Three methods of forecasting currency crises: Which made the run in signaling the South African currency crisis of June 2006?

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1 Introduction

Forecasting currency crises is a difficult, if not impossible task. However, the challenge to predict crises always inspired economists and econometricians. The list of methods to forecast currency crises is accordingly long. In this paper we test the ability of three of the most popular methods to forecast the South African currency crisis of 2006.

The South African economy is characterized by volatile foreign exchange market conditions. The volatility appears thereby in repeating cycles of currency crises. Examples of current currency crises in South Africa include the crises of 1996, 1998, 2001 and now June 2006. While the exchange rate regime changed over the period since the democratic changes in South Africa in 1994, the appearance of currency crises seems to persist.

To identify currency crises we use the standard definition of the Exchange Market Pressure Index (EMP).[1] The index mirrors changes in exchange rates, interest rates and currency reserves. A depreciation, an increase in interest rates, as well as shrinking reserves increase the index. A higher index indicates, therefore, higher pressure on foreign exchange markets. It not only detects crises that show up in large depreciations but also crises that caused policy reactions but did not lead to significant depreciations of the exchange rate. The three components of the EMP are weighted according to their inverse standard deviation. If the index exceeds a certain bound, the event is called a currency crisis. The standard bound is an increase of the index of above the mean of the index time series plus 1.645 times the standard deviation. The use of this threshold identifies five percent of the periods as crises periods, if the time series is normally distributed. Figure I shows the development of the Exchange Market Pressure and currency crises in South Africa.

Taking a closer look at the sub-components of the index shows, that the depreciation is the only component that shows extra-ordinary changes in June 2006. This indicates that monetary policy – in line with the policy of independent floating exchange rates – did not significantly react to the crisis. This makes the crises different from currency crises of the 1990s, where the Reserve Bank intervened in foreign exchange markets and increased interest rates. Taking this change in policy into account, it might be difficult for all methods to correctly predict the currency crisis of June 2006.

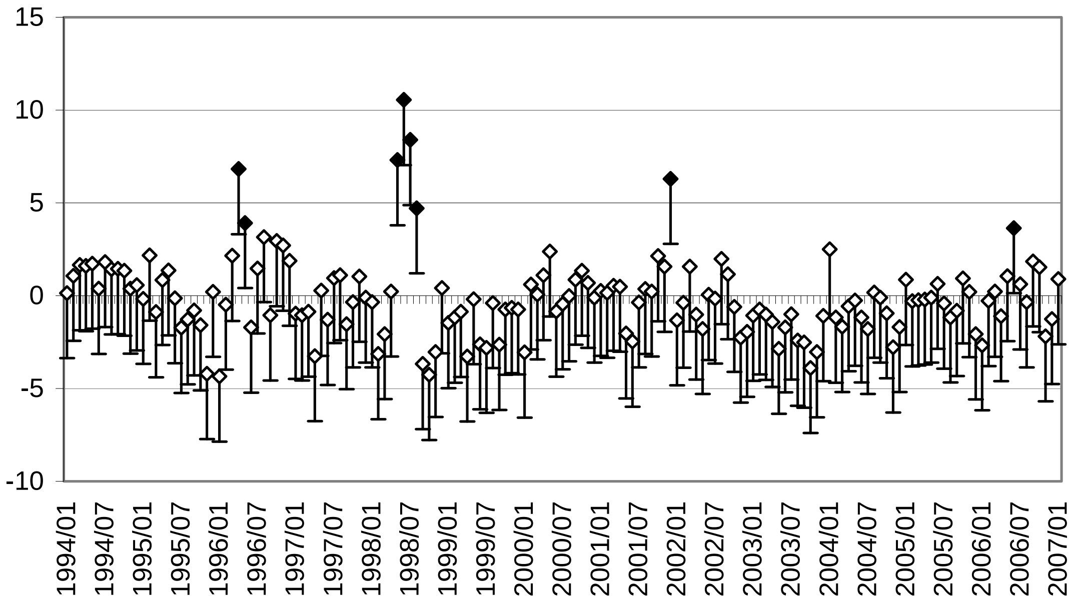
2 Three methods of forecasting currency crises

The theoretical literature on currency crises is centered on the paradigm of the three generations of currency crises models. The first generation, owed to Krugman (1979) and

[1] See Eichengreen, Rose and Wyplosz (1996). For a discussion of different EMP measures for South Africa see Knedlik (2006).

Flood & Garber (1984), described currency crises as speculative attacks which result from monetary or fiscal policies that were not in line with a fixed exchange rate target. The run on foreign currency reserves occurred because market participants could foresee the depreciation and tried to avoid losses. The models described the currency crises of the 1970s and 1980s in Latin America. The second generation, based on Obstfeld (1986), stresses the trade-off between the central banks intentions to target a fixed exchange rate and to follow other policy targets, e.g. to achieve low levels of unemployment. If speculators assume that the policy response could be devaluation, the event may become self-fulfilling without (in contrast to first generation models) worsening economic fundamentals. The models addressed, for example, the EMS crises in Europe. Third generation models stress the connection between banking and currency crises, and address problems such as contagion of crises and herd effects. These models were developed in response to the Asian crises of 1997/1998.

Figure I: Currency crises identified by the Exchange Market Pressure Index



Note: full dots indicate crises months. Source: own calculations.

