecasts, timing of crisis predicted within t-3 and t.

7.5 Out-of-sample forecasts of currency crisis probabilities

	Number of crises predicted	Share of predicted crises	Sensitivity Pr(crisis>th) | crisis	Specificity Pr(crisis<th) | tranquil	Share of correctly classfied obs	Pearson Chi-squared test	P-value	Cramer's V
Model 4 probit								
Threshold (th)								
0.10	3	5.36 %	5.36 %	98.61 %	94.52 %	5.4674	0.019	0.0654
0.15	1	1.79 %	1.79 %	99.75 %	95.46 %	4.0712	0.044	0.0564
0.25	0	0.00 %	0.00 %	99.92 %	95.54 %	0.0459	0.830	-0.0060
0.50	0	0.00 %	0.00 %	100.00 %	95.62 %	.	.	.
Model 4 ANN								
Threshold (th)								
0.10	1	1.79 %	1.79 %	99.18 %	94.91 %	0.5872	0.443	0.0214
0.15	1	1.79 %	1.79 %	99.35 %	95.08 %	0.9796	0.322	0.0277
0.25	1	1.79 %	1.79 %	99.35 %	95.08 %	0.9796	0.322	0.0277
0.50	1	1.79 %	1.79 %	99.67 %	95.38 %	2.9224	0.087	0.0478

Model 4 refers to a forecasting sample of 1/1997 - 12/2001.

Table 10: Out-of-sample forecasts for probit and ANN models, exact timing of crisis predicted correctly.

	Number of crises predicted	Share of predicted crises	Sensitivity Pr(crisis>th) | crisis	Specificity Pr(crisis<th) | tranquil	Share of correctly classfied obs	Pearson Chi-squared test	P-value	Cramer's V
Model 4 probit								
Threshold (th)								
0.10	4	7.14 %	5.36 %	98.77 %	88.65 %	52.4617	0.000	0.1433
0.15	1	1.79 %	1.79 %	99.74 %	89.13 %	4.2388	0.120	0.0576
0.25	0	0.00 %	0.00 %	99.91 %	89.20 %	0.1202	0.942	0.0097
0.50	0	0.00 %	0.00 %	100.00 %	89.28 %	.	.	.
Model 4 ANN								
Threshold (th)								
0.10	2	3.57 %	1.79 %	99.30 %	88.89 %	31.0851	0.000	0.1103
0.15	2	3.57 %	1.79 %	99.47 %	89.04 %	31.6118	0.000	0.1112
0.25	2	3.57 %	1.79 %	99.47 %	89.04 %	31.6118	0.000	0.1112
0.50	1	1.79 %	1.79 %	99.74 %	89.20 %	19.0219	0.001	0.0863

Model 4 refers to a forecasting sample of 1/1997 - 12/2001.

Table 11: Out-of-sample forecast for probit and ANN models, timing of crisis predicted within t-3 and t.

7.6 Goodness-of-fit measures

	In-sample			Out-of-sample
	1	2	3	4
Probit model	12/1980 - 12/2001	12/1980 - 12/1989	1/1990 - 12/2001	1/1997 - 12/2001
Mean probability of outcome (crisis)	0.0367	0.0366	0.0372	0.0438
Mean probability of forecast	0.0367	0.0367	0.0370	0.0145
ROC area	0.7841	0.8758	0.7866	0.6335
Brier Quadratic Probability Score	0.0307	0.0239	0.0313	0.0420
Sander's modified Quadratic Probability Score	0.0326	0.0300	0.0334	0.0420
Spiegelhalter's z-statistic	-0.5005	-0.1934	-0.1576	8.9898
P-value	0.6916	0.5767	0.5626	0.0000
ANN model				
Mean probability of outcome (crisis)	0.0367	0.0366	0.0372	0.0438
Mean probability of forecast	0.0174	0.0293	0.0363	0.0068
ROC area	0.7226	0.8671	0.7115	0.4687
Brier Quadratic Probability Score	0.0231	0.0155	0.0243	0.0459
Sander's modified Quadratic Probability Score	0.0284	0.0273	0.0287	0.0442
Spiegelhalter's z-statistic	55.9788	6.1077	0.5507	33.1186
P-value	0.0000	0.0000	0.2909	0.0000

Table 12: Goodness-of-fit measures.

7.7 Comparison of results

	Probit[1]	**ANN**[1]	KLR signal[2]	BP probit[2]	BF multin. logit[3]
Share of observations correctly classified	90.3 %	91.5 %	77.0 %	81.0 %	83.9 %
Share of crises correctly classified	22.1 %	45.6 %	41.0 %	44.0 %	73.7 %
Share of tranquil periods correctly classified	99.5 %	99.7 %	85.0 %	89.0 %	95.0 %
Share of false alarms of total alarms	41.2%+	26.2%++	63.0 %	57.0 %	44.1 %

1) Threshold 25%. (Pre)crisis period is correctly classified when the estimated probability of crisis is above the cut-off probability and a crisis ensues within 3 months. Estimation sample: 12/1980 - 12/2001 with 24 countries.
+ There were a total of 51 alarms of which 21 were incorrect, ++ there were a total of 84 alarms of which 22 were incorrect.
2) Source: Berg and Pattillo (1999), page 570 with a threshold 25%. KLR refers to Kaminsky et al. (1998), while BP probit refers to Berg and Patillo (1999). (Pre)crisis period is correctly classified when the estimated probability of crisis is above the cut-off probability and a crisis ensues within 24 months. Estimation sample: 1/1970 - 4/1995 with 23 countries.
3) Source: Bussière and Fratzscher (2002), page 25 with a threshold of 20%. (Pre)crisis period is correctly classified when the estimated probability of crisis is above the cut-off probability and a crisis ensues within 12 months. Estimation sample: 12/1993 - 9/2001 with 20 countries.

Table 13: Comparision of in-sample fit to selected earlier papers.

