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

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

Abstract

In this paper we test the ability of three of the most popular methods to forecast the South African currency crisis of June 2006. In particular we are interested in the out-of-sample performance of these methods. Thus, we choose the latest crisis to conduct an out-of-sample experiment. In sum, the signals approach was not able to forecast the out-of-sample crisis of correctly; the probit approach was able to predict the crisis but just with models, that were based on raw data. Employing a Markov-regime-switching approach also allows to predict the out-of-sample crisis. The answer to the question of which method made the run in forecasting the June 2006 currency crisis is: the Markov-switching approach, since it called most of the pre-crisis periods correctly. However, the "victory" is not straightforward. In-sample, the probit models perform remarkably well and it is also able to detect, at least to some extent, out-of-sample currency crises before their occurrence. It can, therefore, not be recommended to focus on one approach only when evaluating the risk for currency crises.

Key words: Currency crises, forecast, predictability, signals approach, Probit approach, Markov regime switching approach, South Arica

JEL: C14, C22, C53, E47, F31, F37

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

Zusammenfassung

In diesem Beitrag wird die Prognosefähigkeit von drei populären Ansätzen anhand der südafrikanischen Währungskrise im Juni 2006 getestet. Von besonderem Interesse ist die Out-of-sample-Prognosegüte der Methoden. Deshalb wird die jüngste Währungskrise in Südafrika als Out-of-sample-Experiment genutzt. Im Ergebnis zeigt sich, dass der Signalansatz nicht in der Lage war die Währungskrise vorherzusagen; Probit-Ansätze konnten die Krise vorhersagen wenn sie auf Rohdaten und nicht auf Signalen des Signalansatzes basierten. Auch die Verwendung eines Markov-regime-switching-Ansatz führte zu korrenkten Prognosen der Out-of-sample-Krise. Die Antwort auf die Titelfrage des Beitrags, welche Methode die Krise vom Juni 2006 am besten vorhersagen konnte ist: der Markov-regime-switching-Ansatz, weil dieser die meisten Vorkrisenperioden korrekt erkannte. Dennoch ist der „Sieg“ nicht überragend. So ist die In-sample-Prognosegüte des Probit-Ansatzes besser und dieser Ansatz ist auch in der Lage zumindest einige der Vorkrisenperioden als solche zu erkennen. Es kann daher nicht empfohlen werden Währungskrisenprognosen auf nur einen Ansatz zu stützen.

Schlagworte: Währungskrisen, Prognose, Prognosegüte, Signalansatz, Probit-Ansatz, Markov-regime-switching-Ansatz, Südafrika

JEL: C14, C22, C53, E47, F31, F37

Three methods of forecasting currency crises: Which made the run in signaling the South African currency crisis of June 2006?[1]

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. In particular we are interested in the out-of-sample performance of these methods. Thus, we choose the latest crisis in 2006 to conduct an out-of-sample experiment. Whilst the literature knows meta-studies that compare the performance of different approaches[2] there are only few studies, which compare the out-of-sample performance of the different approaches with one data set.[3]

The South African economy is characterized by volatile foreign exchange market conditions. The volatility appears thereby in frequent 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. That is why the South African case is of particular interest. The high frequency of currency crises allows for calibrating forecasting models based on South African experiences. Thus, the analysis does not depend on data from other countries.

The rest of the paper is structured as follows: Section 2 introduces to the signals approach, the probit approaches and the Markov-regime-switching approach as methods of forecasting currency crises. In Section 3 the methods are employed to forecast South African currency crises. Section 4 compares the performance of the three approaches and section 5 concludes.

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1 The authors are thankful to Abdul Abiad for providing his program code to run Markov-switching models in Eviews.

2 E.g. *Abiad* (2003).

3 Notable exceptions are *Berg and Pattillo* (1999), and *Berg, Borensztein and Pattillo* (2004). But there are no out-of-sample model comparisons so far, that include a Markov-switching approach.

2 Three methods of forecasting currency crises

The theoretical literature on currency crises is centered on the paradigm of the three generations of currency crisis models. The first generation, owed to Krugman (1979), and Flood and 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 European Monetary System's crisis in 1992. 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 crisis of 1997/1998.