The empirical literature on signaling or forecasting currency crises is based on the theoretical transmission processes described above, but approaches vary with regard to the employed techniques. Standard approaches are binary Logit/Probit-models, signals approaches as developed by Kaminsky & Reinhart (1996, 1998) and Markov-switching approaches.[2] Signals

[2] For a more detailed survey on Early-Warning Systems presented in this section see Abiad (2003).

approaches are non-parametric approaches that examine the behavior of potential explanatory variables prior to the detected crises and compare it with non-crises periods. If some of the variables pass a certain threshold their changes are used as crisis signals.[3] Logit/Probit-models use the bivariate variable crisis/no crisis as endogenous variable and estimate the impact of different sets of explanatory variables.[4] Markov-switching approaches do not depend on an a priori definition of crises. Besides these three techniques, further concepts are outlined in the literature. These include artificial neural networks (ANN), whose advantage is the reflection of complex interaction between the variables;[5] value-at-risk models, exposing several factors of risk to the ability of central banks to target a fixed exchange rate;[6] and restricted VAR models.[7]

2.1 The Signals approach

This paper largely follows the signals approach as developed by Brüggemann & Linne (2002), which is generally based upon Kaminsky & Reinhart (1996, 1998). The signals approach is used, because of its simple applicability and because it was found to outperform alternatives.[8]

The first step in employing a signals approach is to define currency crises that occurred in the period of observation. This has been undertaken in the previous section. The second step is to identify potential explanatory variables, which may send signals for currency crises. These variables should be derived from theories about currency crises. Variables, which may have an influence on the occurrence of currency crises in South Africa, are identified in section 3. The third step is to generate appropriate time series, as well as to decide on a sample period and data frequency. The fourth step is to decide on the crises window, i.e. the time prior to a crisis in which the variables are expected to send their signals. The literature uses different sample periods and data frequencies; most common are sample periods starting in the 1980s or 1990s and monthly data frequency.[9] The time-window spans from 18 months to 24

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[3] See Brüggemann & Linne (2002). Other examples include Berg & Pattillo (1999), and Edison (2000).

[4] Examples include Berg & Pattillo (1999), Kamin, Schindler & Samuel (2001), and Kumar, Moorthy & Perraudin (2002).

[5] E.g. Nag & Mitra (1999) and Peltonen (2006).

[6] E.g. Blejer & Schumacher (1998).

[7] E.g. Krkoska (2001).

[8] Abiad (2003: 3).

[9] Abiad (2003: 9).

months.[10] In this paper we use an 18 months crises window and a 12 month crises window. The later is included to allow for comparison with other approaches, which usually employ shorter crises windows.

The fifth step is to calculate individual crisis thresholds for each variable, which cuts tranquil periods from crises periods. The difficulty lies in the problem that the threshold should neither be too high (and probably not detecting crises) nor too low (and probably give false alarm). The instrument to detect the optimal threshold is to minimize the noise-to-signal ratio:[11]

$$(4) \qquad \omega_j = \frac{B/(B+D)}{A/(A+C)}.$$

Whereby A is the number of months a good signal was sent (a crisis is correctly signaled), B is the number of months a false alarm signal was sent, C is the number of months in which no signal was sent but a crises followed, D is the number of months in which no signal was sent and no crises followed. In other words, the noise-to-signal ratio is the ratio between false alarms as part of non-crises followed months and good signals as part of crises followed months. The noise-to-signal ratio is calculated with different crisis thresholds ranging from 5 to 30 percent or 70 to 95 percent of the distribution, depending on the expected impact of the variable, for each measure. The thresholds yielding the best-fit or lowest noise-to-signal ratios are used in the further calculation of the signals approach. Indicators which produce more false alarms than good signals, i.e. those having a noise-to-signal ratio of above one, are excluded from further analysis.

The sixth step is the calculation of a composite indicator. Following Brüggemann & Linne (2002) the signals approach is extended by introducing a second threshold in order to discriminate weak from strong signals, and by considering the timing of a signal (i.e. more current signals are higher weighted in the composite indicator). The weighting of the single indicators according to their prognostic quality is in line with standard literature.

The three stages of calculation are conducted by first calculating the second threshold, which is done by halving the percentile of the frequency distribution which was calculated for the first threshold. If a single indicator remains below its first threshold it takes the value of zero, if it passes the first threshold its value is defined as one, if it passes the second threshold its value is defined as two:

$$(5) \qquad I_t^j = \begin{cases} 0 & I_t^j < T_1^j \\ 1 \ \ for & T_1^j \le I_t^j < T_2^j \\ 2 & I_t^j \ge T_2^j \end{cases} \qquad j = 1, \ldots, k.$$

[10] See for example Brüggemann & Linne (2002: 9) and Kaminsky, Lizondo & Reinhart (1998: 17) respectively.

[11] See Brüggemann & Linne (2002: 10).

Second, a moving 12- or 18-months window is calculated, depending on the time-window defined before, to calculate geometrically weighted signal of each indicator:

$$(6) \qquad Z_t^j = \sum_{i=1}^{l} \frac{I_{t+1-i}^j}{i} \qquad l = \begin{cases} 12 \\ 18 \end{cases}, \; for\ t \geq \begin{cases} 12 \\ 18 \end{cases}.$$

Third, these so-calculated Z-signals of each variable are combined by accounting for their prognostic quality i.e. by then dividing them by their respective noise-to-signal ratio.

$$(7) \qquad CI_t = \sum_{j=1}^{k} \frac{Z_t^j}{\omega_j}.$$

The procedure yields a composite indicator of currency crises.

While the composite indicator itself can be used to observe changes in the intensity of currency crisis signals, the level of the index cannot be interpreted. Thus, it is not possible to draw inferences on the probability of currency crises from the index. Therefore, following Brüggemann & Linne (2002) and Edison (2000) conditional probabilities for currency crises can be calculated:

$$(8) \; P(crises_{t,t+18} \mid CI_l \leq CI_t < CI_u) = \frac{\sum \#months\ for\, CI_l \leq CI_t < CI_u\ and\ crisis\ follows}{\sum \#months\ for\, CI_l \leq CI_t < CI_u}.$$

For each interval between a lower and an upper limit the conditional probability can be calculated. This conditional probability is the probability of a crisis occurring within 12 or 18 months under the condition that the indicator ranges between the lower and the upper band. While the calculated probability is explicitly not the probability of the occurrence of future crises, it is used to signal the risk for currency crises.

2.2 Logit/Probit approaches

Another set of methods employs probit or logit estimation models. The common characteristic of all of these methods is the limited dependent variable that takes a value of zero in non-crises or tranquil periods, while it takes a value of one in crises periods and in differently defined "window" periods before a crisis. In general the Probit models takes the form of:

$$(9) \; Pr(y_t = 1 \mid x_t \beta) = \Phi(x_t{}' \beta).$$

The method developed by Berg & Pattillo (1999) uses the singles approach as a starting point. The authors use the signals sent by individual indicators (compare equation (5) although the Berg & Pattillo use just one threshold) as independent variables. Their panel data analysis and the performance test of the methods shows, that the probit approach has advantages over the signals approach regarding the predictability of currency crises. In the course of their paper they vary the method and also use percentiles of the distribution of the independent variables as well as the slope below the crises thresholds, the leap at the threshold and the slope above the threshold as variations of the independent variables.[12] The Berg & Pattillo approach is element of the Developing Country Studies Division model, which is used by the International Monetary Fund.[13] In this paper we reproduce the approach of Berg and Pattillo, using the individual indicator signals as independent variables. However, we extend the approach by the use of second thresholds and we use a 12 and an 18 months crisis windows.

