A FOREWARNING INDICATOR SYSTEM FOR FINANCIAL CRISES : THE CASE OF SIX CENTRAL AND EASTERN EUROPEAN COUNTRIES

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Abstract

We propose a measure of the probability of crises associated with an aggregate indicator, where the percentage of false alarms and the proportion of missed signals can be combined to give an appreciation of the vulnerability of an economy. In this perspective, the important issue is not only to determine whether a system produces true predictions of a crisis, but also whether there are forewarning signs of a forthcoming crisis prior to its actual occurrence. To this end, we adopt the approach initiated by Kaminsky, Lizondo and Reinhart (1998), analyzing each indicator and calculating each threshold separately. We depart from this approach in that each country is also analyzed separately, permitting the creation of a more "custom-made" early warning system for each one.

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Non-technical summary

In this paper we propose a measure of the probability of crises associated with an aggregate indicator, where the percentage of false alarms and the proportion of missed signals are combined to give an appreciation of the vulnerability of an economy. In this perspective, the important issue is not only to determine whether a system produces true predictions of a crisis, but also whether there are forewarning signs of a forthcoming crisis prior to its actual occurrence. To this end, we adopt a signal extraction approach, following the methodology suggested in previous papers by Kaminsky, Lizondo and Reinhart (1998), Berg and Patillo (1999), Goldstein et al. (2000), and Edison (2003). However, our interpretation contrasts with previous studies in the conception of what a good warning system must be for an emerging economy. In the case of the countries treated in this study, a monitoring system with a high proportion of false crisis signals is not necessarily something bad, as is suggested in the majority of the literature, since it may simply mean that the warning system detects situations of increased vulnerability in a context of deteriorating macroeconomic fundamentals. An intertemporal accumulation of false signals can indicate a high probability that a severe crisis will actually occur in the near future. Therefore, false alarms may simply indicate the deterioration of economic fundamentals and potential forthcoming crises. We propose such an indicator in this paper and show that the predicted probabilities of a currency crisis in Russia and, to a lesser extent, Kazakhstan, have remained high during the early and mid nineties. In contrast, a comparison with other Central and Eastern European countries (such as the Czech Republic, Hungary and Poland) reveals that the probabilities of a crisis were high only a few periods prior to the observed crises and low otherwise.

The forewarning model we propose in this paper differs with respect to several aspects when compared to more conventional forewarning system models based on the signal extraction approach. The main differences are threefold.

Firstly, we choose the real exchange rate instead of the nominal exchange rate for the market pressure index. Many papers dealing with the signal extraction approach consider the nominal exchange rate to define the market pressure index that identifies crisis episodes. However, it is important to note that our study concerns countries which went through a transition period at the beginning of the 1990s and adopted, throughout the years, many different exchange rate regimes, many of them fixed. The historical volatility of the nominal exchange rate in these counties, which is quite low, would hinder the correct identification of crisis episodes, a “crisis” being defined as a sudden and marked depreciation of the exchange rate (and/or a rapid loss of reserves). For this reason, we substitute the real exchange rate for the nominal one, which we believe gives a more realistic view of the occurrence of turbulence episodes.

Secondly, we use quarterly data, rather than annual or monthly data. An annual periodicity is not informative of financial phenomena that occur at infra-annual frequencies. Further, with annual data, one is unable to predict whether a crisis happened in the beginning or in the end of the year. Monthly data would be better, but are not available for many ‘real variables’. Besides, a monthly periodicity introduces the problem of autoregressive effects with possibly complicated lag structures.

Thirdly, we compare the pooling model to a country-specific approach. Though the pooling estimations might imply some advantages as far as the power of the results is concerned, they are not as appropriate in the presence of an heterogeneous group of countries. This is the case here : we find differences between Kazakhstan and Russia on one hand and the other countries on the other hand. Country-specific forewarning systems have been applied successfully in the empirical literature to Asian and Latin American emerging economies (see Edison (2003)). Here, the approach is extended to emerging economies in Eastern and Central Europe.