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 and Reinhart (1996, 1998) and Markov-switching approaches.[4] Signals approaches are non-parametric approaches that examine the behavior of potential explanatory variables prior to the detected crises and compare it with non-crisis periods. If some of the variables pass a certain threshold their changes are used as crisis signals.[5] Logit/probit-models use the binary variable crisis/no crisis as endogenous variable and estimate the impact of different sets of explanatory variables.[6] Markov-switching approaches do not depend on an a priori definition of crises. Besides these three techniques, further concepts are outlined in the literature.[7]

4 See *Abiad* (2003, p. 3). For a more detailed survey on Early-Warning Systems presented in this section see *Abiad* (2003).

5 See *Brüggemann and Linne* (2002). Other examples include *Berg and Pattillo* (1999), and *Edison* (2000).

6 Examples include *Berg and Pattillo* (1999); *Kamin, Schindler and Samuel* (2001); *Kumar, Moorthy and Perraudin* (2002).

7 These include artificial neural networks (ANN), whose advantage is the reflection of complex interaction between the variables (e.g. *Nag and Mitra* (1999); *Peltonen* (2006)); value-at-risk models, exposing several factors of risk to the ability of central banks to target a fixed exchange rate (e.g. *Blejer and Schumacher* (1998)); and restricted VAR models (e.g. *Krkoska* (2001)).

Signals approaches as well as probit approaches often base model parameter calculations on panel data.[8] This has the advantage, that the models can be employed to predict currency crises in countries with no or rare history of currency crises.[9] The disadvantage of a panel approach is that country specifics might be neglected. Thus, if a history of country specific currency crises is applicable, a single country approach is preferable.[10] In the case of South Africa, country specific indicators might dominate since the economy is not imbedded in a cluster of similar economies and shows special characteristics, e.g. the exceptional importance of gold and platinum prices.[11] The high number of currency crises in South Africa allows for a country specific approach.

2.1 The Signals approach

This paper largely follows the signals approach as developed by Brüggemann and Linne (2002), which is generally based upon Kaminsky and Reinhart (1996, 1998). The signals approach is used, because of its simple applicability and because it was found to outperform alternatives such as bond spreads and credit ratings.[12]

The first step in employing a signals approach is to define currency crises that occurred in the period of observation. This is done by the use of the Exchange Market Pressure index as outlined in section 3. 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.[13] 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 crisis 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.[14] The time-window spans from 18 months to 24 months.[15] In this paper we use an 18-months crisis window and a 12-month crisis window. The later is included to allow for comparison with other approaches, which usually employ shorter crisis windows.

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8 E.g. *Kaminsky, Lizondo and Reinhart* (1998).

9 See *Brüggemann and Linne* (2002: 8, 14-15).

10 E.g. *Abiad* (2003, p. 45), *Kittelmann et al.* (2006).

11 Compare section 3.

12 *Abiad* (2003, p. 3).

13 Variables, which may have an influence on the occurrence of currency crises in South Africa, are identified in section 3.

14 *Abiad* (2003, p. 9).

15 See for example *Brüggemann and Linne* (2002, p. 9) and *Kaminsky, Lizondo and Reinhart* (1998, p. 17) respectively.

The fifth step is to calculate individual crisis thresholds for each variable, which cuts tranquil periods from crisis 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:[16]

$$\omega_j = \frac{B/(B+D)}{A/(A+C)}. \tag{1}$$

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 crisis followed, *D* is the number of months in which no signal was sent and no crisis followed. In other words, the noise-to-signal ratio is the ratio between false alarms as part of non-crisis followed months and good signals as part of crisis 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 that 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 and 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 calculation is 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:

$$I_t^j = \begin{cases} 0 & I_t^j < T_1^j \\ 1 \ \ for & T_1^j \le I_t^j < T_2^j \ ; \ j = 1,...,k. \\ 2 & I_t^j \ge T_2^j \end{cases} \tag{2}$$

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:

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16 See *Brüggemann and Linne* (2002, p. 10).

$$Z_t^j = \sum_{i=1}^{l} \frac{I_{t+1-i}^j}{i};\ l = \begin{cases}12\\18\end{cases},\ for\ t \geq \begin{cases}12\\18\end{cases}. \tag{3}$$

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.

$$CI_t = \sum_{j=1}^{k} \frac{Z_t^j}{\omega_j}. \tag{4}$$

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 and Linne (2002), and Edison (2000) conditional probabilities for currency crises can be calculated:

$$P(crises_{t,t+18} \mid CI_l \leq CI_t < CI_u) = \frac{\sum \#\,months\ for\,CI_l \leq CI_t < CI_u\ and\ crisis\ follows}{\sum \#\,months\ for\,CI_l \leq CI_t < CI_u}. \tag{5}$$