A second option of dealing with the independent variables is not to include the calculated signals but the data itself as it is done in Frankel and Rose (1996). The advantage of using the original data might be that the loss of information due to the transformation of the data can be avoided. We therefore also employ the Frankel and Rose approach to forecast the South African currency crisis of 2006.

Several studies have reproduced, modified and extended the above-described approaches. One interesting modification is to focus the dependent variable on crises periods only and include a lag structure on the right hand side of the estimation equation.

One problem with the signals approach and the probit approach is that in the current period we cannot know, whether a crisis as defined by the EMP index follows or not. The same counts for the past periods that lay within the crises window. Therefore, to calibrate our forecasting model we can only use data from before the window period. Thus, for the out of sample forecasts of the crises in June 2006, we can only use data up to November 2004 (in the 18 months crisis window case) for model calibration. The dependency on a specific crisis definition and on a crisis window is overcome by the use of Markov-switching models.

2.3 Markov-switching models

Models of regime switching have a long history in empirical macroeconomic research.[14] Especially Hamilton´s (1989) state-dependent Markov-switching model has become a useful tool in describing time series, which undergo different episodes, while their character change quite dramatically. In contrast to earlier work we follow Diebold, Lee and Weinbach (1994) and Filardo (1994) in allowing for time-varying crisis probabilities - assuming that the probability of switching may depend on some underlying economic fundamentals.

The Markov-switching approach to signal currency crises has a number of advantages compared to its competitors. First, it is not necessary to define crisis episodes. Instead, the identification procedure is done simultaneously with the crisis forecast probability. In doing

[12] See Berg & Pattillo (1999: 572-4).

[13] See IMF and World Bank (2005: 37).

[14] See for example Quandt (1958), Goldfeld & Quandt (1973).

so, one avoids problems with the potentially arbitrary dating of crises. Second, we can use more information by examining the Exchange Market Pressure Index directly instead of transforming it into a binary variable. Thus, the dynamics (including the volatility) may be also important in explaining future crisis. Finally, the Markov-switching model provides concrete crises probability for the following periods (which is a common feature of both probit/logit models and Markov switching models).

The assumptions underlying the Markov approach can be shortly summarized. We assume two different states (or regimes): tranquil periods and crisis periods. We cannot directly observe these states. It can be seen as a latent variable s_t which is equal to 0 if we are in the tranquil state and equal to 1 if we are in a crisis period. Additionally, we have a direct observable variable y_t – the Exchange Market Pressure Index – whose characteristics change depending on the underlying state. This variable depends on s_t as follows:

$$y_t \mid s_t \overset{iid}{\sim} N(\mu_{s_t}, \sigma^2_{s_t}) \tag{10}$$

Thus, the data generating process for y_t varies with the state s_t and differs in respect to its mean μ_{s_t} and variance $\sigma^2_{s_t}$. For example, we expect higher average depreciations and a greater exchange rate volatility during the crisis state (which will also lead to a higher and more volatile EMP variable). Thus, the conditional density of y_t given s_t is equal to

$$f(y_t \mid s_t) = \frac{1}{\sqrt{2\pi}\sigma_{s_t}} \exp\left(\frac{-(y_t - \mu_{s_t})^2}{2\sigma^2_{s_t}} \right). \tag{11}$$

Finally, given the actual state the probability of staying in the same state or moving to the other state depends on variables describing the country's fundamental condition. So the behavior of s_t is described by the transition probability matrix P_t:

$$P_t = \begin{pmatrix} p_t^{00} & p_t^{01} = (1 - p_t^{00}) \\ p_t^{10} = (1 - p_t^{11}) & p_t^{11} \end{pmatrix} \tag{12}$$

where p_t^{ij} is the probability of moving from state i in period t-1 to state j in period t. In our case we assume logistic forms of the transition probabilities in the following way:

$$P(s_t = 0 \mid s_{t-1} = 0, x_{t-1}; \beta_0) = \frac{\exp(x'_{t-1}\beta_0)}{1 + \exp(x'_{t-1}\beta_0)} \tag{13}$$

$$P(s_t = 1 | s_{t-1} = 0, x_{t-1}; \beta_0) = 1 - \frac{\exp(x_{t-1}^{'}\beta_0)}{1+\exp(x_{t-1}^{'}\beta_0)}$$

$$P(s_t = 0 | s_{t-1} = 1, x_{t-1}; \beta_1) = 1 - \frac{\exp(x_{t-1}^{'}\beta_1)}{1+\exp(x_{t-1}^{'}\beta_1)}$$

$$P(s_t = 1 | s_{t-1} = 1, x_{t-1}; \beta_1) = \frac{\exp(x_{t-1}^{'}\beta_1)}{1+\exp(x_{t-1}^{'}\beta_1)}$$

The (kx1)-vector x_{t-1} includes the early-warning indicators which may affect the transition probabilities through the (kx1) parameter vectors β_0 or β_1 which can have different constants across the states.

From this setting a natural step would be to estimate the parameters μ_0, μ_1, σ_0^2, σ_1^2, β_0 and β_1 by maximum likelihood. But there is some practical difficulty concerning this procedure: the complete-data log likelihood cannot be constructed, because the complete data are not observed. Therefore we follow Hamiliton (1989) for the case of constant transition probabilities and Diebold, Lee and Weinbach (1994) with time-varying transition probabilities and use the EM ("expectation" – "maximization") algorithm for maximization of the incomplete-data likelihood.[15]

The Markov-switching model estimates one-month ahead forecast probabilities. To make these probabilities comparable to other early warning systems one can transform them into long-horizon crises probabilities, using[16]:

Pr(crises over next n months) = 1-Pr(no crises over next n months)

= 1-Pr(no crises over next 1month)^n

= 1-(1-Pr(crises over next 1month))^n

In most applications it has become standard to define a binary "alarm signal" which is equal to 1 if the crises probability exceeds a general threshold, and 0 otherwise. We set this threshold inline with other studies equal to 50%. Thus, when ever the crises probability lies above this number our model forecasts a crises during the next 12 month.