A FOREWARNING INDICATOR SYSTEM FOR FINANCIAL CRISES : THE CASE OF SIX CENTRAL AND EASTERN EUROPEAN COUNTRIES

1. Introduction and motivation

The proliferation of financial crises in the emerging economies during the nineties led economists to spend great efforts in the building of forewarning indicator systems that could help prevent the detrimental effects of financial turbulence and assist policymakers in taking appropriate actions. In the literature, several modeling approaches have been suggested as frameworks for forecasting financial crises. The so-called first generation models focus on the factors that generate currency crises : balance of payments crises as described by Krugman (1979) and Flood and Garber (1984); speculative attack models based on investors' expectations of monetary policy; financial bubble models with moral hazard behaviors (see Krugman, 1998). Second generation models suggest that the occurrence of financial crises is a consequence of contagion channels : commercial trade, portfolio re-allocations, political channels (see, among others, Eichengreen et al. (1996), Sachs et al. (1996), Glick and Rose (1998), Bussière and Fratzscher (2002), Komulainen and Lukkanila (2002)). Third generation models use empirical-based methodologies. They are based on value at risk analysis, logit/probit regressions, Early Warning Systems, and Markovian models (see, among many others, Burkart and Coudert (2002), Abiad (2003), Kumar et al. (2003)).

In this paper we adopt the last approach by proposing a measure of the probability of crises associated with an aggregate indicator, where the percentage of false alarms and the proportion of missed signals are combined to give an appreciation of the vulnerability of an economy. In this perspective, the important issue is not only to determine whether a system produces true predictions of a crisis, but also whether there are forewarning signs of a forthcoming crisis prior to its actual occurrence. To this end, we adopt a signal extraction approach, following the methodology suggested in previous papers by Kaminsky, Lizondo and Reinhart (1998), Berg and Patillo (1999), Goldstein et al. (2000), and Edison (2003). However, our interpretation contrasts with previous studies in the conception of what a good warning system must be for an emerging economy. It is common wisdom that in constructing warning systems, economists usually face a dilemma. On one hand, they attempt to construct a system that yields a high percentage of correctly predicted crises : in this case, the counterpart is a high proportion of false crisis signals. On the other hand, they try to minimize the proportion of false signals, and in this case, they must also accept a low proportion of good crisis predictions. In the case of the countries treated in this study, a monitoring system with a high proportion of false crisis signals is not necessarily something bad, since it may simply mean that the warning system detects situations of increased vulnerability in a context of deteriorating macroeconomic fundamentals. An intertemporal accumulation of false signals can indicate a high probability that a severe crisis will actually occur in the near future. Therefore, false alarms may simply indicate the deterioration of economic fundamentals and potential forthcoming crises. We propose such an indicator system in this paper and show that the predicted probabilities of a currency crisis in Russia and, to a lesser extent, Kazakhstan, have remained high during the early and mid nineties. In contrast, a comparison with other Central and Eastern European countries (such as the Czech Republic, Hungary and Poland) reveals that the probabilities of a crisis were high only a few periods prior to the observed crises and low otherwise.

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The structure of the paper is as follows. Section 2 presents ten macroeconomic leading indicators and shows that their behavior differs around crisis periods. In Section 3, a composite indicator is proposed to estimate the probability of a crisis. Finally, Section 4 concludes.

2. Single leading indicators for predicting the financial crises

The methodological approach draws upon the works of Kaminsky *et al*. (1998), though some modifications and extensions are considered. Financial crises can manifest themselves in several ways : currency crises, banking system collapses, high increase of short-term debt, pressure on the domestic interest rate markets, high inflationary periods yielding financial bubbles, etc. As shown in the aforementioned paper, one of the cornerstones of financial turbulence in emerging markets is the observation of severe pressure on the domestic currency with high costs on the external balance. Their work focuses on a mix of developed and emerging economies using data from 1970 to 1997. They find that banking and currency crises do arrive with some early warnings, though their model has a better predictive power for the latter than for the former.

We adopt a criterion for the definition of a crisis that accounts for both pressures occurring in the exchange rate market and diminishing foreign reserves. The market pressure index is defined as follows:

$$IND_t = \phi_1 \Delta REER_t - \phi_2 \Delta RESERV_t \qquad (1)$$

where *REER* is the real exchange rate and *RESERV* stands for the country's foreign reserves. As argued in the introduction, the real exchange rate – rather than the nominal one – gives a more realistic view of turbulence episodes in the emerging economies considered here. This avoids a 'mis-identification' of crises, that may or may not be detected, according to the different exchange rate regimes that were in place during the period under examination. Market pressure is observed when the real exchange rate depreciates and when a country is confronted with reserve losses.

