An Early Warning Model for Currency Crises in Central and Eastern Europe [1]

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Abstract

In this study, an early warning model for currency crises was developed for a sample of quarterly data from twelve Central and Eastern European transition countries. After reviewing the relevant literature, it was shown that a number of indicators contain useful information for early warning purposes when evaluated according to the signal approach. In a next step, the appropriateness of the signal appoach's underlying functional specification was investigated by means of bivariate regressions on one economic variable in different functional specifications.

On the basis of this analysis, two multivariate probit regressions with all statistically significant economic variables on a (0,1)-distributed crisis variable were estimated. For in-sample forecasts, the predictions of both model specifications proved to perform significantly better than random guesses as well as some comparable early warning models. Overall, the model appears to track developments in individual countries rather well, with the exception of countries with consistenly strong macroeconomic fundamentals. With respect to economic interpretations, the results of this study lend support to the hypothesis that currency crises in Central and Eastern Europe may be considered as "first-generation" types of crises.

JEL-Codes: C25, F31, F47
Keywords: Currency crises, crisis prediction, Central and Eastern Europe

1 Introduction

The large number of financial crises that erupted in the course of the 1990s has ignited great interest in the development of early warning models for financial crises. At the same time, advances in economic theory suggest that the development of reliable early warning systems for financial crises is likely to meet with considerable difficulties. While empirical studies for broad samples of emerging markets are relatively abundant, rather few investigations have been made for geographically constrained samples. This is particularly true for the Central and Eastern European transition countries, where the scarcity of available data imposes additional limitations on empirical research. On the other hand, the ongoing processes of liberalization of capital flows and convergence toward the present EU Member States is likely to pose considerable challenges for the macroeconomic stability of these countries. As a result, tools for the detection of vulnerabilities in these countries could provide an important contribution to the stable macroeconomic development in the region and the smooth integration of candidate countries into the European Union and – finally – into the euro area.

The focus of this study lies on one particular type of disturbances to macroeconomic stability, namely currency crises. In the course of this paper the terms “currency crisis” and “balance of payments crisis” will be used synonymously. As will be outlined in more detail below, the definition of crises used in this paper focuses on discrete events rather than on continuous measures of downward pressure on a currency.

The first section of this paper contains a brief overview of the relevant theoretical literature on this subject and a categorization and discussion of existing empirical studies. Next, the so-called “signal approach,” which is strongly associated with the work of Kaminsky, Lizondo and Reinhart (1998), will be applied to a sample of quarterly data from twelve Central and Eastern European transition economies. In this section the aim is to identify the empirical relevance of individual economic indicators for the prediction of currency crises. The selection of these indicators is based mainly on the results of Berg and Pattillo (1998). In a further step the appropriateness of the functional form implicitly embedded in the signal approach will be investigated. On the basis of this analysis, the aim of the subsequent part of this paper is to develop a multivariate probit model incorporating all relevant economic variables simultaneously, with a dummy crisis variable as the regressand. Finally, the predictive power of such a model will be evaluated by a number of statistical tests which provide the basis for the conclusions presented in the final section of the paper.

2 Literature Review

2.1 Theory

Although this paper has an empirical focus, I should like to review very briefly some key insights from the theory of currency crises, as this theory makes some important predictions regarding the ability of empirical models to correctly forecast currency crises.

The so-called first-generation crisis models, pioneered by Krugman (1979), strongly emphasize economic fundamentals in their explanation of balance of payments/currency crises. According to Krugman (1979), currency crises are the consequence of inconsistencies in economic fundamentals with governmental attempts to maintain a fixed exchange rate peg. In Krugman's model, the root of currency turbulences lies in an excessive expansion of domestic credit used to finance fiscal deficits or to support a weak banking system. A critical assumption is the government's inability to fulfill its financing needs by tapping capital markets, which results in a monetization of deficits. The expansion of money supply leads to downward pressure on domestic interest rates, capital outflows and losses of official reserves. As a result, the vulnerability of the currency to a speculative attack increases. There are a number of extensions of Krugman's (1979) initial model (for instance Flood and Garber (1984), Connolly and Taylor (1984)), but a common feature of these models is the explanation of curreny crises by the inconsistency of a fixed peg with domestic policies. Therefore, according to these models, currency crises are predictable.

The difficulties of first-generation models in explaining contagion effects and the occurrence of balance of payments crises in countries with relatively sound fundamentals led to the development of second-generation models. In this approach, features of speculative attacks are explicitly incorporated. Second-generation models regard currency crises as shifts between different monetary policy equilibriums in response to self-fulfilling speculative attacks.

According to Kaminsky, Lizondo and Reinhart (1998), a crucial assumption of these models is that economic policies are not predetermined, but respond instead to changes in the economy and that economic agents take this relationship into account in forming their expectations. At the same time, the expectations and actions of economic agents affect some variables to which economic agents respond. This circularity creates the possibility for multiple equilibria; the economy may move from one equilibrium to another without a change in fundamentals. Thus, the economy may initially be in an equilibrium consistent with a fixed exchange rate, but a sudden worsening of expectations may lead to changes in policies that result in a collapse of the exchange rate regime, thereby validating agents' expectations. For instance, Obstfeld (1994, 1996) presents models in which a loss in confidence increases the costs of maintaining a fixed peg for the government. In the former model, expectations of a currency crash drive up wages, which negatively affects output. In the latter model, higher interest rates increase the government's debt servicing costs. In both models, the government decides to abandon the peg as the cost of maintaining the peg exceeds the cost of abandoning it.

Because of the much more import role of unpredictable changes in market sentiment in this approach, these models suggest that currency crises are very difficult to predict. Nevertheless, economic fundamentals do still play a role.

2.2 Empirical Studies

The large number of financial crises that occurred in emerging markets in the course of the 1990s has ignited great interest in early warning models for financial crises. As a result, literature on this subject has become abundant. Vlaar (2000), who provides an excellent methodological comparison of currency crises models, distinguishes three main types of such models: The first type comprises case studies concentrating on specific episodes of financial turmoil. While these models are less geared towards predicting the exact timing of financial crises, they rather aim at explaining the severity of financial crises. Papers by Blanco and Garber (1986), Sachs, Tornell and Velasco (1996) or Bussieré and Mulder (1999) are notable examples for this kind of model class.