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[15] Details about the EM algorithm can be found in Hamilton (1994, pp. 692-695) and Diebold, Lee and Weinbach (1994, sec. 3).

[16] It is assumed that the indicators that influence the crises probability neither worsen nor improve during that period.

3 Currency crises forecasts for South Africa

The above-described techniques are now employed to forecast the risk of currency crises in the advent of the June 2006 currency crises in South Africa. A set of variables in the style of those that have been found to be useful in signaling currency crises in previous studies as extracted by Brüggemann & Linne (2002) are used. These variables include: (1) growth of industrial production, (2) the ratio of budget deficits to GDP, (3) the appreciation of the real exchange rate, (4) the change in the international liquidity position, (5) growth rate of merchandise exports, (6) growth rate of merchandise imports, (7) growth rate of ratio of domestic credit to GDP, (8) the growth rate of the ratio of M2 to currency reserves, (9) the domestic interest rate, (10) the interest rate differential to the US, (11) growth rate of bank deposits of individuals, (12) growth rate of foreign debt of the government, (13) the ratio of lending rates to deposit rates. The Commission of Inquiry into the rapid depreciation of the exchange rate of the rand and related matters, the so-called Myburgh Commission (2002), was officially established to investigate the 2001 currency crisis in South Africa. The commissions report indicates variables, which may contribute to the explanation of currency crises in South Africa. Some of them are already included in standard set of variables, such as the open forward position of the SARB which is reflected in the international liquidity position. Additionally, from this report variable (14), the inflation differential to the US is included. Other "weak" factors found to explain part of the 2001 depreciation, such as privatizations and negative sentiments could not be included due to a lack of computable data. Additionally, another factor mentioned in the literature as explaining factor to currency crises in South Africa (15) the change of the price of gold is included.[17] The metric signs of all variables are adjusted, so that a positive change of any variable indicates a higher risk for currency crisis. All data is taken or derived from SARB online statistics.

3.1 The Signals approach

The signals approach is employed as described above. We use data from 1994 onwards. The latest data used to calibrate the model is December 2004 and June 2005 for the 18-month and the 12-month time window case, respectively. Thus, the June 2006 crisis is left out of the calibration exercise.

In the 18-month case there are seven indicators which send more good then bad signals and are, therefore, included in the calculation. These variables are: the ratio of budget deficits to GDP, the change in the international liquidity position, growth rate of merchandise imports, growth rate of ratio of domestic credit to GDP, the domestic interest rate, and the change of

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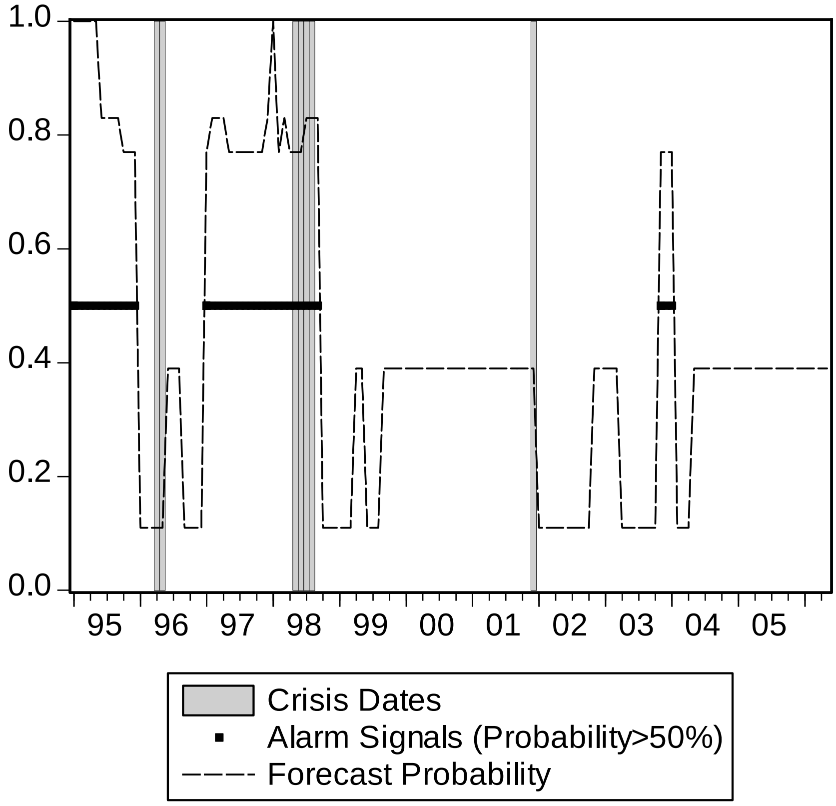
[17] E.g. Aron & Muellbauer (2005: 30).

the price of gold. The calculation of conditional probabilities yields figures as reported in figure 2.

Figure 2: Conditional probabilities for currency crises in South Africa using an 18-months crises window signals approach