For each arbitrarily chosen 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 that the limited dependent variable takes a value of zero in non-crisis or tranquil periods, while it takes a value of one in crisis periods and in differently defined “window” periods before a crisis. In general the probit models take the form of:[17]

$$Pr(y_t = 1 \mid x_t) = \Phi(x_t'\beta). \tag{6}$$

The method developed by Berg and Pattillo (1999) uses the signals 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

17 Compare e.g. *Wooldridge* (2001, chapter 15).

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 crisis thresholds, the leap at the threshold and the slope above the threshold as variations of the independent variables.[18] The Berg & Pattillo approach is element of the Developing Country Studies Division model, which is used by the International Monetary Fund.[19] 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 window.

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.[20]

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 crisis 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 crisis 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.[21] 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 changes 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.

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18 See *Berg and Pattillo* (1999, pp. 572-574).

19 See *IMF and World Bank* (2005, p. 37).

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

21 See for example *Quandt* (1958); *Goldfeld and Quandt* (1973).

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 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 crises. Finally, the Markov-switching model provides concrete crisis probabilities 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 that 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:

$$y_t \mid s_t \overset{iid}{\sim} N(\mu_{s_t}, \sigma^2_{s_t}) \tag{7}$$

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 higher exchange rate volatility during the crisis state (which will also lead to a higher and more volatile EMP variable). The conditional density of y_t given s_t is equal to

$$f(y_t \mid s_t) = \frac{1}{\sqrt{2\pi}\sigma_{s_t}} \exp\left(\frac{-(y_t - \mu_{s_t})^2}{2\sigma^2_{s_t}}\right). \tag{8}$$

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:

$$P_t = \begin{pmatrix} p_t^{00} & p_t^{01} = (1 - p_t^{00}) \\ p_t^{10} = (1 - p_t^{11}) & p_t^{11} \end{pmatrix} \tag{9}$$

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:

$$P_t(s_t = 0 \mid s_{t-1} = 0, x_{t-1}; \beta_0) = \frac{\exp(x_{t-1}^{'}\beta_0)}{1+\exp(x_{t-1}^{'}\beta_0)} \tag{10}$$

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

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

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

The (kx1)-vector x_{t-1} includes the early-warning indicators which may affect the transition probabilities through the (*k*x1) 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.[22]

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 crisis probabilities, using[23]:

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

= 1-Pr(no crisis over next 1month)^{n}

= 1-(1-Pr(crisis over next 1month))^{n}

In most applications it has become standard to define a binary "alarm signal" which is equal to 1 if the crisis probability exceeds a general threshold, and 0 otherwise. We set this threshold inline with other studies equal to 50%.[24] Thus, whenever the crisis probability lies above this number our model forecasts a crisis during the next 12-month.

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

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

24 *Berg and Pattillo* (1999)

3 Currency crisis forecasts for South Africa

Now we use the above-described techniques to show to what extend these methods are able to detect currency crises in South Africa. First, we look at their in-sample fit to evaluate the model specific forecasting performance for the sample period from 1995 to December 2004 and June 2005 for the 18-month and the 12-month time window case respectively. Second, we do an out-of-sample experiment where we employ forecasts for the risk of currency crises until the advent of the June 2006 currency crisis. Since it is well known from recent forecasting literature that good in-sample forecasting performance does not necessarily translate into good out-of-sample forecasts.[25] Due to the fact that currency crises occur very infrequently we can only use one crisis for the forecasting exercise. So these results should be interpreted with caution.

To identify currency crises we use the standard definition of the Exchange Market Pressure Index (EMP).[26] 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.[27] The use of this threshold identifies five percent of the periods as crisis periods, if the time series is normally distributed. Figure 1 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 floating exchange rates – did not significantly react to the crisis. This makes the crisis 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.