	Probit[1]	**ANN**[1]	KLR signal[2]	BP probit[2]	KL RE probit[3]
Share of observations correctly classified	89.2 %	89.0 %	69.0 %	76.0 %	89.2 %
Share of crises correctly classified	0.0 %	3.6 %	25.0 %	16.0 %	50.0 %
Share of tranquil periods correctly classified	99.9 %	99.5 %	85.0 %	93.0 %	95.2 %
Share of false alarms of total alarms	100%*	71.4%**	63.0 %	61.0 %	10.0 %

1) Threshold 25%. (Pre)crisis period is correctly classified when the estimated probability of crisis is above the cut-off probability and a crisis ensues within 3 months. Forecasting sample: 1/1997 - 12/2001 with 24 countries.
* There was only 1 alarm, which was incorrect, ** there were 7 signals of which 5 were incorrect.
2) Source: Berg and Pattillo (1999), page 576 with a threshold 25%. KLR refers to Kaminsky et al. (1998), while BP probit refers to Berg and Patillo (1999). (Pre)crisis period is correctly classified when the estimated probability of crisis is above the cut-off probability and a crisis ensues within 24 months. Forecasting sample: 5/1995 - 12/1997 with 23 countries.
3) Source: Komulainen and Lukkarila (2003), page 259 with a threshold of 25%. (Pre)crisis period is correctly classified when the estimated probability of crisis is above the cut-off probability and a crisis ensues within 12 months. Forecasting sample: 1/1997 - 12/2001 with 31 countries.

Table 14: Comparision of out-of-sample forecasts to selected earlier papers.

7.8 Graphs of in- and out-of-sample forecasts

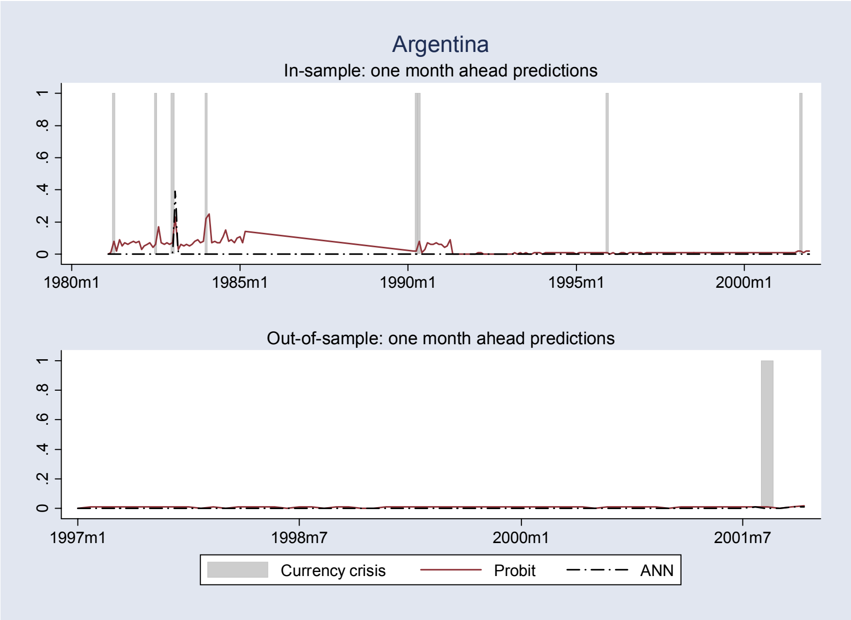

Figure 2: Currency crisis predictions for Argentina.

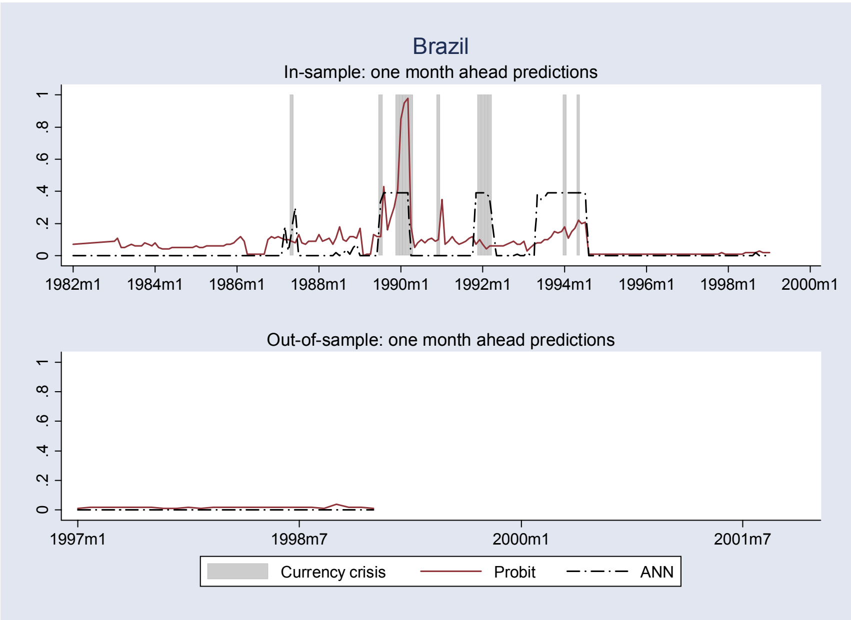

Figure 3: Currency crisis predictions for Brazil.

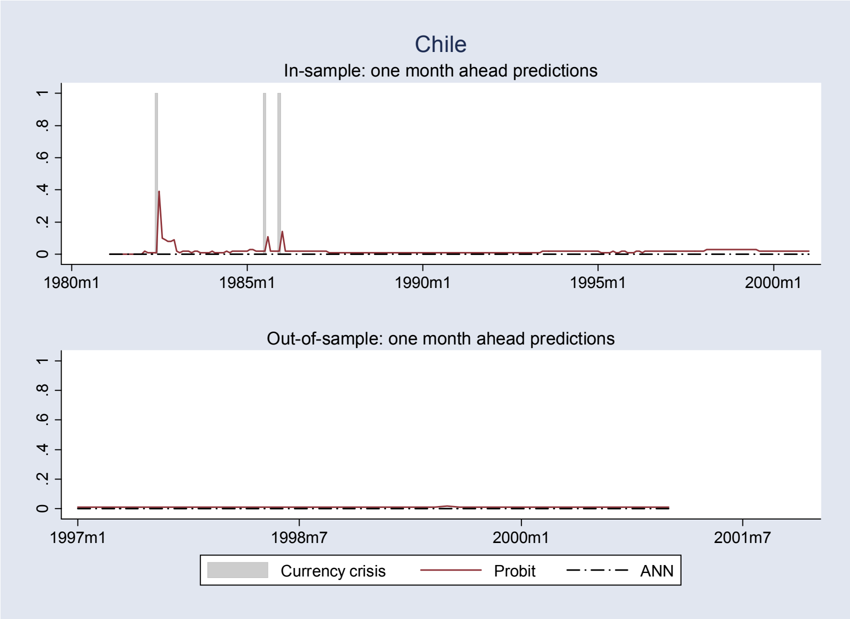

Figure 4: Currency crisis predictions for Chile.