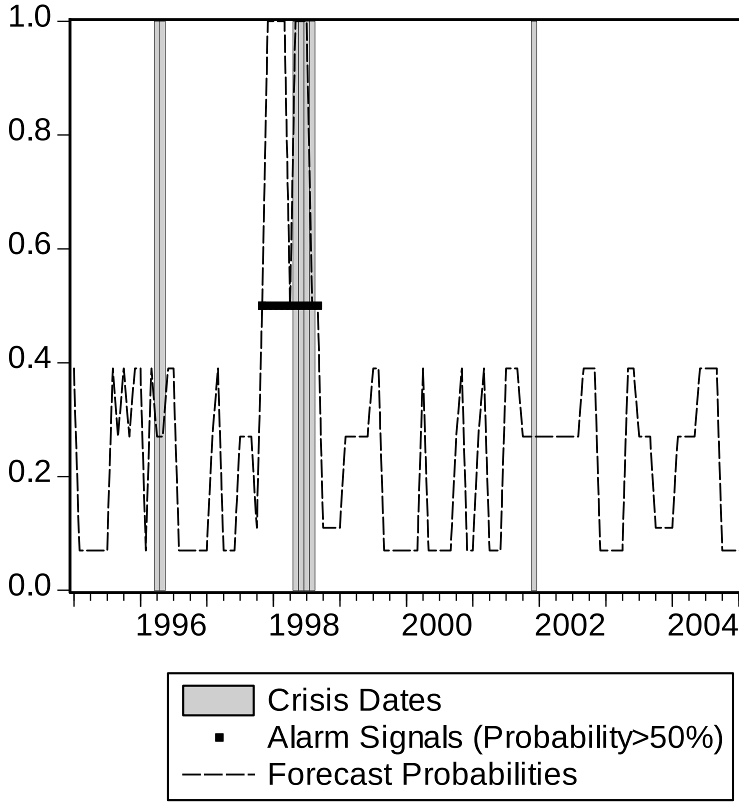
Source: own calculations.

Figure 2 shows that there are high (in sample) indications for currency crises in the periods before the 1996 and the 1998 crises. However, there are rare indications of the currency crises of 2001 (in sample) and 2006 (out of sample). There also seems to be some false alarms in late 2003 and early 2004 (in sample).

The figure looks worse when considering a 12-month crisis window only. The results of the calculations of the signal approach are reported in figure 3. The calculation of this version of the signals approach uses six time series for the calibration of the model: growth of industrial production, the ratio of budget deficits to GDP, the domestic interest rate, growth rate of foreign debt of the government, the ratio of lending rates to deposit rates, and the change of the price of gold.

The figure only shows correct predictions of the 1998 crisis. In all other crisis cases no strong signal was sent. That includes the period prior the 2006 crises, where the signal approach shows the lowest risk of the whole sample.

Figure 3: Conditional probabilities for currency crises in South Africa using a 12-months crises window signals approach



Source: own calculations.

For both versions of the signals approach counts, and that was to test for here, the crisis of June 2006 could not have been anticipated relying on a signals approach as early warning system for currency crises. The next section asks whether or not the Probit approach is doing any better.

3.2 Logit/Probit approaches

We first conduct a logit approach that uses the signal variables of the signals approach as independent variables and an 12-months crisis window as binary independent variable, i.e. the dependent variable takes the value of one in crises months and up to twelve months prior a crises and takes the value of zero in all other months. Data up to May 2005 is used to calibrate the model. Then forecasts of currency crisis probability for the whole sample, up to May 2006 were run. The results of the estimation are shown in the column "signals" in table 1 and the forecasts are presented in figure 4.

Table 1: Probit estimations

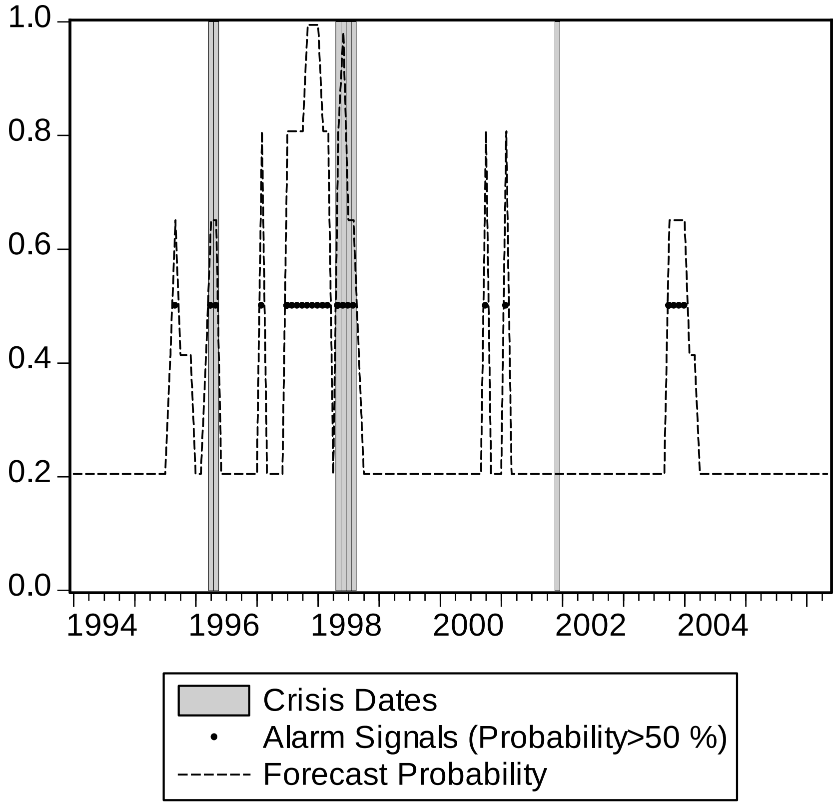
	signals		**theory**		**statistics**		**18-month window**	
Indicator	Coeff.	z-stat.	Coeff.	z-stat.	Coeff.	z-stat.	Coeff.	z-stat.
Constant	-0.768420	-4.434103	-3.270365	-4.809954	-13.25811	-4.865644	-6.136506	-3.870321
Budget deficits	0.023948	0.052210	-	-	-	-	-	-
Dom. Interest rate	0.674951	2.974535	-	-	0.531360	3.968982	-	-
Foreign debt	-0.016829	-0.090445	-	-	-	-	-2.746186	-3.196873
Gold price	1.644067	3.550193	7.437073	3.402566	-	-	-	-
Industrial prod.	-0.016869	-0.088945	18.98190	2.235175	-	-	-	-
Lend./deposit rates	-0.221897	-0.868994	-	-	-	-	-	-
Credit/GDP	-	-	-	-	-	-	-34.98147	-3.067163
Bank deposits	-	-	-17.74994	-4.195692	-49.79818	-4.689993	-51.89294	-4.698855
Exports	-	-	-9.512551	-3.159028	-16.24210	-3.245967	-	-
M2	-	-	-	-	-9.797407	-4.167970	-4.216687	-3.281309
Inflation differential	-	-	-	-	0.275377	2.009916	-	-
Inter. liq. position	-	-	-5.68E-05	-2.306406	-0.000111	-2.188903	0.000103	2.376320
Dom. interest rate	-	-	-	-	-	-	1.697444	3.955857
Interest differential	-	-	-	-	-	-	-1.871654	-4.098943
Imports	-	-	-	-	-	-	13.10876	3.787279
Number of obs.	137		137		137		131	
LR-Test joint sign.	31.11669		87.94863		133.7354		132.2941	
p-Value	2.41E-05		0.000000		0.000000		0.000000	
McFadden R^2	0.182532		0.515912		0.784500		0.730964	

Source: Eviews-Output, own calculations.