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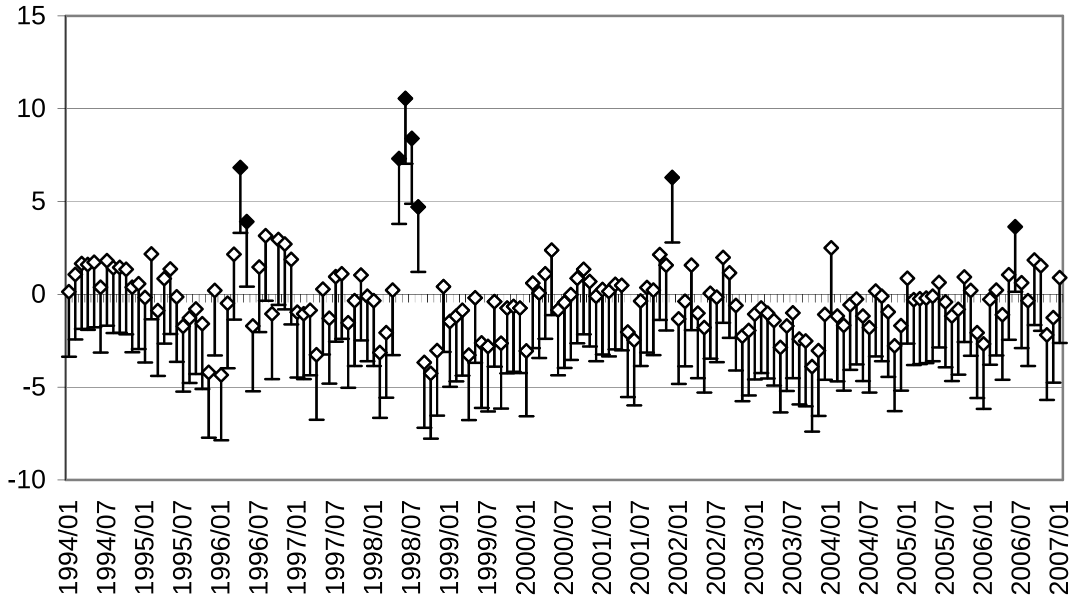
25 See e.g. *Clements and Hendry* (2001) for a general discussion as well as *Berg, Borensztein and Pattillo* (2004) who emphasize the importance of out-of-sample prediction performance for early-warning-system models of currency crises.

26 See *Bhundia and Ricci* (2005, p. 157), *Kaminsky and Reinhart* (1996, p. 4), *Eichengreen, Rose and Wyplosz* (1996, pp. 474-475). For a discussion of different EMP measures for South Africa see *Knedlik* (2006).

27 See e.g. *Bhundia and Ricci* (2005).

Figure 1:
Currency crises identified by the Exchange Market Pressure Index



Source: own calculations. Note: The figure presents current values of the EMP index for each period. If the confidence interval, marked with the lines below the dots, lays completely above the zero line, the period is called a crisis month, also full dots indicate crisis months.

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 and 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 South African Reserve Bank (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.[28] Whilst the variables were derived from considering the theory of currency crises is not always possible to indicate which generation of currency crisis models is addressed by a specific indicator. Most variables play important roles in more then one currency crisis model. A typical indicator for currency crises of the first generation would be (12) the growth rate of foreign debt of the government. A variable derived from second generation models would be (14) the inflation differential to the US, indicating that exchange rate developments might be in conflict with other policy targets, e.g. inflation. Typical for third generation models are indicators related to the banking sector such as (10) the interest differential to the US and (13) the ratio of lending to deposit rates. 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 for all approaches is taken or derived from SARB online statistics.

3.1 The Signals approach

The signals approach is employed as described above. 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 the price of gold. The calculation of conditional probabilities yields figures as reported in Figure 2.

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 crisis, where the signal approach shows the lowest risk of the whole sample.