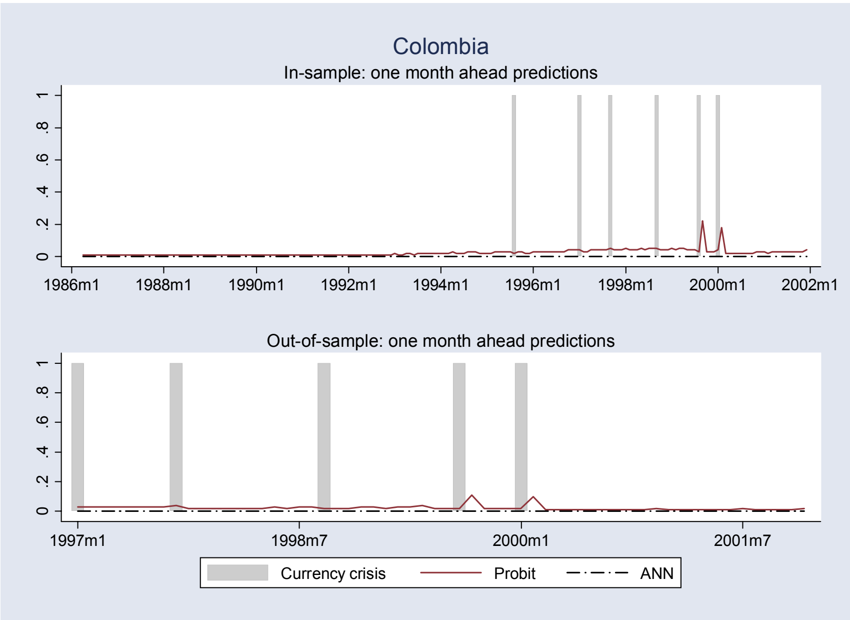

Figure 5: Currency crisis predictions for Colombia.

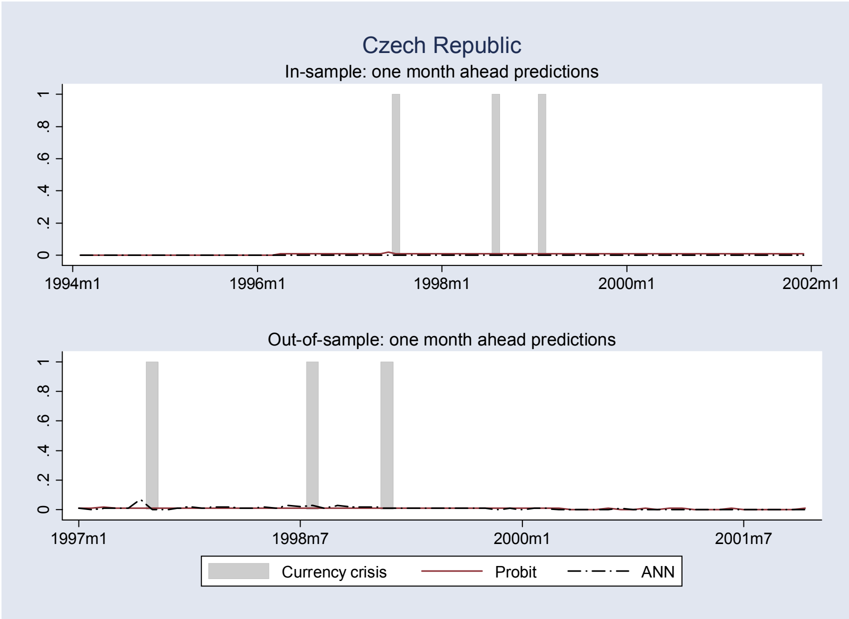

Figure 6: Currency crisis predictions for Czech Republic.

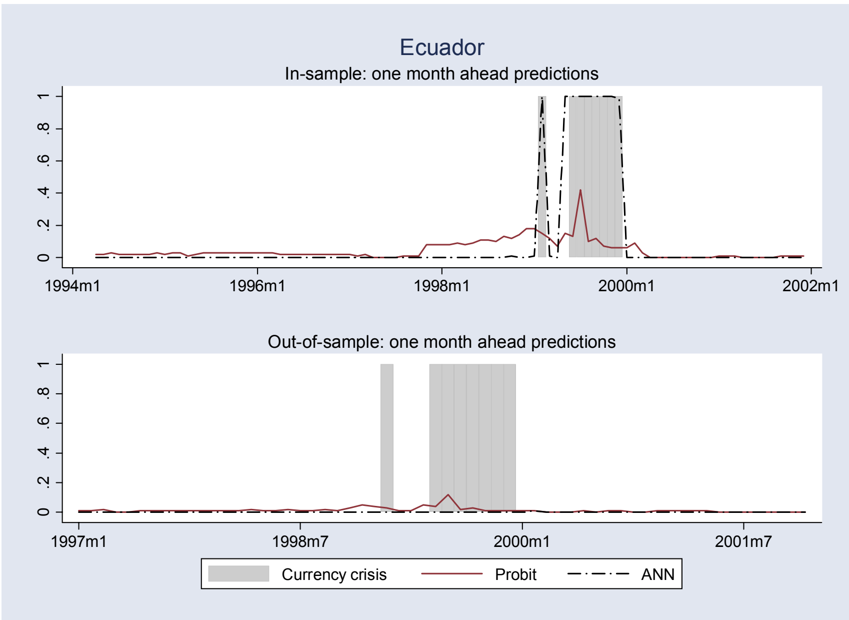

Figure 7: Currency crisis predictions for Ecuador.