For the forecasting purpose the estimation model is reduced by insignificant variables so that only domestic interest rates and the gold price, besides the constant, are left. While the pure use of the signals approach in the 12-months window case could only signal the 1998 crisis, the probit approach, using the same data, shows an impressive improvement of in-sample predictability of currency crises. The figure shows stronger signals prior the 1996 and 2001 crises. However, the crises probability prior the 2006 crisis is not above the critical value of 50 percent. The use of an 18-months crisis window yields similar and also better results as compared with the 18-months signals approach.

The next approach is to estimate probit estimations that use the original data instead of signal variables as right-hand side variables. We use two versions of the variable selection process. The first is to estimate each of the above-described variables in a one-to-one estimation. If the correlation is positive, which is equivalent with a theory conform behavior, the variable is included in an "economically meaningful" model. This model is then reduced by insignificant variables. The result is an "economically and statistically meaningful" model. The second version is to include all variables that contribute significantly to the statistically explanation. Thereby we do not care about the expected signs of the parameters and derive a "theory free" model. Both versions are again calculated for the 12 and the 18-months crisis window.

Figure 4: Probit forecast (12-months crisis window, based on signals)

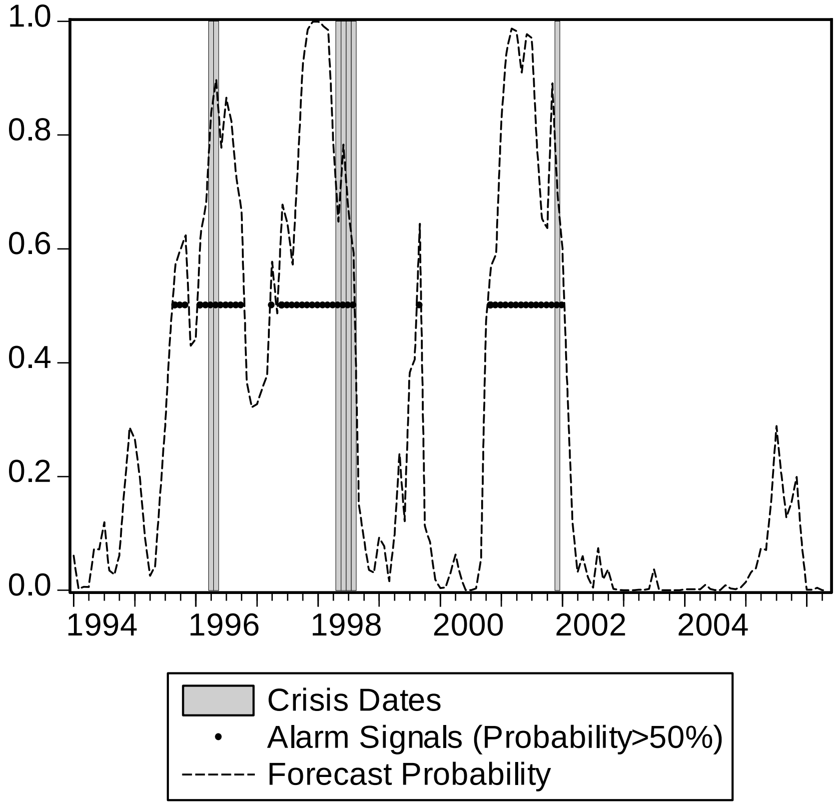


Source: Eviews-Output, own calculations.

The 12-months window "economically and statistically meaningful" model leaves us with six explanatory variables: a constant term, growth of industrial production, the change in the international liquidity position, growth rate of merchandise exports, growth rate of bank deposits of individuals, the change of the price of gold (compare column "theory" in table 1).

The forecasting results are presented in Figure 5. The model leads to signals prior to the 1996, 1998 and 2001 crises (all in sample). However some false alarms were sent in the aftermath of the 1996 crises (in sample) and the crisis of 2006 (out-of-sample) is not predicted. The forecast results of the 18-months window “economically and statistically meaningful” model (not reported) show some better prediction of the in sample crisis of 1996 than the 12-months crisis window model but also fail to predict the 2006 event.

Figure 5: Probit forecast (12-months crisis window, “economically and statistically meaningful” model)

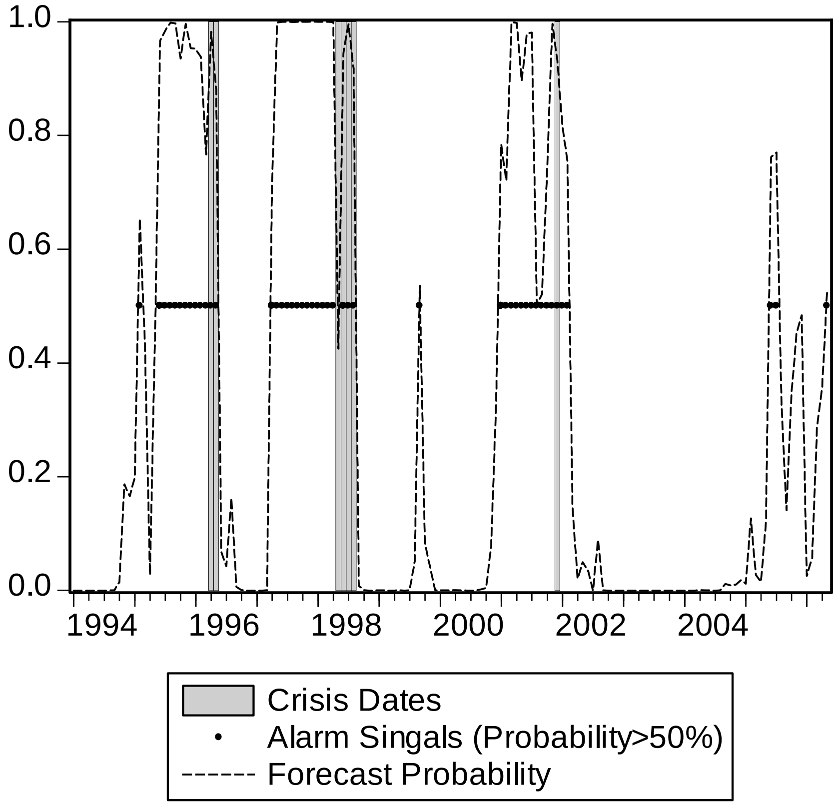


Source: Eviews output, own calculations.