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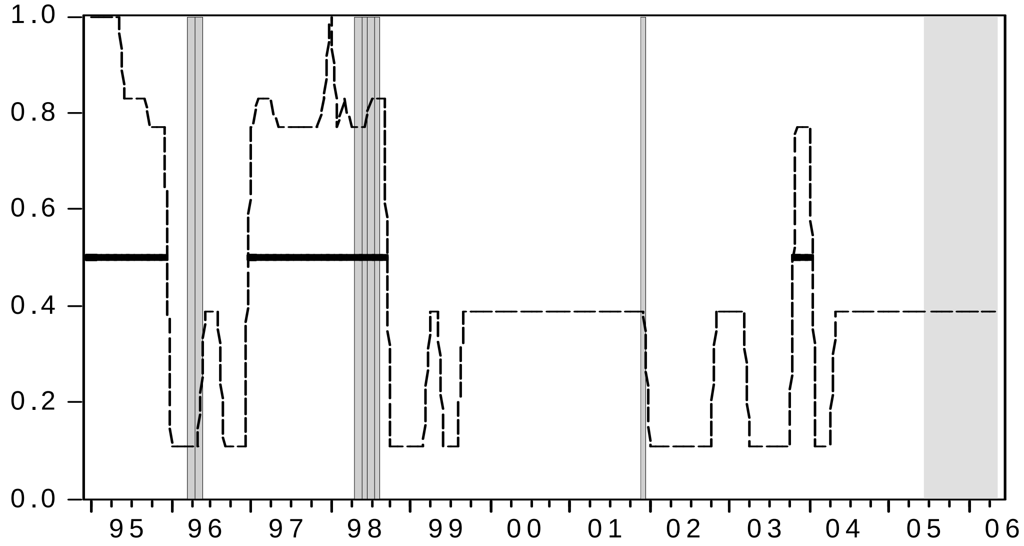
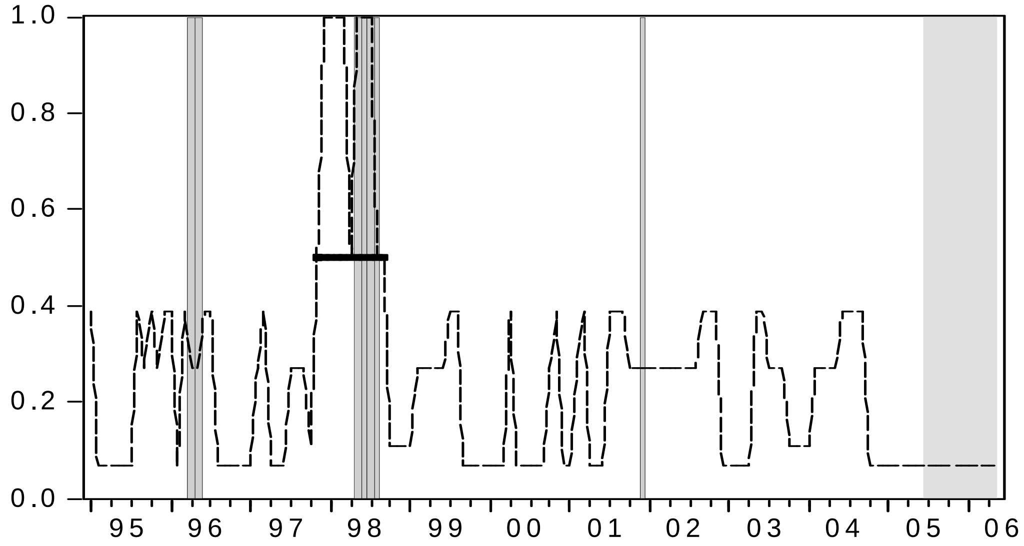
28 E.g. *Aron and Muellbauer* (2005, p. 30).

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



Source: own calculations. Note: The gray columns indicate crisis months, the bold black line/dots indicate that alarm signals were sent, the dashed line is the current crisis probability in the respective periods, the gray shaded area indicates the out-of-sample period

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

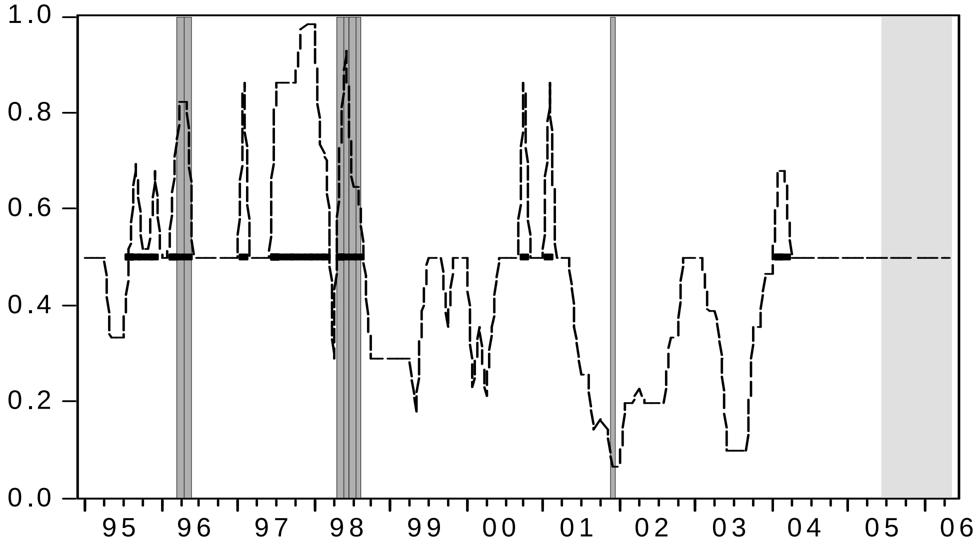
We first conduct a probit approach that uses the signal variables of the signals approach as independent variables and an 12-months crisis window as binary independent variable, i.e. the dependent variable takes the value of one in crisis months and up to twelve months prior a crisis and takes the value 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 "Based on signals" in Table 1 and the forecasts are presented in Figure 4.