A second category of studies, which may be summarized under the label "signal approach" is strongly associated with the work of Kaminsky, Lizondo and Reinhart (1998), Kaminsky (1998) as well as Kaminsky and Reinhart (1999). In their papers, the levels of individual variables, such as the real exchange rate or the export growth rate during a specified period before the outbreak of a crisis are compared with tranquil periods. A variable is deemed to issue a signal if it exceeds a certain threshold. The threshold is set such that the noise-to-signal ratio (defined as the share of wrong signals that are preceded by tranquil periods divided by the share of correct signals that are followed by crises) is minimized.

The third type of model consists of limited dependent (probit or logit) regression models. In these models, the currency crisis indicator is modeled as a zero-one variable, as in the signal approach. However, unlike in the signal approach, the explanatory variables do not take the functional form of a dummy variable, but enter the model mostly in a linear fashion. Moreover, the significance of all variables is analyzed simultaneously, while the signal approach investigates the relationship between dependent and explanatory variables in a bivariate way. Frankel and Rose

(1996), Berg and Pattillo (1998) and Kumar, Moorthy and Perraudin (2002) may be cited as examples of this genre. Vlaar (2000) presents a model which combines elements of the severity of crises and the limited dependent regression approach.

There are a number of advantages and disadvantages that are associated with each methodological approach: While the case study type of papers are able to avoid the need to define crises as discrete events, they focus on crisis times only. As a consequence, they neither incorporate information from tranquil times, nor are they well suited for predicting the timing of a crisis.

The signal approach uses information from crisis and non-crisis times and takes the timing of crises explicitly into account. A major advantage of this method is the evaluation of each indicator's predictive power on an individual basis, which facilitates the establishment of indicator rankings. Moreover, this method is useful for designing policy responses, as the economic variables which issue warning signals can be immediately identified. However, owing to the bivariate character of this approach, the interaction among indicators is not taken into account. A related drawback is the fact that these models do not directly produce a composite early warning indicator that incorporates all available information from individual indicators. Kaminsky (1998) offers a solution to this problem by proposing a single composite early warning indicator that is calculated as a weighted sum of the individual indicators. In her paper, each indicator is weighted according to the inverse of its noise-to-signal ratio.

Another possibly problematic aspect of this approach is the implicit assumption of a very specific functional relationship between explanatory and dependent variables. The probability of crisis is modeled as a step function of the value of the indicator, taking on a value of zero when the indicator variable is below the threshold and a value of one if the opposite is true. Thus, for instance, these models do not distinguish whether the indicator variable just exceeds the threshold or whether it does so by a wide margin. Finally, the signal approach does not easily allow the application of some standard statistical evaluation methods, such as the testing of hypotheses.

Most of the disadvantages associated with the signal approach are resolved in limited dependent regression models: Results are easily interpreted as probabilities for the outbreak of a crisis and standard statistical tests are immediately available. Moreover, these models capture the effect of all explanatory variables simultaneously and they are flexible enough to deal with different functional forms for the relationship between dependent and explanatory variables, inclusive of dummy variables. A problem is posed to these models by the fact that the number of crises in the underlying sample is usually very small in comparison with the number of tranquil periods. As a result, the statistical properties of limited dependent regressions are often rather poor.

Most empirical studies dealing with currency crises use a broadly based sample of emerging markets. In some cases industrial countries are included, too, while the number of studies that focus exclusively on a particular region are relatively scarce. A recent example for a regionally focussed study is provided by Wu, Yen and Chen (2000) who estimate a logit model for South East Asian countries.

Studies which are based on samples with a large number of countries bear the advantage of being able to produce very strong results, as they are neither subject to criticism of using too small or biased samples. However, such studies could produce less reliable warning signals for a specific region that is characterized by common structural features. According to Weller and Morzuch's (2000) results it seems plausible to assume that the Central and Eastern European transition economies (CEECs) bear some common structural features that affect their proneness to financial crises and differentiate them from other emerging economies. Therefore, an early warning model based entirely on a sample of Central and Eastern European countries could be capable of producing superior results in terms of predictive power than a horizontally strongly diversified sample.

Empirical studies dealing with early warning models for currency crises in Central and Eastern Europe are scarce, mainly for the obvious reason of the shortness of time series. Notable examples include Brüggemann and Linne (1999, 2001) and Krkoska (2001). Brüggemann and Linne (1999, 2001) basically apply the Kaminsky-Lizondo-Reinhart (1998) framework with a few extensions to 13 CEECs and three Mediterranean countries (Cyprus, Malta and Turkey). Krkoska (2001) estimates a VAR-model for four countries (Czech Republic, Hungary, Poland, Slovak Republic) with an index of speculative pressure (comprising changes in exchange rates, international reserves and interest rates) as a dependent variable measuring downward pressure on the exchange rate (in a linear fashion).

3 An early warning model for currency crises in Central and Eastern Europe

The approach employed in this paper draws greatly from the work of Berg and Pattillo (1998). For a 23 country sample with monthly data covering the time period from 1970 to April 1995 they identify (1) the deviation of the real exchange rate from a trend, (2) the current account, (3) the growth of reserves, (4) the growth of exports, (5) the ratio of M2/reserves and (6) the growth of M2/reserves as statistically significant variables for explaining currency crises. In addition to these variables, the budget balance/GDP is used in this paper.

In a first step, the predictive power of these variables is analyzed according to the signal approach. Next, I run probit regressions on the dummy crisis variable for each explanatory variable separately, but with different functional specifications for the explanatory variable in order to check whether the dummy variable specification employed in the signal approach or alternative specifications seem more appropriate. Finally, I will present a probit model using the variables mentioned above.

3.1 Data and Definitions

This study uses all available quarterly data from twelve transition countries from the beginning of 1989 up to the end of 2001. Data sources include the Vienna Instiute for Comparative Studies' database, the IMF's international financial statistics and the BIS database. However, data for all variables and countries generally do not exist for the full 1989-2001 period. Mostly, time series start in the first quarter of 1992 and end in the third quarter of 2001. The country dimension of the sample consists of: Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Russia, Slovak Republic, Slovenia. All explanatory variables are measured in percentiles of the country-specific distribution of this variable.