We, therefore, go ahead by estimating a model that does not control for economic theory and originally includes all variables from the data set. The model is then successively reduced by insignificant variables. In the 12-months case the final model includes seven variables: a constant term, the change in the international liquidity position, growth rate of merchandise exports, the growth rate of the ratio of M2 to currency reserves, the domestic interest rate, the interest rate differential to the US, growth rate of bank deposits of individuals, the inflation differential to the US (see column “statistics” in Table 1).

Figure 6 reports the forecast results of the 12-months crisis window, “theory free” model. The model predicts all currency crises (in sample and out-of-sample) correctly and does only limited set off false alarms.

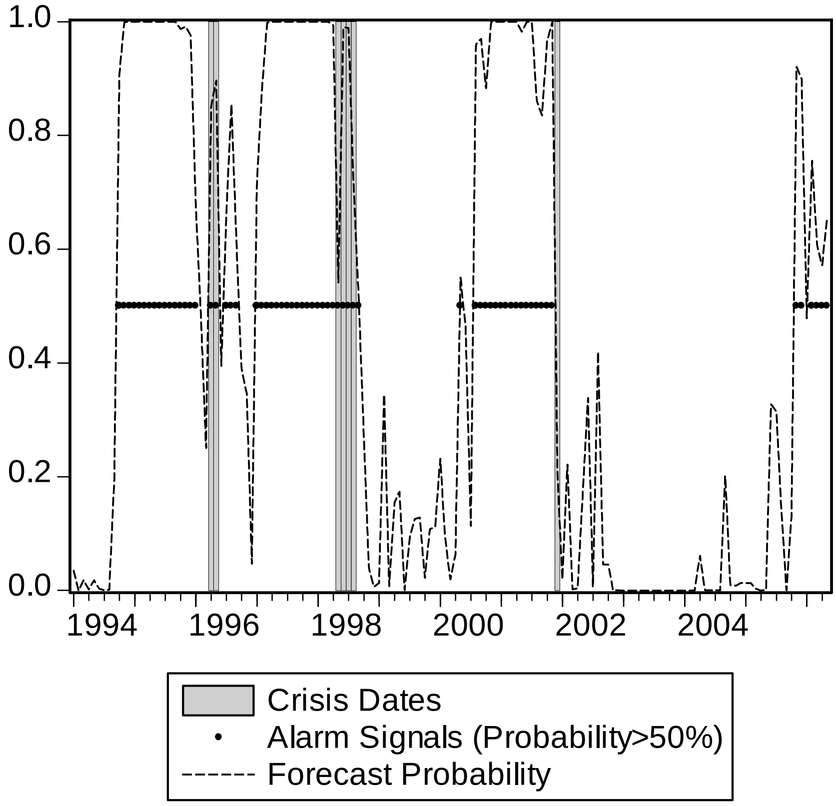
Figure 6: Probit forecasts (12-months crisis window, “theory free” model)



Source: Eviews output, own calculations

With a longer crisis window of 18 months nine variables become significant: a constant term, the change in the international liquidity position, growth rate of merchandise imports, growth rate of ratio of domestic credit to GDP, the domestic interest rate, the interest rate differential to the US, growth rate of bank deposits of individuals, growth rate of foreign debt of the government (see figure 7 and column “18-month window” in table 1). The model with the longer crisis window performs better with regard to out-of-sample forecasts.

Figure 7: Probit forecast (18-months crisis window, “theory free” model)



Source: Eviews output, own calculations.

The results of the probit analysis of currency crisis forecasts leads to the conclusion that some of the models variations are able to predict the 2006 currency crisis in South Africa. It remains however somewhat unsatisfying that the goodness of the predictions seems to depend on theory contrarious models. This reminds us on the late Milton Friedman, from whose famous Essays in Positive Economics (1953) it is quoted that one should use the method or the model that predicts best and not the one based on the descriptive realism of the assumptions.

3.3 Markov-Switching Approach

To make our Markov-Switching model as comparable as possible to our other approaches we consider all early warning indicators from the signal approach. In the first step we follow Abiad (2003) and estimate bivariate models where we try to extract important variables which influence the transition probability. Each indicator together with a constant is included one by one into the regression and is evaluated by its significance level. Of course, we are aware that this step-by-step approach may be misleading when the exogenous variables are correlated. But we will test our final model of joint significance of our selected indicators and can thus evaluate if the variables are together important.

We estimate the model with a sample period from 1995:01 to 2006:04. Due to possible problems with convergence in the maximum likelihood estimation we rescale each indicator to be mean zero and unit variance. Since we defined our variables in such a way that a positive sign of the variable lead to an increase in the probability moving into the crises state, we expect only positive signs for our indicators. For South Africa we found only the growth rate of bank deposits of individuals and the change of the international liquidity position to be important early warning indicators.[18]

These two indicators enter into our final multivariate model. Table 5 shows the results of this model specification. The tranquil state ($s_t = 0$) is identified with low mean and low volatility whereas state 1 is a high-mean and high-volatility regime. These differences are both significant. Our two early warning indicators show no significant coefficient itself, but they are correctly signed and the joint test is highly significant.