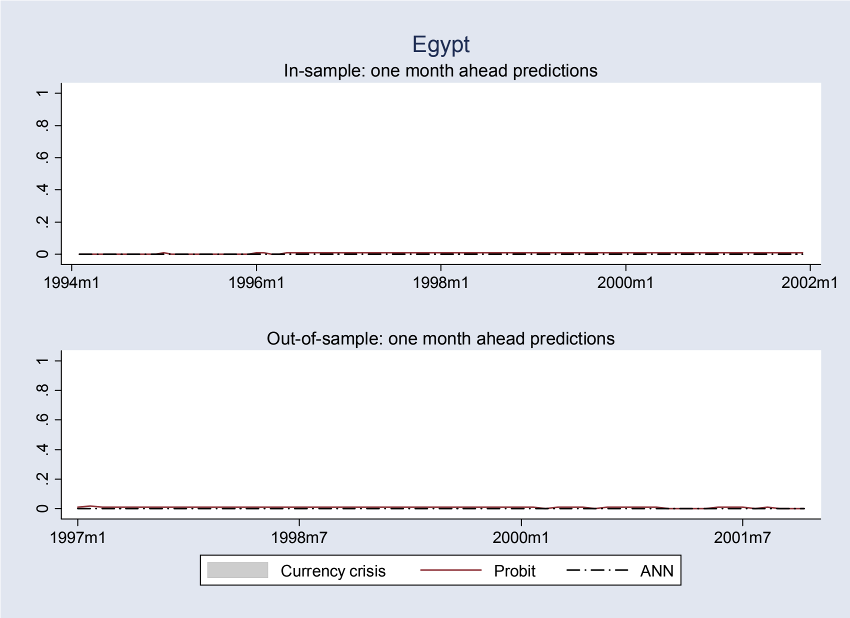

Figure 8: Currency crisis predictions for Egypt.

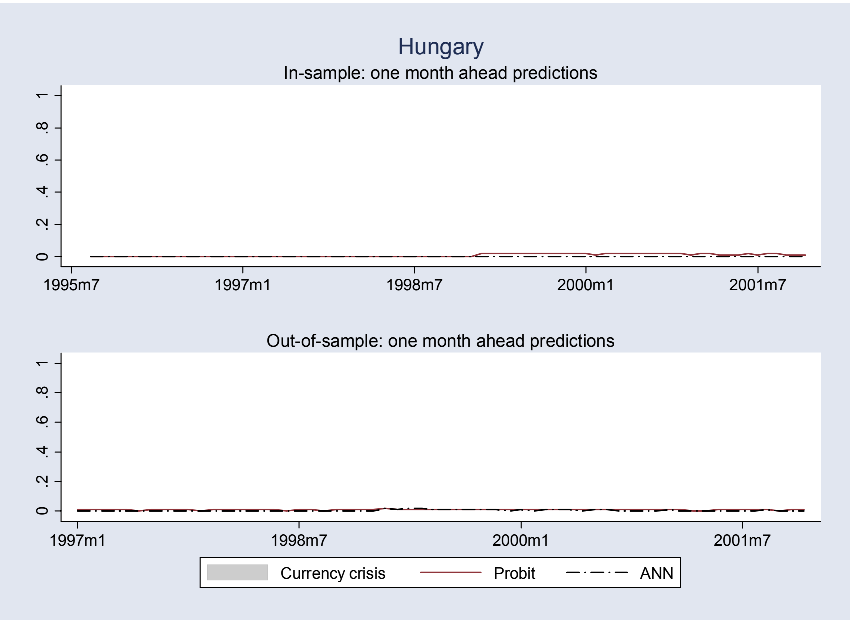

Figure 9: Currency crisis predictions for Hungary.

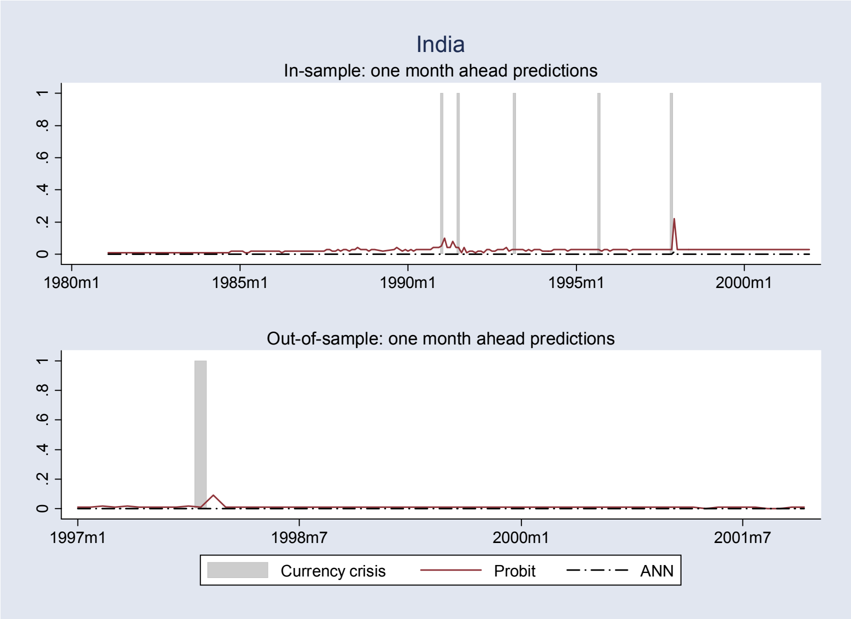

Figure 10: Currency crisis predictions for India.

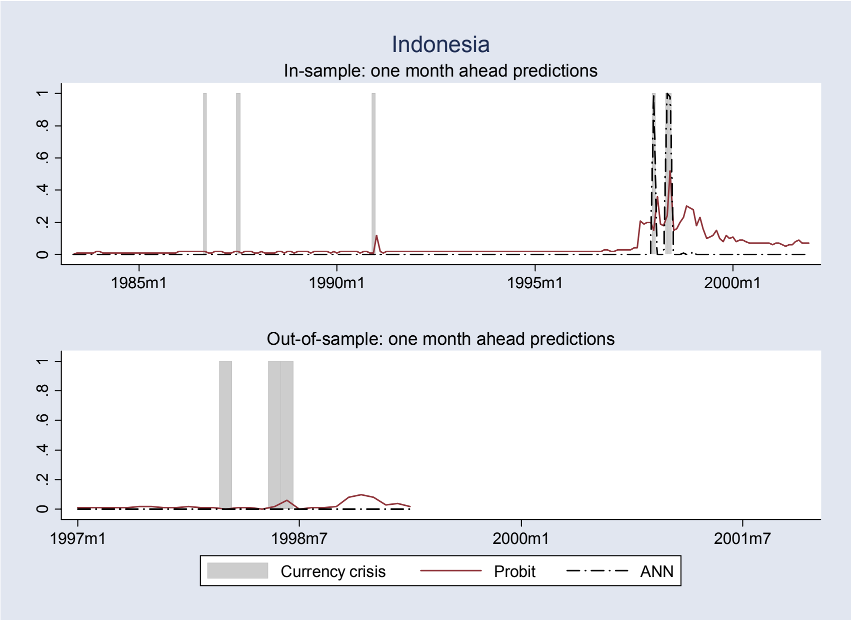

Figure 11: Currency crisis predictions for Indonesia.