Table 1:
Probit estimations

	Based on signals (12-months window)		**Based on raw data (12-months window)**		**Based on raw data (18-months window)**	
Indicator	Coeff.	z-stat.	Coeff.	z-stat.	Coeff.	z-stat.
Constant	0.77	-4.43	-13.26	-4.87	-6.14	-3.87
Budget deficits	0.02	0.05	-	-	-	-
Dom. Interest rate	0.67	2.97	0.53	3.97	-	-
Foreign debt	-0.02	-0.09	-	-	-2.75	-3.20
Gold price	1.64	3.55	-	-	-	-
Industrial prod.	-0.02	-0.09	-	-	-	-
Lend./deposit rates	-0.22	-0.87	-	-	-	-
Credit/GDP	-	-	-	-	-34.98	-3.07
Bank deposits	-	-	-49.80	-4.69	-51.89	-4.70
Exports	-	-	-16.24	-3.25	-	-
M2	-	-	-9.80	-4.17	-4.22	-3.28
Inflation differential	-	-	0.28	2.01	-	-
Inter. liq. position	-	-	-0.0001	-2.19	0.0001	2.38
Dom. interest rate	-	-	-	-	1.70	3.96
Interest differential	-	-	-	-	-1.87	-4.10
Imports	-	-	-	-	13.11	3.79
Number of obs.	137		137		131	
LR-Test joint sign.	31.12		133.74		132.30	
p-Value	0.00		0.00		0.00	
McFadden R^2	0.18		0.78		0.73	

Source: Own calculations.

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



Source: 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 crisis 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.[29]

The next approach is to estimate probit estimations that use the original data instead of signal variables as right-hand side variables. We include all variables that contribute significantly to the statistical explanation. The probit model is again calculated for the 12 and the 18-months crisis window.

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 “Based on raw data (12-months window)” in Table 1).

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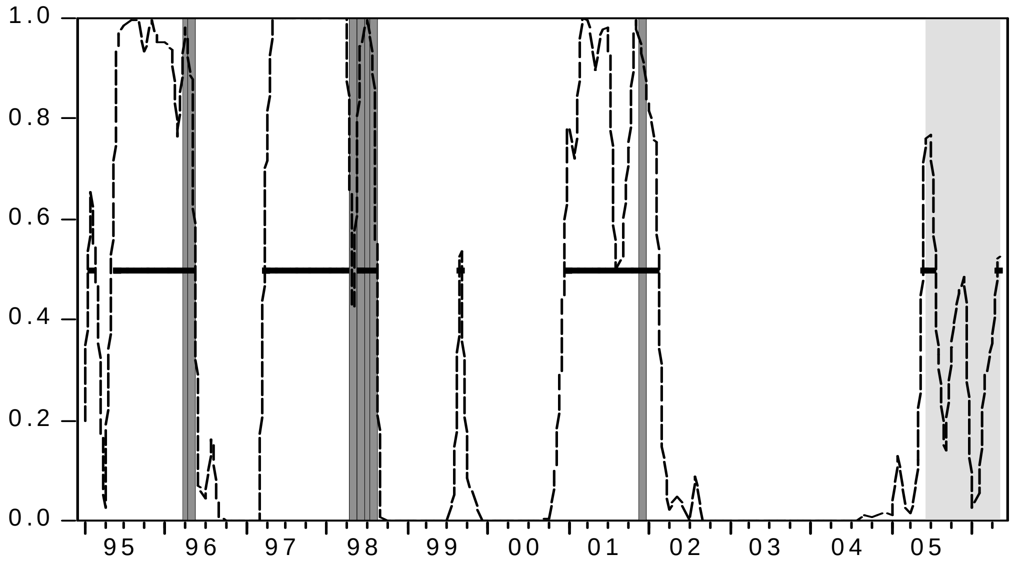
29 Results are not reported but are available from the authors on request.