Table 5: Estimation of the Markov-Switching model

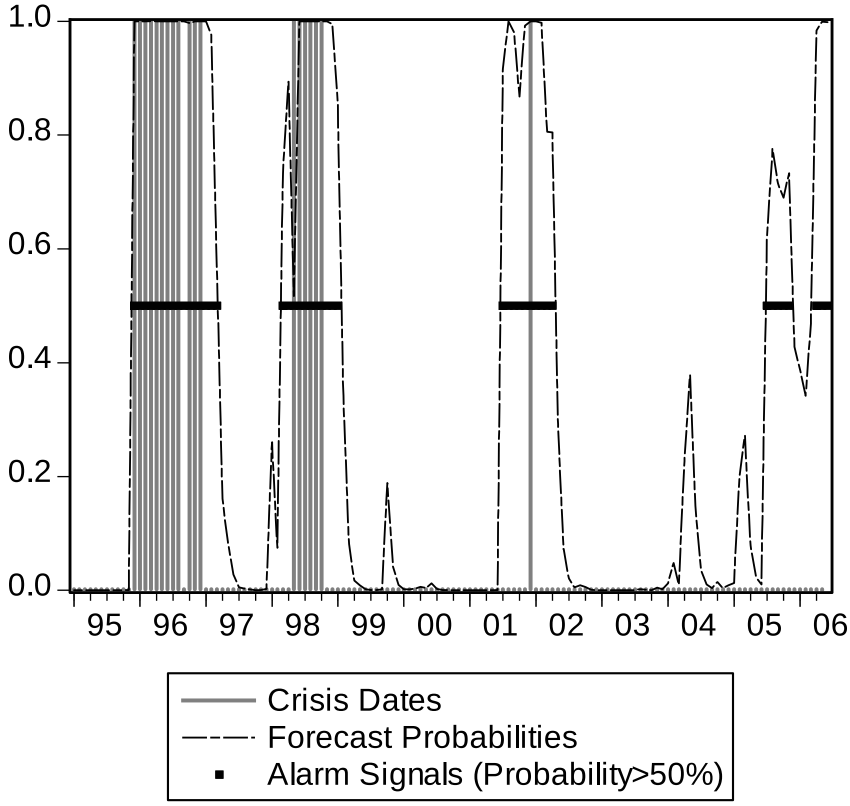
Indicator	Coeff.	t-stat.
Mean (State 0)	-0.70	-5.05
Mean (State 1)	2.40	2.41
Sigma (State 0)	1.42	13.18
Sigma (State 1)	3.84	5.30
International liquidity position, difference	5.42	0.71
Bank deposits of individuals, growth rate	1.87	0.78
Constant (β_0)	6.20	0.86
Constant (β_1)	0.81	1.61
Number of observations	137	
LR-Test for joint significance of indicators	11.79	
p-Value	0.00	

Source: Own estimations based on Abiad (2003).

[18] We evaluate significance with a Likelihood-ratio test. The regression results from the first step are available from the authors on request.

If one examines the crises dates determined by the Markov-switching model we find the first and longest crises period in South Africa during December 1995 until December 1996 (with exception of the September). Interestingly, this model identifies a much longer crisis time span as compared to the signal approach where the crisis is dated only in April and May 1996. The next crisis begins in May 1998 which is totally in line with the signal approach. But again the Markov-model identifies a longer crises period (until October instead of August). The last dated crisis in December 2001 is exactly the same as with the signal approach.

Figure 8: Markov-Switching Forecast



Source: Own calculations based on Abiad (2003).

Before the first crisis, the model did not send any alarm signal and thus could not forecast the crisis event a priori. But after the first crises month the model started to send signals and anticipated the following episodes correctly. In contrast to the first crises, the second one was predicted before the event arose (namely two months before). The same is true for the last crises in our sample. In this case the alarm signal was sent as of July 2001 and the crises occurred in December.

More interestingly is the out-of-sample predictive ability of our model. Since we know that in June 2006 there will be crises, we could like to investigate the properties of the model before this crisis will arise. Figure 8 indicates a rising crisis probability already in 2005. The model sends alarm signals from June until November 2005 and again from April 2006 onwards. Clearly the model anticipates our crisis of interest in June 2006. Therefore we can conclude that the Markov-switching approach is able to detect the upcoming crises very well.

4 Comparing the forecast performance of the tree approaches

The in-sample and out-of-sample performance of our models concerning its forecasting properties is summarized by several goodness-of-fit measures. Table 6 gives a flavor of these indicators.

Table 6: Forecasting performance of different approaches (all based on 12 months crisis window)

Goodness-of-fit (cut-off-prob. of 50%)	Signals	Probit (signals)	Probit (theory)	Probit (statistics 12)	Probit (statistics 18)	Markov Switching
Percent of observation correctly called	77	62	88	93	76	67
Percent of pre-crisis periods correctly called	25	40	81	91	89	45
Percent of tranquil periods correctly called	98	72	90	94	66	82
False alarms as percent of total alarms	18	4	20	11	8	10
Out-of-sample: Percent of pre-crisis periods correctly called	**0**	**0**	**0**	**25**	**33**	**67**

Source: Own calculations.

The last column of table 6 provides a measure for the out-of-sample performance of the methods, while all other columns of the table provide measures of in-sample performance. The “theory free” Probit approach forecasts by far the most in-sample crises correctly. The Probit approach based on signals yields the lowest figure of false alarms. While the signals approach provides the best figure in forecasting tranquil periods, it is outperformed by almost all versions of the Probit approach with regard to all observation that are correctly called. The comparability of the signals and Probit approaches with the Markov approach is somewhat hampered by the fact that different crisis detection methods are used and subsequently different crisis dates are identified. The only methods with correct out-of-sample forecasts are the Markov Switching approach and the “theory free” Probit approach.

5 Conclusions

In sum, the signals approach was not able to forecast the out-of-sample crisis of June 2006 correctly; the probit approach was able to predict the crisis but just with models, which are not in line with the theory of currency crises; with employing a Markov-regime-switching approach allows to predict the out-of-sample crisis in a theory conform manner. The answer to the question of which method made the run in forecasting the June 2006 currency crisis is: the Markov-Switching approach. However, the “victory” comes with mixed feelings. Is it possible to predict currency crises using just two explanatory variables, as implied by the Markov approach results? Why does the probit approach yield best results if it is not controlled for economic theory? Even if it could be shown, that econometric methods are able to predict currency crises in this case, the question of why it works that way is open.

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