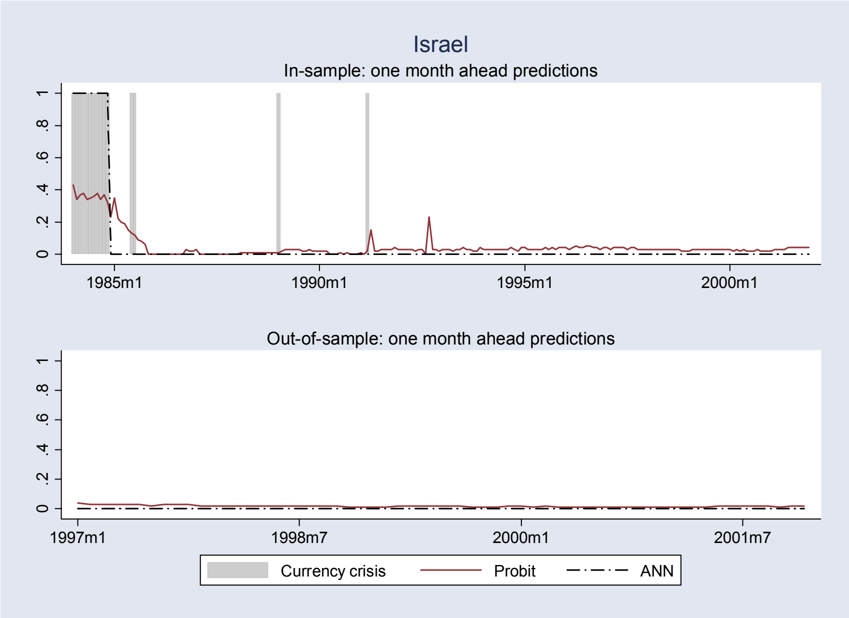

Figure 12: Currency crisis predictions for Israel.

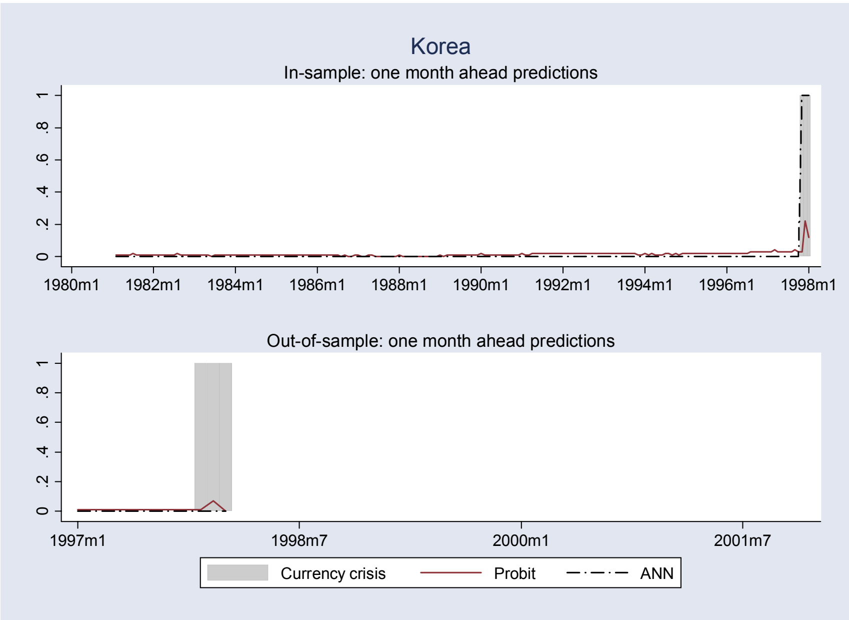

Figure 13: Currency crisis predictions for Korea.

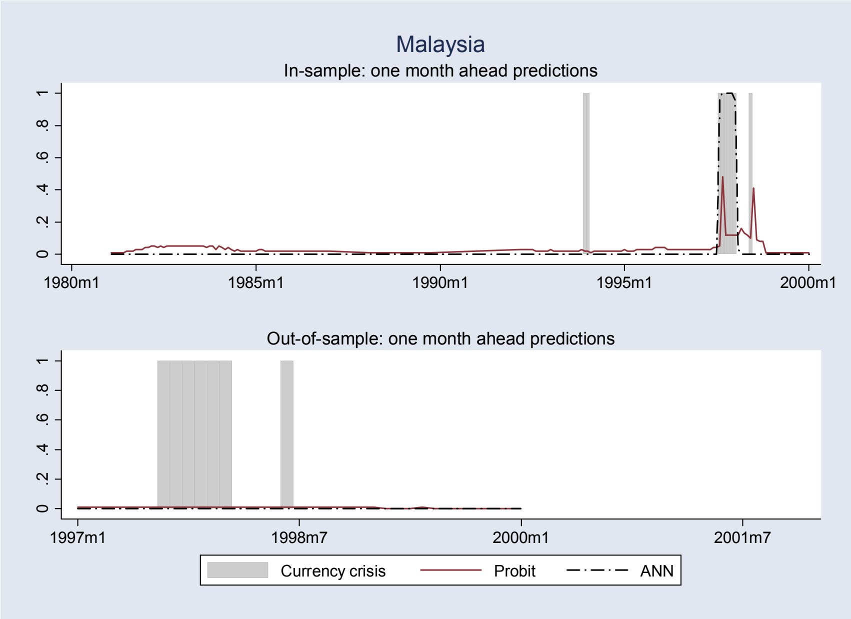

Figure 14: Currency crisis predictions for Malaysia.