A financial crisis is then defined as follows:

$$crisis_t = \begin{cases} 1, & if\ IND_t \geq c \\ 0, & otherwise \end{cases} \tag{2}$$

A crisis occurs when pressures in the exchange rate market and foreign reserve losses are very high. By 'high', one means that exchange rate depreciation and foreign reserve losses have reached a threshold value above which their continued decline is not sustainable. The identification of a crisis is thus conditioned by three important parameters, ϕ_1, ϕ_2, c. The latter must be parameterized (or sometimes estimated) by the modeler. It is common wisdom to interpret the weights ϕ_1, ϕ_2 as measures of the volatility of the changes occurring in the real exchange rate and foreign reserves. We normalize ϕ_1 to 1 and define ϕ_2 as the ratio of the standard deviation of the rate of change of the real exchange rate and the standard deviation of foreign reserve variation : $\phi_2 = \sigma_{\Delta REER} / \sigma_{\Delta RESERV}$. The threshold parameter is thus defined as

$$c = \overline{IND} + \delta\sigma_{IND} \tag{3}$$

where $\overline{IND}$ is the empirical mean of *IND* and σ_{IND} is the standard deviation. A crisis occurs when the indicator is δ standard deviations above its mean. *C* must be determined optimally, in such a way that the crises identified correspond, at least, to the observed episodes of currency crises in the exchange rate markets. The choice of δ deserves some further consideration. This value is not fixed in an ad-hoc manner by adopting, for instance, the conventional choice of a value between 2.5 and 3 standard deviations. We instead implement a grid-search methodology, by considering a great number of values of δ in the interval [0,3]. Ideally, we consider the percentiles of δ in this interval. The value that is finally retained is the one that best reproduces the actual crisis history of the countries under study. We find that the value 0.75 correctly identifies the crises. For illustration purposes, Figures 1 and 2 provide the graphs for crisis identification in Russia for δ=0.75 and δ=1. The value 1 does detect some crisis episodes, but we lose several observations of turbulence per country. The value 0.75 best corresponds to these countries' crisis history, but it is also important to stress here that the objective of this paper is not only to develop a forewarning system for crises in the strict sense, but more importantly, to detect situations of increased vulnerability. When δ=2.5, no crisis is detected for any country, although currency crises did actually occur during the years under study[5]. With this objective in mind, it seems logical to use a value of delta that is lower than the one usually used in the literature.

Our study covers the period starting from the first quarter of 1996 and ending at the last quarter of 2003. We use quarterly data for the following countries : Russia, Hungary, Poland, the Slovak Republic, the Czech Republic and Kazakhstan. Our series are taken from the IMF database (IFS statistics). A detailed description of the variables used is given in the appendix.

Evidence of crises provided by the Market Pressure Index

Figure 1 shows signs of tension in 1996. Furthermore, the market pressure index crosses its threshold value from the third quarter of 1997 until mid-1998. The index as defined above has the following advantage. Not only does it detect the year 1998 as a crisis period, but it also corroborates the observation that in Russia the 1998 crisis did not appear suddenly, but was the height of an economic crisis that lasted many years (cumulative decline in GDP by more than 40% between 1989 and 1996, near-hyperinflation) in a context of failure of the reform strategies undertaken during the transition period. Indeed, macroeconomic fundamentals began to seriously deteriorate in 1996 and 1997 and this was the consequence of a combination of factors: deterioration of the terms of trade, a fall in oil prices, sharp depreciation of the Ruble, increases in interest rates and internal problems (fiscal and debt crises). In addition, the index provides evidence of tension in mid to late 1999, as well as at the end of the year 2003.

Figures 3-7 depict the case of the other five countries. The Russian crisis and the slowdown of the Western European countries' economies had a negative impact on the Central and Eastern European countries' exports, as well as Foreign Direct Investment, thereby inducing an important slowdown of their activity from 1998 onwards. Moreover, internal issues such as faster growth and higher inflation, as well as fiscal problems, put

[5] To avoid too many graphs, we only report this example. Other similar examples with different values of δ for the different countries are available upon request to the authors.

pressures on these countries' exchange rates. Contagion channels have also been important in explaining financial market turmoil. Figure 7 gives a good illustration of contagion in Kazakhstan. As one can see, the market pressure index has crossed its threshold several times between the first quarter of 1998 and the end of 1999, in the aftermath of the Russian crisis. This can be expected, given the relations and closeness of the two economies. A similar observation could apply to Hungary, Poland and the Slovak and Czech Republics, though the contagion effects have been delayed over time. The graphs corroborate the historical observation that these countries have continued to suffer from contagion effects in the 2000's. It is also important to note that for all of these countries the index gives evidence of the influence of the 1997 Czech crisis (triggered by speculative attacks due to weakening fundamentals and the Asian crisis), which encouraged the CEECs to move towards greater exchange rate flexibility.