In my definition of currency crises, I focus on the following events which were identified by Brüggemann and Linne (1999) as the beginning of currency crises:

- Bulgaria
    - January 1997: Hyperinflation and massive depreciation of the lev. Later, currency stability is reestablished by means of a currency board.
- Czech Republic
    - May 1997: After ten days of heavy pressure on the koruna, the fixed exchange rate regime is abandoned and the koruna is left to float.
- Hungary
    - December 1994: The government acknowledges the necessity for the launch of an austerity package (including a 9% one-off devaluation of the forint and the introduction of a crawling peg regime) after the current account deficit has exceeded 9%. Actual measures took effect in March 1995.
- Romania
    - January 1997: The lei devalues 20% in the space of one week.
- Russia
    - August 1998: Forced devaluation of the rouble, switch to a flexible exchange rate regime, moratorium on debt payments

In addition to these events, the following episodes were defined as currency crises[2]:

[2] A few other episodes of sharp currency depreciations occurred during the sample period, but there are no data for the economic variables available.

- Poland[3]
    - February 1992: Having a crawling peg exchange rate regime in place, Poland has to undertake an extra-devaluation of the zloty of 10.7%.
- Russia
    - First quarter of 1994: Following an episode of hyperinflation the rouble begins to fall sharply versus the US dollar: In the course of the first quarter of 1994 the rouble's depreciation amounts to more than 40% relative to the end of the preceding quarter
- Slovak Republic
    - October 1998: Abandonment of the fixed exchange rate regime after prolonged downward pressure on the koruna

There are a few other episodes of sharp falls in Central and Eastern European currencies. However, these events occurred in the early nineties for which data are not available and thus, these events are not represented in the sample. Given the crisis definitions listed above, in the following sections the dependent variable always equals one if there is a crisis and zero otherwise. In the regression equations reported below, not only the periods marking the beginning of a crisis were set equal to zero, but also the eight periods preceding the crisis. This procedure, which was successfully applied by Berg and Pattillo (1998), has some important advantages: Provided the signals of a crisis are indeed visible two years before the actual event, this method identifies the optimal model which is able to issue warnings two years in advance. Taking account of the time lag until data are published, the signaling horizon is long enough to take action in response to the predictions of the model. Obviously this also avoids the need to work with lagged variables. From the statistical point of view this procedure strongly increases the number of ones in the sample, which is beneficial for the statistical properties of the model.

3.2 Using the Signal Approach

In the signal approach, an indicator is understood to issue a signal, if the level of the indicator exceeds a certain threshold. The threshold, in turn, is defined relative to the percentiles of the country-specific distribution of the indicator. For instance, if the threshold for the current account is set at the 80th percentile, all values of the current account that exceed the 80th percentile in country A would constitute a signal. Obviously, the time horizon between the signal's time of issuance and the outbreak of the crisis needs to be set appropriately: Signals that are sent too early to credibly stand in any relationship with subsequent crises should be avoided, as should be signals that are sent too late to prompt action. In this paper, I opted for a signaling horizon of eight

[3] This crisis episode was used in some, but not all investigations, as most, but not all data are available for these time periods

quarters for the evaluation of indicators. An indicator is considered to send a “good signal” if the indicator variable exceeds the threshold and a crisis occurs within the limits of the signaling horizon. Correspondingly, a signal is deemed “bad” if the indicator emits a signal, but no crisis follows during the signaling horizon.

The performance of each indicator can be evaluated according to the following matrix, as proposed by Kaminsky, Lizondo and Reinhart (1998):

	Crisis (within 8 quarters)	No crisis (within 8 quarters)
Signal was issued	A	B
No signal was issued	C	D

In this matrix, A means the number of months in which a good signal was sent, B is the number of bad signals, C is the number of months in which the indicator failed to issue a signal (which would have been a good signal) and D is the number of months in which the indicator rightly refrained from emitting a signal, as it was not followed by a crisis in the signaling horizon. Using the input from the matrix, the noise-to-signal (NtS) ratio for an indicator can be computed according to the following formula:

(1) $NtS = [B/(B+D)] / [A/(A+C)]$

The signaling threshold is to be set such that NtS reaches a minimum. Ideally, one would want a NtS that comes as close as possible to zero. In the literature[4], often a distinction is made between indicators providing useful information that is reflected in a noise-to-signal ratio below one and indicators that have a noise-to-signal ratio above one. Results for each indicator are reported in Table 1.

Most of the variables identified as relevant indicators by Berg and Pattillo (1998) exhibit noise-to-signal ratios below one in our sample. However, NtS ratios are generally lower than in Brüggemann and Linne (1999). A possible explanation could be the relatively small number of observations per country, which results in rather crude country-specific distributions. Among the indicators, the budget balance as a percentage of GDP seems to be relatively less important than in Brüggemann and Linne (1999), where this indicator was identified as the secondmost important.

[4] For instance, Berg and Pattillo (1998)

Table 1: Performance of indicators according to the signal approach

	Number of observations used in calculation	Good signals, % of possible good signals A/(A+C)	Bad signals, % of possible bad signals B/(B+D)	Noise-to-signal ratio NtS
Real effective exchange rate, deviation from HP trend	480	5	2	0.47
M2 / gross official reserves	465	73	44	0.61
% change in M2 / gross official reserves, yoy	425	68	44	0.64
% change in exports in USD, yoy	389	15	10	0.64
Gross official reserves	478	68	64	0.94
Budget balance, % of GDP	358	95	91	0.96
% change in gross official reserves, yoy	449	95	97	1.02
Current account, % of GDP	399	92	97	1.05

3.3 Is there a case for an alternative functional specification?

Having confirmed the empirical relevance of a number of variables as early warning indicators according to the signal approach methodology, I will deal next with the question whether the implicitly embedded functional relationship between the (0,1) crisis variable and individual indicators is justified. According to Vlaar (2000), the transformation of the indicator variable into a dummy variable, based on the criterion whether its value is above or below the threshold, can be expected to yield the best results if there is a clear distinction between crisis periods and periods of tranquillity. Presumably this condition is best fulfilled if only the most severe crises are above the threshold or if the crisis definition is related to a currency peg.

Although the crisis definition employed in this study is probably largely in line with this condition, the results reported in Table 1 suggest that other functional specifications than the step function relationship between the crisis variable and the indicators could be more appropriate for some variables. In particular, this seems to be the case for the real effective exchange rate variable, the budget balance, the change in gross reserves and the current account. For these variables, the optimal thresholds are very close or equal to the ends of the distributions. Moreover, for these variables, both the percentage of good signals and bad signals is either very low or very high. Nevertheless, some of these variables have rather high noise-to-signal ratios, which could mean that the probability of a currency cisis is a linear function of the indicator rather than rising sharply when the indicator exceeds a certain threshold.