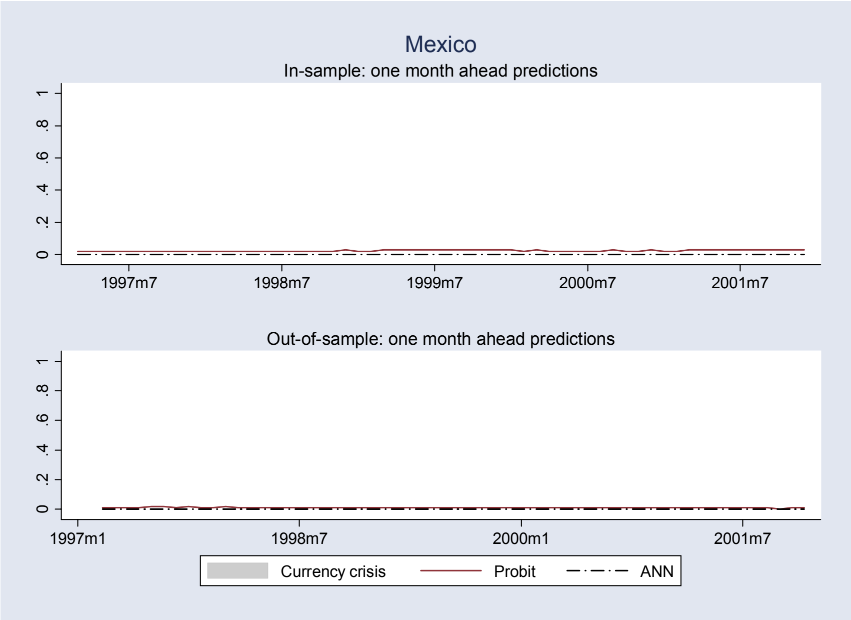

Figure 15: Currency crisis predictions for Mexico.

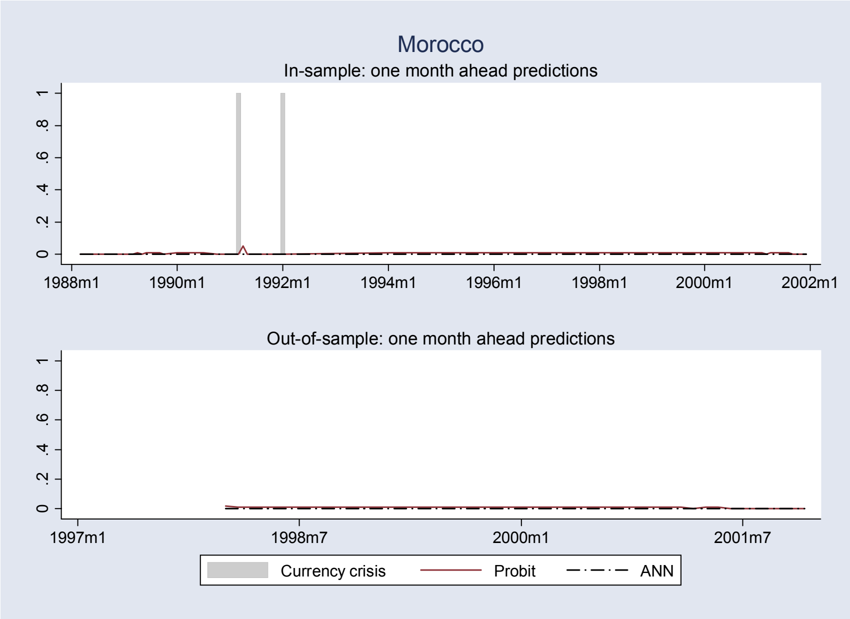

Figure 16: Currency crisis predictions for Morocco.

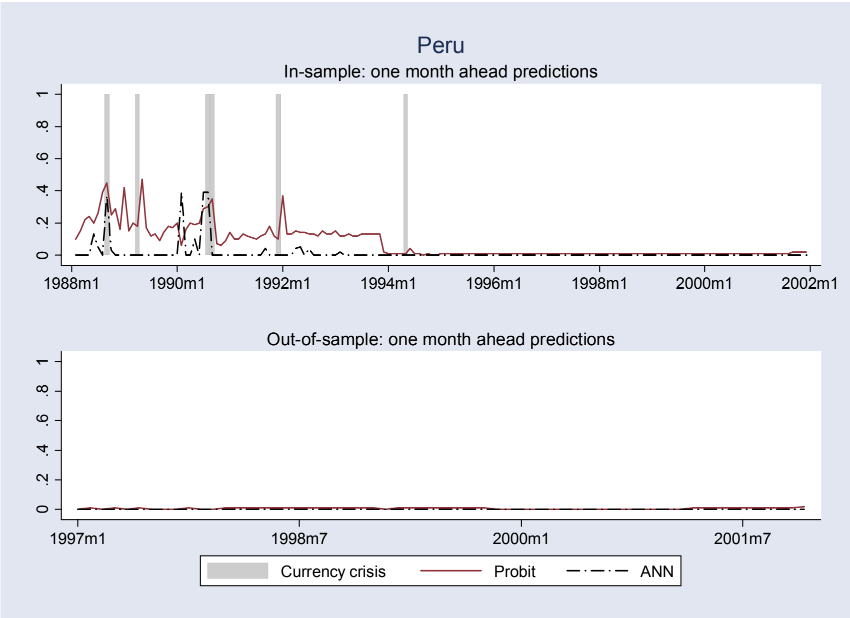

Figure 17: Currency crisis predictions for Peru.

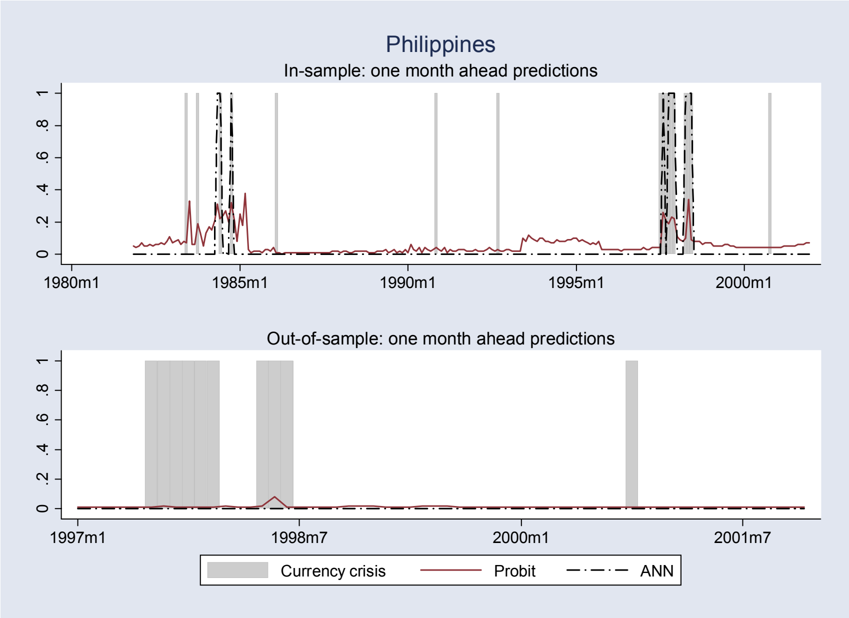

Figure 18: Currency crisis predictions for Philippines.