Figure 5 reports the forecast results of the 12-months crisis window probit model. The model predicts all currency crises (in sample and out-of-sample) correctly and does only limited set off false alarms.

Figure 5:
Probit forecasts (12-months crisis window, model based on raw data)

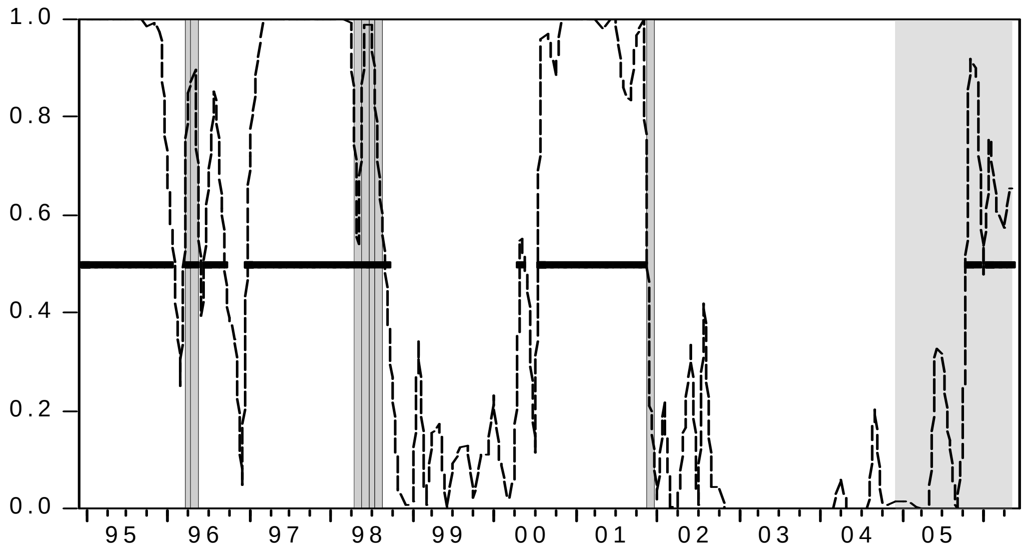


Source: own calculations.

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 6 and column "18-months window" in Table 1). The model with the longer crisis window performs better with regard to out-of-sample forecasts.

The results of the probit analysis of currency crisis forecasts leads to the conclusion that the models are able to predict the 2006 currency crisis in South Africa.

Figure 6:
Probit forecast (18-months crisis window, model based on raw data)



Source: own calculations.

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 that 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 of common importance.[30]

We estimate the model with a sample period from 1995:01 to 2005:05. 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 crisis state, we expect only positive signs for our indicators. For South Africa we found

30 This is not a substitute for a test of omitted variables. Such a test is not feasible in our setting because it is not possible to run the model with all variables together due to problems in the convergence of the likelihood function.

only the growth rate of bank deposits of individuals and the change of the international liquidity position to be important early warning indicators.[31]

These two indicators enter into our final multivariate model. Table 2 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 2:
Estimation of the Markov-switching model