In order to investigate this question in more detail, I run probit regressions on the crisis variable for the pooled panel with different functional specifications for one particular explanantory variable, as suggested by Berg and Pattillo (1998). For each indicator, I estimate equations which assume the following format:

$$(2)\ \text{Prob}\ (c8 = 1) = f(\alpha_0 + \alpha_1 p(x) + \alpha_2 I + \alpha_3 I(p(x)-T))$$

Where c8 = 1 if a crisis occurs during the next eight quarters, p(x) is the percentile of the variable x and I = 1 if the percentile is above some threshold T and zero otherwise. For the thresholds T the results from the signal approach calculations are used. Thus, if the threshold concept provides an appropriate functional specification, only the coefficient α_2 should be statistically significantly different from zero. Significant coefficients α_1 and α_3 would point to a linear functional relationship between crisis variable and indicator and a different (higher) slope coefficient when the indicator is above the threshold, respectively. Table 2 summarizes the results of these regressions.

For a few indicators the closeness of thresholds to one end of the distribution resulted in meaningless estimation results, which is indicated by the empty cells. In these cases the equation was estimated again without the variable causing the problems. Although the jump coefficients (α_2) are statistically significant in a number of cases, the results reported in Table 2 provide empirical support for more general specifications, too. This hypothesis gains further support by Berg and Pattillo's (1998) observation that the procedure applied above produces a bias in favor of finding significant jump coefficients. As the data themselves were used to identify the biggest jumps (through the signals method), the subsequent tests will tend to find that the jumps identified in the preceding section are unusually large. Thus, the t-tests performed on these regressions overestimate the statistical significance of the dummy variable coefficient α_2.

Generally, the variables specified as changes seem to be better captured by the linear specifications. Considering the nature of the variables, this is a very plausible result, as it seems difficult to imagine for instance that there is a threshold for the growth rate of exports that is associated with a jump in the proneness of the country to a financial crisis. On the contrary, it seems very well possible that the probability of a currency crisis decreases with every unit of an increase in the growth rate of exports. However, even for some level variables, e.g. the balances of the budget and the current account, the linear specifications seem to make more sense than the dummy variable specification.

Table 2: Bivariate probit regressions for individual indicators

	Coefficients for alternative specifications, t-statistics in brackets			
Variable	**Percentile (α_1)**	**Dummy (α_2)**	**Dummy*(percentile treshold) (α_3)**	**Number of observations used**
Real effective exchange rate, deviation from HP trend	0.239976 (0.953674)	0.311680 (0.743470)	n/a	474
M2 / gross official reserves	1.619717 (1.960928)	0.714314 (2.490426)	-3.600123 (-3.354582)	465
% change in M2 / gross official reserves, yoy	-0.029976 (-0.039055)	0.024003 (0.072518)	1.898985 (1.755177)	416
% change in exports in USD, yoy	-0.786224 (-2.376715)	0.860930 (1.890679)	-3.548700 (-0.578218)	395
Gross official reserves	-1.756886 (-1.438976)	1.162194 (3.623216)	-0.856122 (-0.641924)	478
Budget balance, % of GDP	-1.223752 (-3.452239)	0.621120 (1.458146)	n/a	346
% change in gross official reserves, yoy	-0.884787 (-1.560063)	0.264278 (0.831190)	-0.045537 (-0.039305)	481
Current account, % of GDP	-1.400776 (-4.701965)	n/a	n/a	396

3.4 A multivariate probit-based extension

As the results established above are favorable for using other specifications than the dummy variable specification implicitly embedded in the signal approach, a multivariate probit model seems to be the natural extension of the analysis presented in the previous section. In particular, it is the most natural way to incorporate the information provided in different indicators at the same time.

Table 3 shows the results of the multivariate probit model which simultaneously includes all variables from Table 2. The functional form of variables was specified according to the results of Table 2[5], i.e. in general the variables were specified according to the specification with the highest t-ratio. The level of reserves constitutes an exception: The linear specification proved to be highly significant in the multivariate model and was therefore included.

Table 3: Multivariate probit regression including all variables

Included observations: 262
Excluded observations: 300 after adjusting endpoints
Convergence achieved after 6 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.266517	0.718184	-0.371099	0.7106
P_CA	-1.233594	0.481794	-2.560420	0.0105
P_CH_EXPORT	-0.372483	0.416767	-0.893742	0.3715
P_M2RES	0.687352	0.996256	0.689935	0.4902
D_P_M2RES	0.471483	0.444917	1.059710	0.2893
P_REERDEV	0.785438	0.418551	1.876565	0.0606
P_CH_RES	-0.370678	0.485321	-0.763779	0.4450
P_RES	-2.497891	0.771178	-3.239061	0.0012
D_P_RES	1.077219	0.468423	2.299672	0.0215
P_BUDGET	-0.819837	0.414696	-1.976959	0.0480
Mean dependent var	0.141221	S.D. dependent var		0.348916
S.E. of regression	0.292128	Akaike info criterion		0.659318
Sum squared resid	21.50531	Schwarz criterion		0.795514
Log likelihood	-76.37060	Hannan-Quinn criter.		0.714058
Restr. log likelihood	-106.6797	Avg. log likelihood		-0.291491
LR statistic (9 df)	60.61822	McFadden R-squared		0.284113
Probability(LR stat)	1.02E-09			
Obs with Dep=0	225	Total obs		262
Obs with Dep=1	37			

Based on the results reported in Table 3, insignificant variables were gradually eliminated, until the most parsimonious representation of the data was achieved. The final result of this procedure is shown in Table 4 .

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[5] The M2/reserves ratio is significant, but has the wrong sign under the “dummy*(percentile-treshold)”-specification.

Table 4: Multivariate probit regression – #1-most parsimonious representation of data

Included observations: 354
Excluded observations: 269 after adjusting endpoints
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.846737	0.441764	-1.916718	0.0553
P_CA	-1.004523	0.374160	-2.684739	0.0073
D_P_M2RES	0.610379	0.207656	2.939374	0.0033
P_REERDEV	0.907585	0.359478	2.524732	0.0116
P_CH_RES	-0.768816	0.365516	-2.103370	0.0354
P_RES	-2.114569	0.635018	-3.329936	0.0009
D_P_RES	1.088051	0.358065	3.038701	0.0024
Mean dependent var	0.135593	S.D. dependent var		0.342841
S.E. of regression	0.296244	Akaike info criterion		0.647159
Sum squared resid	30.45291	Schwarz criterion		0.723671
Log likelihood	-107.5472	Hannan-Quinn criterion		0.677601
Restr. log likelihood	-140.4964	Avg. log likelihood		-0.303806
LR statistic (6 df)	65.89848	McFadden R-squared		0.234520
Probability(LR stat)	2.83E-12			
Obs with Dep=0	306	Total obs		354
Obs with Dep=1	48			

All variables reported in Table 4 except the dummy variable specification for the level of reserves have the right sign and are highly significant. The positive sign for the dummy variable specification for the level of reserves is somewhat counter-intuitive, but probably has to do with the interaction of other variables with similar information content, in particular the linear specification for the level of reserves and the dummy variable specification for the ratio of M2 to reserves.