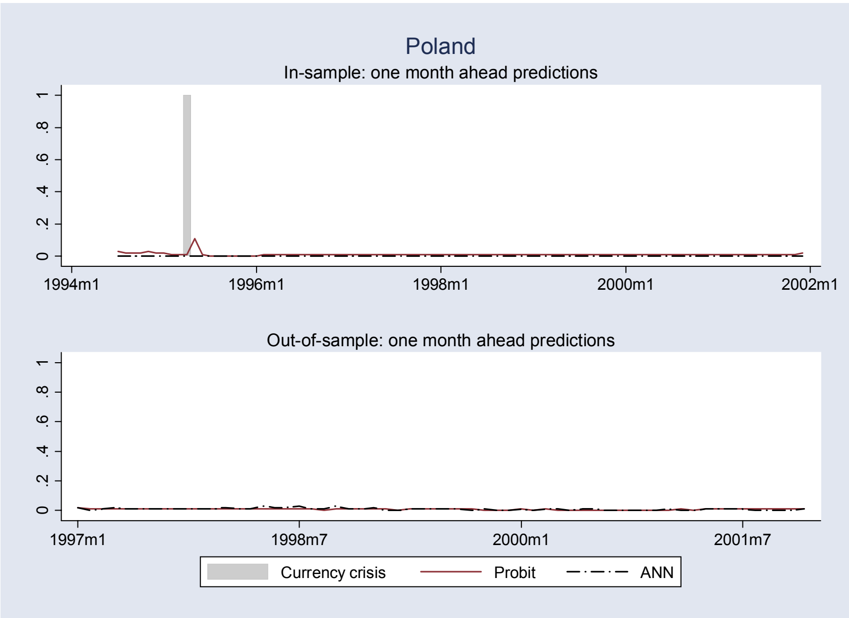

Figure 19: Currency crisis predictions for Poland.

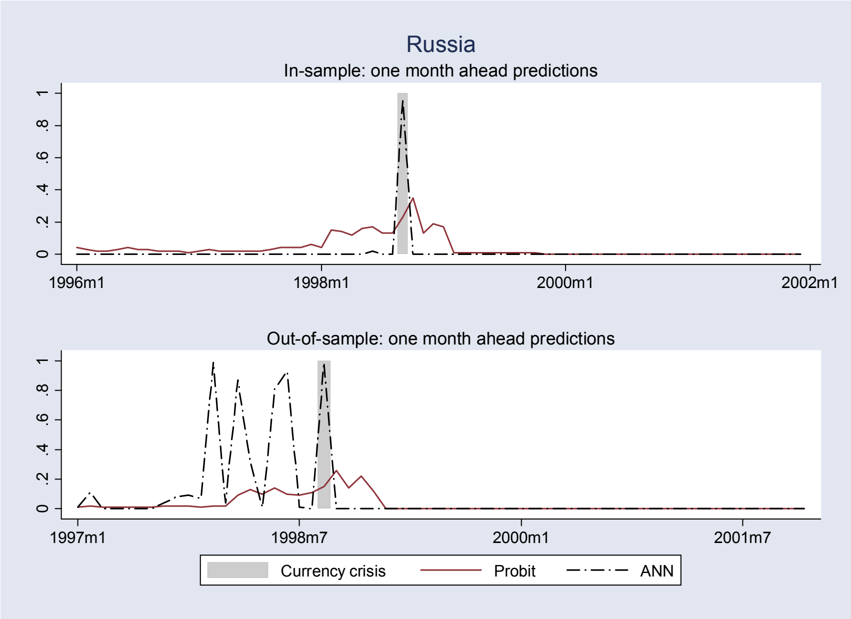

Figure 20: Currency crisis predictions for Russia.

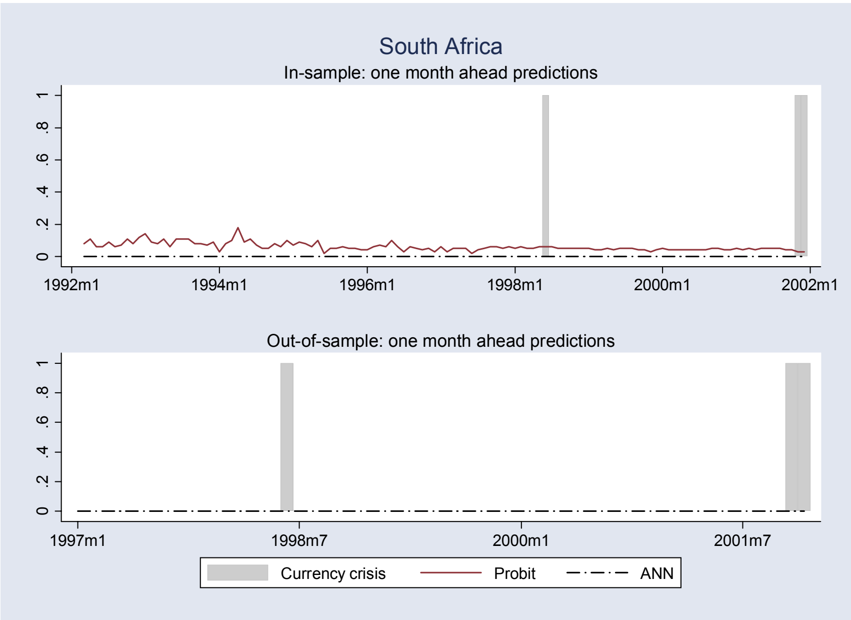

Figure 21: Currency crisis predictions for South Africa.