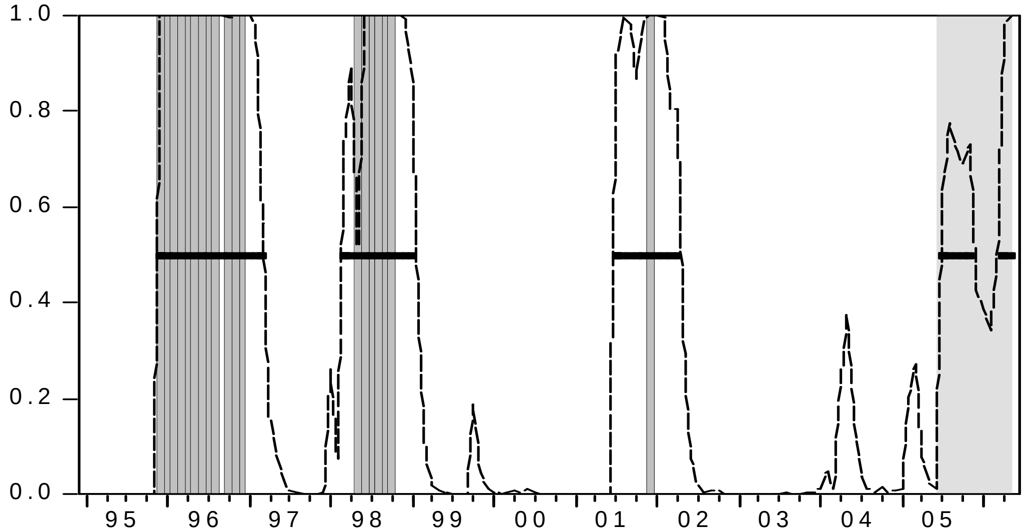
Indicator	Coeff.	t-stat.
Mean (State 0)	-0.70	-5.05
Mean (State 1)	2.40	2.41
Sigma (State 0)	1.42	13.18
Sigma (State 1)	3.84	5.30
International liquidity position, difference	5.42	0.71
Bank deposits of individuals, growth rate	1.87	0.78
Constant (State 0)	6.20	0.86
Constant (State 1)	0.81	1.61
Number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

Source: Own estimations.

If one examines the crisis dates determined by the Markov-switching model we find the first and longest crisis 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 crisis period (until October instead of August). The last dated crisis in December 2001 is exactly the same as with the signal approach.

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

Figure 7:
Markov-switching Forecast



Source: Own calculations.

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 crisis month the model started to send signals and anticipated the following episodes correctly. In contrast to the first crisis, the second one was predicted before the event arose (namely two months before). The same holds true for the last crisis in our sample. In this case the alarm signal was sent as of July 2001 and the crisis occurred in December. The situation is only slightly different when the EMP crisis definition is employed. Here, the model sends alarm signals prior each crisis. But another important feature of the Markov-switching approach is that it still sends alarms signals straight after a crisis occurred. This characteristic leads to some false alarms.

More interestingly is the out-of-sample predictive ability of our model. Since we know that in June 2006 there will be a crisis, 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 up-coming crisis very well.

4 Comparing the forecast performance of the three 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 3 gives a flavor of these indicators.

Table 3:
Forecasting performance of different approaches (all based on 12-months crisis window)

Goodness-of-fit (cut-off-prob. of 50%)	Signals	Probit (signals)	Probit (raw data 12)	Probit (raw data 18)	Markov-switching (model immanent)	Markov-switching (EMP crises)
Percent of observation correctly called	77	62	93	76	67	58
Percent of pre-crisis periods correctly called	25	40	91	89	45	38
Percent of tranquil periods correctly called	98	72	94	66	82	70
False alarms as percent of total alarms	18	4	11	8	10	19
Out-of-sample: Percent of pre-crisis periods correctly called	**0**	**0**	**25**	**33**	**67**	**67**

Source: Own calculations.

The last row of Table 3 provides a measure for the out-of-sample performance of the methods, while all other rows of the table provide measures of in-sample performance. The probit approach based on raw data forecasts 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 the probit approach (based on raw data, 12 months) 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. Therefore, the last column of Table 3 shows the performance of the Markov approach when EMP crisis definition is used. The only methods with correct out-of-sample forecasts are the Markov-switching approach and the probit approach based on raw data.

Other criteria to be considered when applying early warning systems would be the simplicity of the method, where the signals approach has an advantage. However, since probit and Markov-switching models can now also be run by standard econometric software this advantage is narrowing. Another criterion would be the arbitrariness of the definition of currency crises. This problem is often discussed with regard to the EMP index. Here the Markov-switching approach has the advantage of a synchronous identification of crisis periods and the calculation of current risk of currency crises.

5 Conclusions

In this paper we compared three popular methods of forecasting currency crises in South Africa. Our emphasis was on the out-of-sample performance of these models, because we think that this is of primary importance in assessing the actual risk of a currency crisis.

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, that were based on raw data. Employing a Markov-regime-switching approach also allows to predict the out-of-sample crisis. The answer to the question of which method made the run in forecasting the June 2006 currency crisis is: the Markov-switching approach, since it called most of the pre-crisis periods correctly. However, the "victory" is not straightforward. In-sample, the probit models perform remarkably well and it is also able to detect, at least to some extent, out-of-sample currency crises before their occurrence. It can, therefore, not be recommended to focus on one approach only when evaluating the risk for currency crises. Further research is needed to validate our results.

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