The alternative specification shown in Table 5 includes the budget deficit as an additional significant explanatory variable. However, the change in reserves and the deviation of the real effective exchange rate are no longer significant under this specification. Multicollinearity between the budget variable and the two variables that have been dropped is probably not a big issue, as the correlations between them are not very high: The budget balance and the change in reserves have a correlation of 0.16, while it only amounts to -0.05 for the budget balance and the deviation of the real effective exchange rate. I would attribute these changes rather to the change in the sample, which has become smaller because of the shortness of the budget balance time series. In general, the statistical features of specification #2 seem to be slightly worse than specification #1, if one uses the Akaike and Schwarz criterions and the Mc Fadden R-squared as additional evaluation criteria.

Table 5: Multivariate probit regression #2-most parsimonious representation of data

Included observations: 289
Excluded observations: 281 after adjusting endpoints
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.517739	0.450745	-1.148628	0.2507
P_CA	-1.111560	0.394930	-2.814574	0.0049
D_P_M2RES	0.716800	0.227578	3.149693	0.0016
P_RES	-2.534221	0.679518	-3.729436	0.0002
D_P_RES	1.699705	0.428086	3.970474	0.0001
P_BUDGET	-0.878152	0.386886	-2.269795	0.0232
Mean dependent var	0.138408	S.D. dependent var		0.345927
S.E. of regression	0.307746	Akaike info criterion		0.660393
Sum squared resid	26.80223	Schwarz criterion		0.736512
Log likelihood	-89.42672	Hannan-Quinn criter.		0.690893
Restr. log likelihood	-116.1964	Avg. log likelihood		-0.309435
LR statistic (5 df)	53.53928	McFadden R-squared		0.230383
Probability(LR stat)	2.61E-10			
Obs with Dep=0	249	Total obs		289
Obs with Dep=1	40			

4 Results

4.1 Expectation / prediction tables

For a probit model serving as an early warning device, clearly the most important criterion to evaluate its performance is its predictive power. The standard evaluation method of a probit model is a comparison of its estimated crisis probabilities against realized results. For this purpose, a cutoff level for crisis probabilities has to be defined: In case the probability of crisis exceeds the cutoff level, the model is considered to send a signal and vice versa. Using a cutoff level for the probability of crisis of 50%, the model issues hardly any wrong signals, but it is only able to correctly predict 27% of all the crises in the sample. As shown in Table 6 and Table 7, lowering the cutoff level to 25% leads to a strong improvement in the model's ability to recognize crises in advance, while the number of wrong signals rises only moderately.

Table 6: Expectation / prediction table for specification #1:

Dependent Variable: CRISIS
Method: ML - Binary Probit (Quadratic hill climbing)
Included observations: 354
Excluded observations: 269 after adjusting endpoints
Prediction Evaluation (success cutoff C = 0.25)

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	270	16	286	306	48	354
P(Dep=1)>C	36	32	68	0	0	0
Total	306	48	354	306	48	354
Correct	270	32	302	306	0	306
% Correct	88.24	66.67	85.31	100.00	0.00	86.44
% Incorrect	11.76	33.33	14.69	0.00	100.00	13.56
Total Gain*	-11.76	66.67	-1.13			
Percent Gain**	NA	66.67	-8.33			

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	273.72	31.72	305.44	264.51	41.49	306.00
E(# of Dep=1)	32.28	16.28	48.56	41.49	6.51	48.00
Total	306.00	48.00	354.00	306.00	48.00	354.00
Correct	273.72	16.28	290.00	264.51	6.51	271.02
% Correct	89.45	33.91	81.92	86.44	13.56	76.56
% Incorrect	10.55	66.09	18.08	13.56	86.44	23.44
Total Gain*	3.01	20.35	5.36			
Percent Gain**	22.19	23.55	22.87			

*Change in "% Correct" from default (constant probability) specification
**Percent of incorrect (default) prediction corrected by equation

Similar to the statistical properties, the predictive power of specification #2 is somewhat less favorable than specification #2.

Table 7: Expectation / prediction table for specification #2:

Dependent Variable: CRISIS
Included observations: 289
Excluded observations: 281 after adjusting endpoints
Prediction Evaluation (success cutoff C = 0.25)

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	218	15	233	249	40	289
P(Dep=1)>C	31	25	56	0	0	0
Total	249	40	289	249	40	289
Correct	218	25	243	249	0	249
% Correct	87.55	62.50	84.08	100.00	0.00	86.16
% Incorrect	12.45	37.50	15.92	0.00	100.00	13.84
Total Gain*	-12.45	62.50	-2.08			
Percent Gain**	NA	62.50	-15.00			
	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	221.86	27.01	248.87	214.54	34.46	249.00
E(# of Dep=1)	27.14	12.99	40.13	34.46	5.54	40.00
Total	249.00	40.00	289.00	249.00	40.00	289.00
Correct	221.86	12.99	234.86	214.54	5.54	220.07
% Correct	89.10	32.48	81.26	86.16	13.84	76.15
% Incorrect	10.90	67.52	18.74	13.84	86.16	23.85
Total Gain*	2.94	18.64	5.12			
Percent Gain**	21.26	21.63	21.45			

*Change in "% Correct" from default (constant probability) specification
**Percent of incorrect (default) prediction corrected by equation

4.2 Quadratic probability scores and Pesaran-Timmermann test

While the results presented in and clearly look highly promising, the strong predictive power of both models is confirmed by the Pesaran-Timmermann (1992) test (P-T test) and the Quadratic Probability Score (QPS)[6] test.