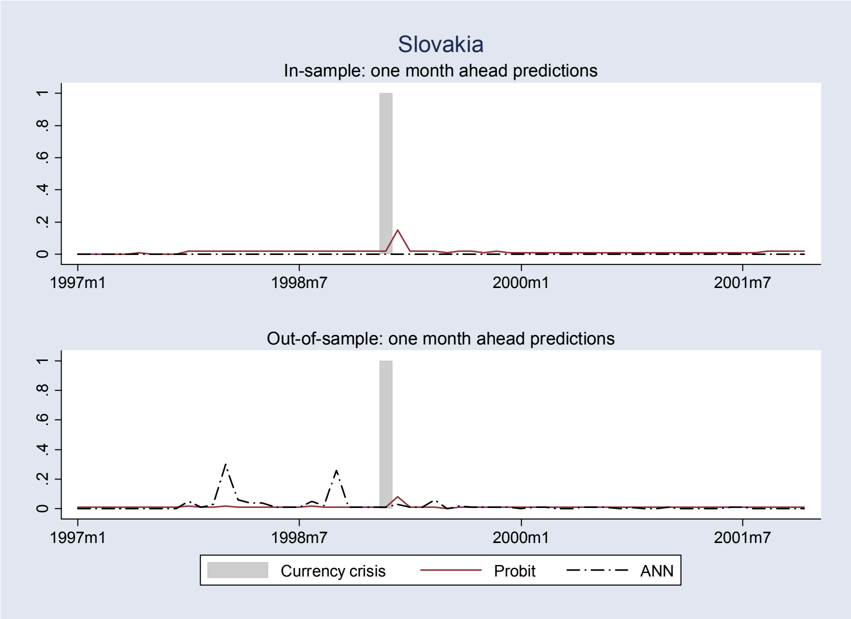

Figure 22: Currency crisis predictions for Slovakia.

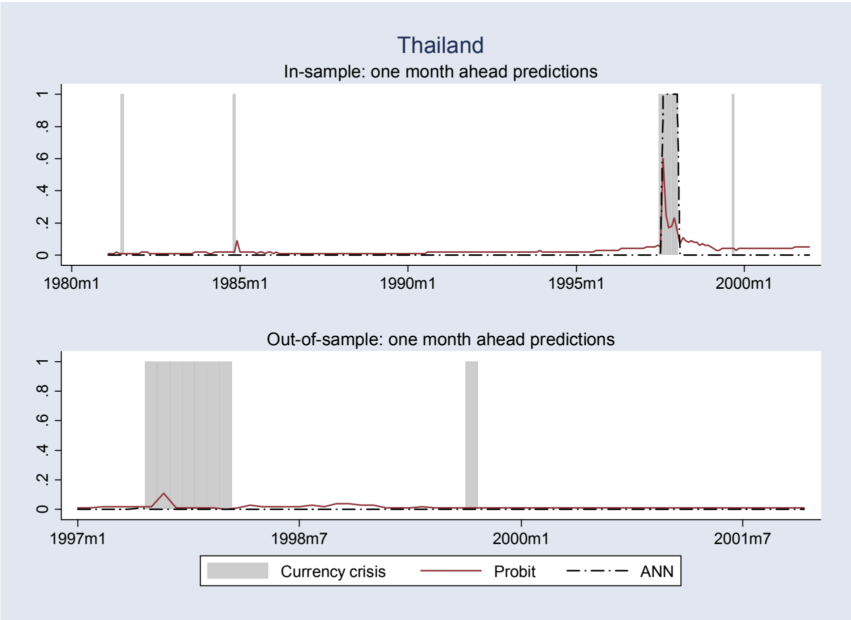

Figure 23: Currency crisis predictions for Thailand.

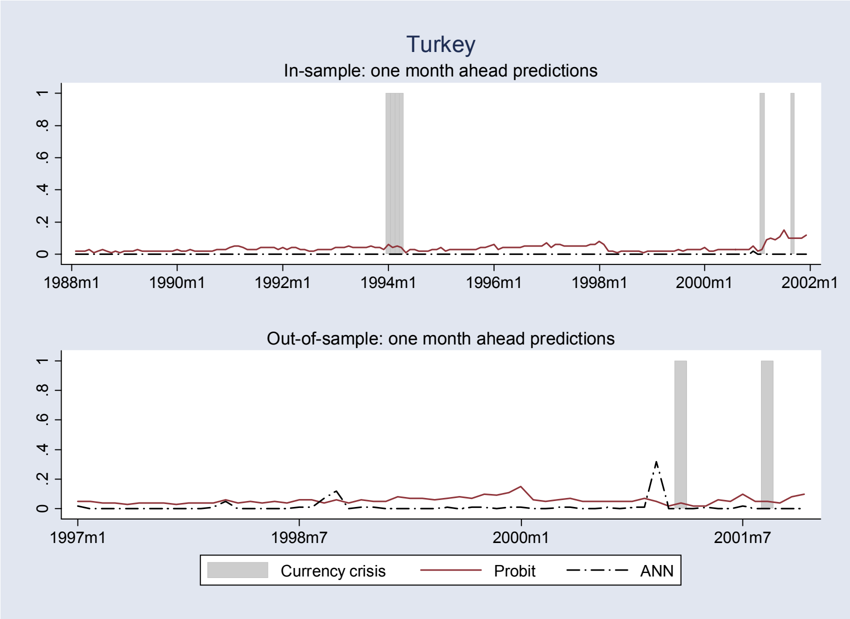

Figure 24: Currency crisis predictions for Turkey.

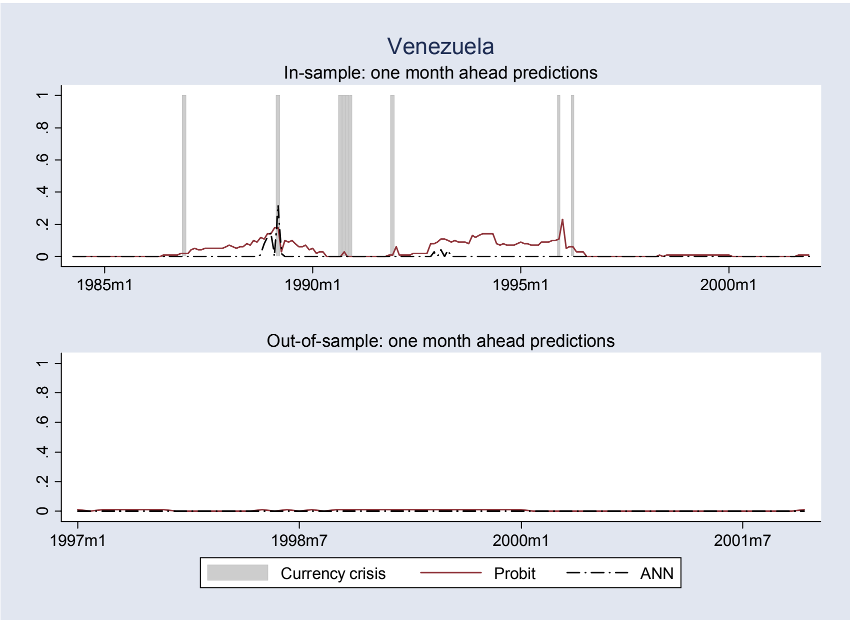

Figure 25: Currency crisis predictions for Venezuela.

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