The QPS test measures the discrepancy between a realization R_t and the estimated probability P_t (as predicted by the probit model) for the realization. In this case, R_t is either one (if there is a crisis period) or zero (in tranquil periods). The QPS can be computed according to the following formula:

$$(3)\quad QPS = \frac{1}{N}\sum_{t=1}^{N} 2(P_t - R_t)^2$$

[6] See Diebold and Rudebusch (1989)

As the formula shows, the values of the QPS are between zero and two, where zero is the best result. The QPS test statistics for both specifications are provided in Table 8. With values of 0.17 and 0.19 both specifications achieve markedly better scores than in comparable studies: For instance, Berg and Pattillo (1998) report quadratic probability scores in the order of 0.23 for their probit-based extensions of Kaminsky, Lizondo and Reinhart's (1998) model. Brüggemann and Linne's (2001) signal approach-based early warning composite indicator achieves a QPS of 0.297.

As the QPS test does not allow conclusions regarding the statistical significance of the results, I computed the P-T test in addition. The P-T test evaluates the predictions of a model (in this case for a binary dependent variable) against the null hypothesis that the forecasts are no better than random guesses. As the squared P-T test statistics follows the Chi-Square distribution with one degree of freedom, it can be evaluated as a common Chi-Square test. As shown in Table 8, for both probit specifications the null hypothesis can be rejected with a very low error probability for two different cutoff levels. Thus, these results lend support to the hypothesis that balance of payments crises in Central and Eastern Europe may be considered as "first-generation" types of crises.

Table 8: Quadratic probability score and Pesaran-Timmermann test

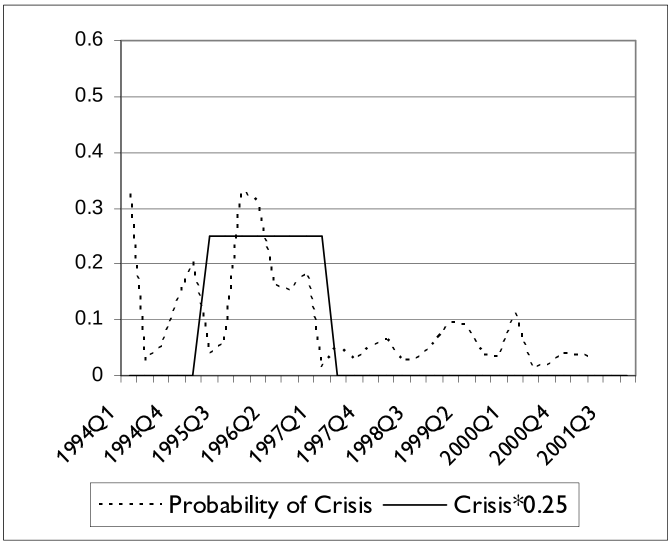
	Probit specification #1		Probit specification #2	
	Cutoff Level		Cutoff Level	
	25%	50%	25%	50%
QPS	0.17205	0.17205	0.18548	0.18548
Squared Pesaran-Timmermann test statistics	80.6	60.3	55.3	23.8
P-value of P-T-statistics	2.7814E-19	8.1415E-15	1.055E-13	1.0815E-06
Critical value for squared P-T-statistics, 5% significance level, 1 degree of freedom	3.841			

4.3 Individual country results

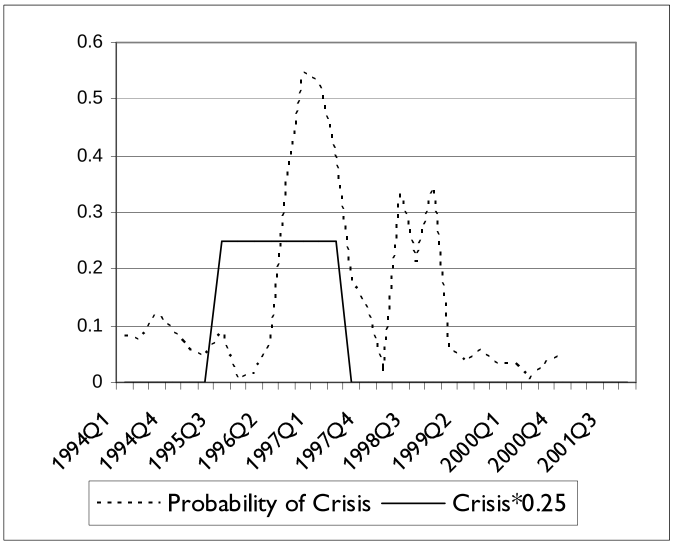
Having statistically confirmed the predictive power of the probit model specifications, the following charts show the development of predicted crisis probabilities of specification #1 against empirical observations for a cutoff level of 25%:

Figure 1: In-sample forecasts of specification#1 versus realizations

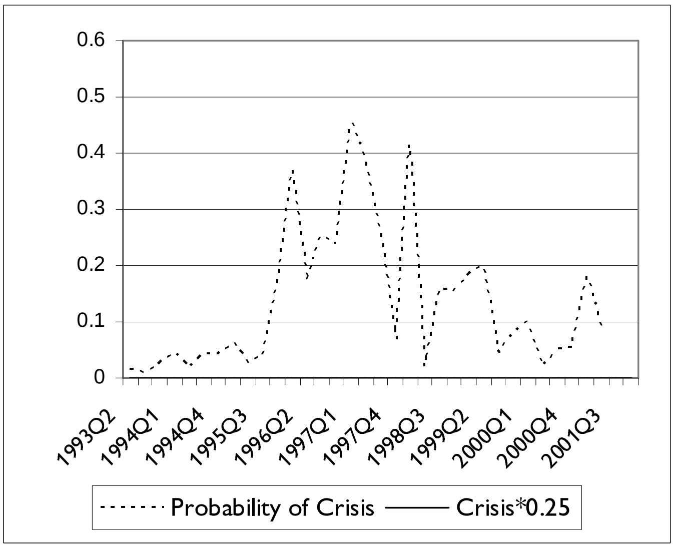
Bulgaria



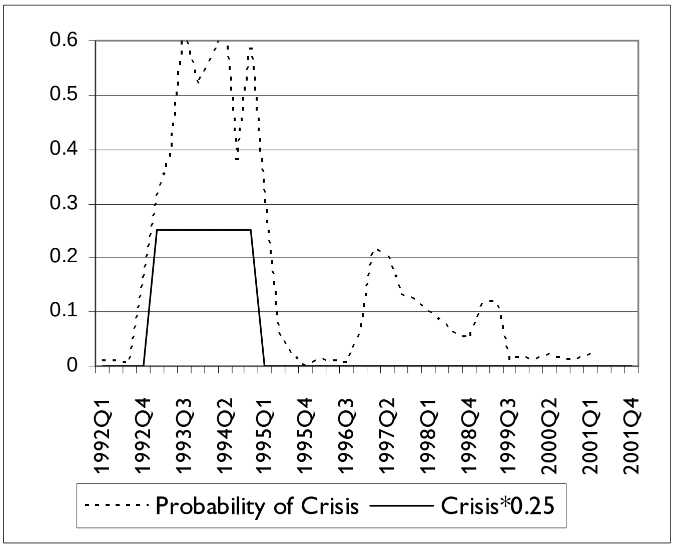
Czech Republic



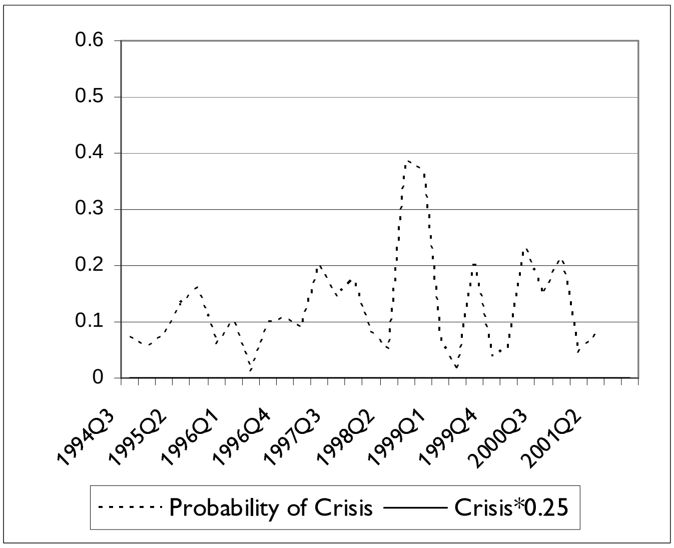
Estonia



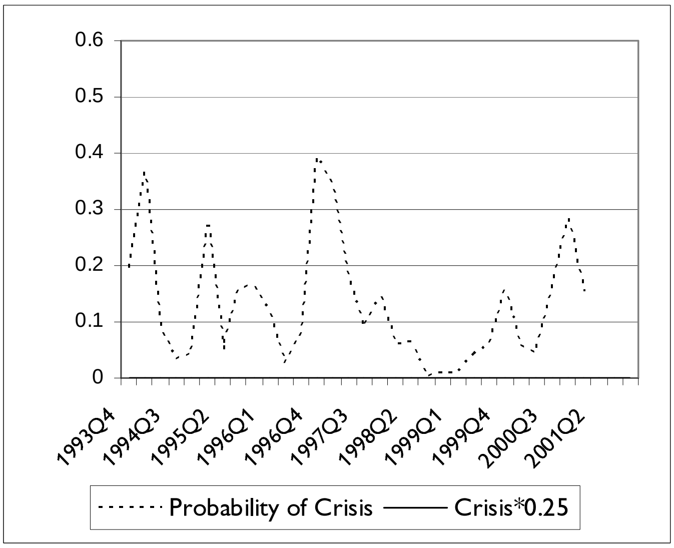
Hungary



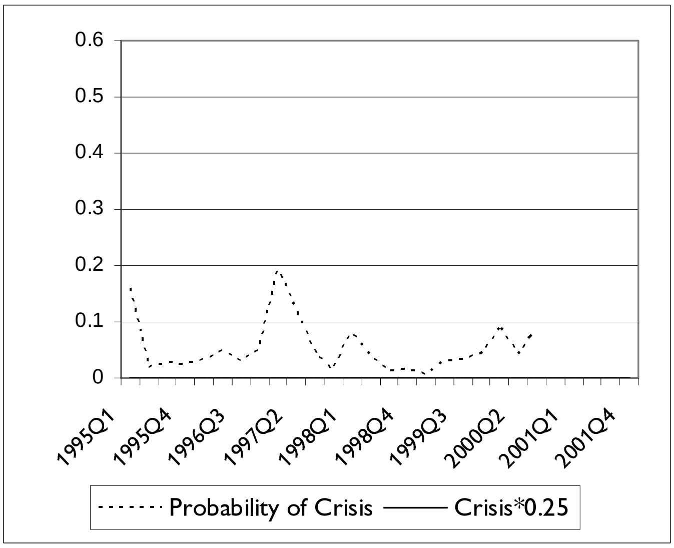
Latvia



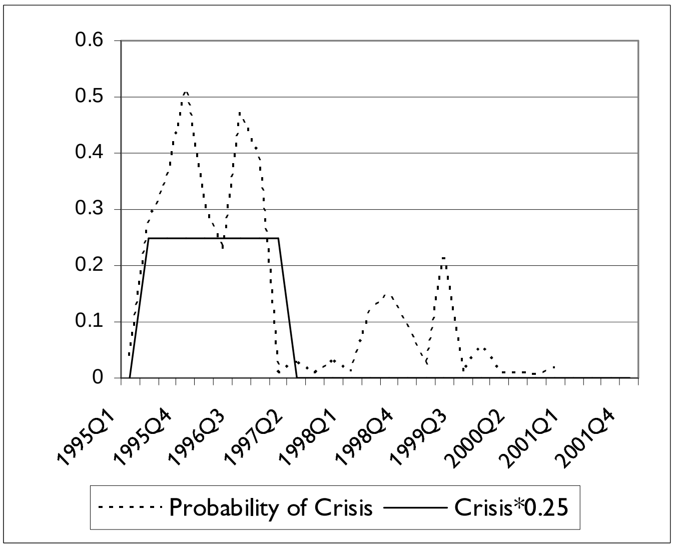
Lithuania



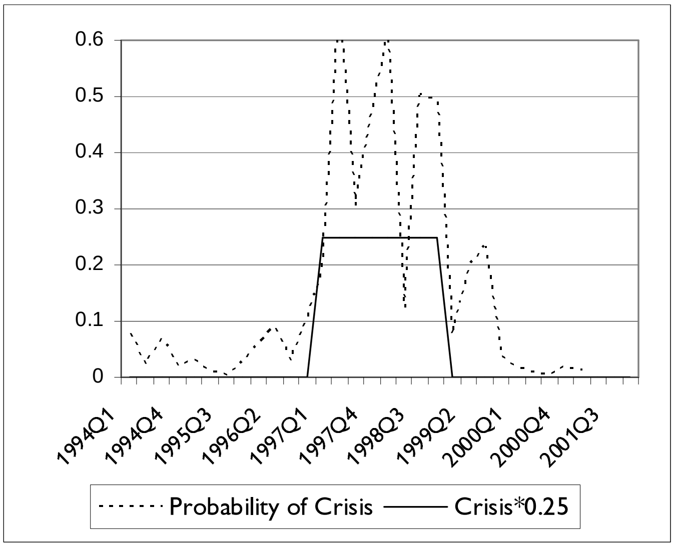
Poland



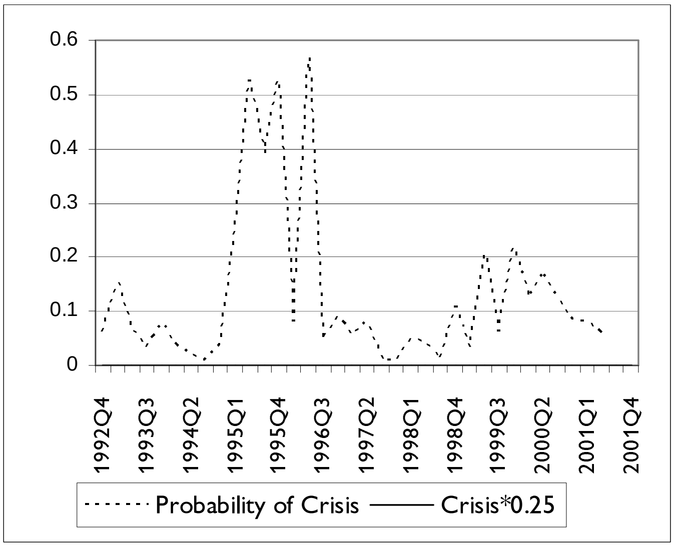
Romania



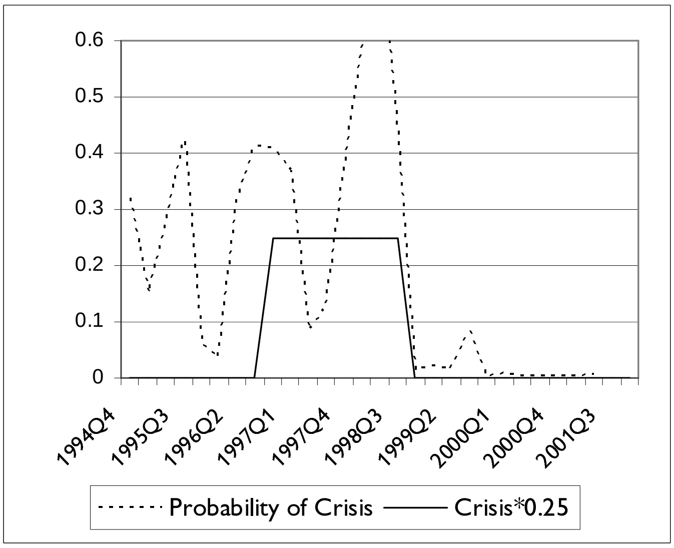
Slovak Republic



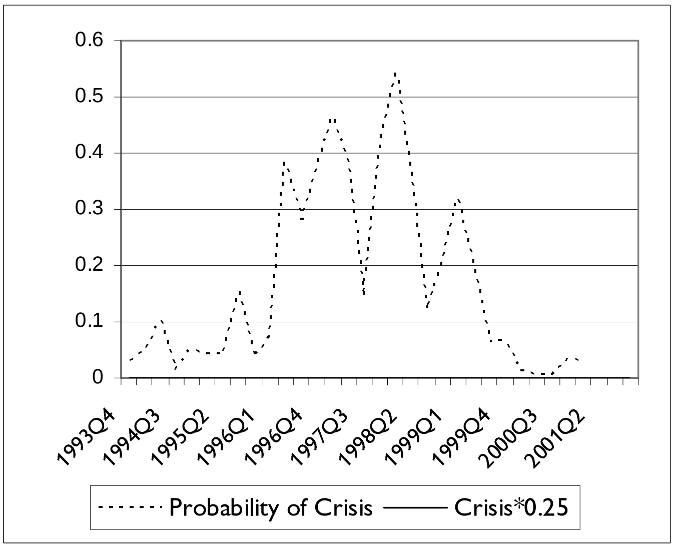
Slovenia



Russia



Croatia



As expected from the statistical tests, the graphical inspection on an individual country basis confirms the good fit of the model's predictions with actual observations. In particular, the Hungarian, Romanian and Slovak crisis episodes can be very well explained. Nearly all currency crises are associated with repeated signals. The model's most recent predictions also appear to be rather plausible, predicting in general rather low probabilities for most countries, but a rather high crisis probability for Poland, compared against its peer group.

However, the model appears to work less well for the very small countries in the sample, in particular for Slovenia, where repeated signals were issued since the fourth quarter of 1994. In the case of Slovenia, the transformation of data into percentiles of the country-specific distributions seems to be disadvantageous, as Slovenia is characterized by a high level of macroeconomic stability throughout the whole sample period. Thus, in this case the model reacts sensitively with respect to a slight worsening of macroeconomic conditions from a very sound level to a still satisfactory level in absolute terms.

Finally, it would of course be very interesting to evaluate the out-of-sample forecasting abilities of the two model specifications proposed above. However, owing to the limited number of observations available per country, this type of analysis faces very tight limits. For instance, as no crisis occurred in the most recent time periods, it is impossible to check whether the model would have correctly predicted these events.

5 Conclusions

In this study, an early warning model for currency crises was developed for a sample of quarterly data from twelve Central and Eastern European transition countries. After reviewing the relevant literature, it was shown that a number of indicators contain useful information for early warning purposes when evaluated according to the signal approach.

However, in addition to some known drawbacks inherent to the signal approach, the noise-to-signal ratios for some indicators reached a maximum at the extreme ends of the indicator-specific distributions. Thus, in a next step, the appropriateness of the signal appoach’s underlying functional specification was investigated by means of bivariate regressions on one economic variable in different functional specifications.

On the basis of this analysis, two multivariate probit regressions with all statistically significant economic variables on a (0,1)-distributed crisis variable were estimated. For in-sample forecasts, the predictions of both model specifications proved to perform significantly better than random guesses as well as some comparable early warning models. Overall, the model appears to track developments in individual countries rather well, with the exception of countries with consistenly strong macroeconomic fundamentals. With respect to economic interpretations, the results of this study lend support to the hypothesis that currency crises in Central and Eastern Europe may be considered as “first-generation” types of crises.

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