Economic indicators

A central question in the signaling approach is the choice of the crises' potential determinants. For the countries examined in this paper, we consider different categories of explanatory variables:

- a monetary variable : the ratio of M2 to nominal GDP. The upper bound is considered for this variable, because expansionary monetary policy and/or a decline in GDP are associated with the onset of a crisis.
- a capital account variable: the ratio of M2 to foreign exchange reserves. We take into account the upper bound for this variable, because expansionary monetary policy and/or sharp declines in reserves usually precede financial crises.
- current account variables :

\- the real exchange rate : lower bound, for real exchange rate overvaluations (-) are linked to currency crises.

\- the value of exports and imports : lower bound for exports and upper bound for imports, because a weak external sector is part of a currency crisis.

\- the current account balance measured as the ratio of the difference of exports and imports to GDP : lower bound, for the aforementioned reasons.

- real sector indicators : GDP and GDP growth. The lower bound is considered for both these variables, due to the fact that recessions often precede financial crises.
- banking variables :

- commercial bank deposits : lower bound, for a loss of deposits occurs as a crisis unfolds.
- the ratio of domestic credit to GDP : upper bound, since credit expands prior to a crisis and contracts afterwards.

Banking system collapses often coincide with the onset of a currency crisis. For example, the biggest difference between Russia and other Eastern European countries was the role of the banking system. In the former, credits have continued to be inefficiently directed towards the big state-owned industrialized conglomerates, bad loans worsened and the absence of supervisory laws induced high inflation and the development of a barter economy. In contrast, in Central and Eastern Europe monetary authorities imposed a control of credits that was part of a tightening monetary policy, signaling the authorities' intention to address appropriately their inflation problem. Such a decision was positively interpreted by the markets and helped assessing the credibility of the monetary policy. In view these observations, it seems interesting to include among the set of leading indicators a macroeconomic variable that captures the influence of banking crises. Here, we use *commercial bank deposits and the ratio of credits to GDP* as proxies. The decrease of commercial bank deposits or the rapid expansion of credits are two vectors of banking crises.

The important issue here is the stability of the financial sector, as is highlighted in third generation currency crisis models. The motivation behind such a choice is rather intuitive. The Russian crisis was part of a huge financial crisis characterized by a weak banking sector and several bankruptcies of financial intermediaries. For the other countries, the reasons for choosing variables that reflect the stability of the financial sector are similar to those evoked when considering the currency crises in the South-East Asian countries: the degree of the severity and spread of a currency crisis occurring in a neighboring country depends upon the fragility of their own financial markets, or in other words, the strength of the banking sector.

The above variables can be considered as forewarning indicators of a forthcoming financial crisis for several reasons. First, prior to a crisis, domestic credit tends to increase and the rapid growth of credit is transformed into a sharp contraction when the crisis appears. Furthermore, credit expansion is usually observed in the context of an expansionary monetary policy inducing an increase in the ratio of *M2* to *GDP*. Second, a currency crisis generally follows a sharp deterioration of the external balance : loss of competitiveness, current account deficits and foreign reserve losses. Third, an unstable economic situation is a vector of financial crises. Finally, in a context of immature banking sectors, crisis episodes are accompanied by losses of commercial bank deposits.

Computing noise-to-signal ratios for single indicators

We consider an on/off signal and a variable, S_t, that takes the value 1 if a crisis is signaled and 0 otherwise. The prediction of a crisis or a calm period depends upon the behavior of a macroeconomic variable. A crisis signal is detected when this variable deviates from its usual values beyond a certain threshold level:

$$signal: \quad S_t = \begin{cases} 1, & if\ |X_t| \geq \overline{X} \\ 0, & |X_t| < \overline{X} \end{cases} \tag{4}$$

where X is a macroeconomic variable. Note that we need a signaling horizon, that is the time horizon at which a variable is expected to predict a crisis. In this paper, we consider a signaling period of four quarters. To define the optimal value of the threshold $\overline{X}$, we proceed as follows. Consider the following events:

A: the variable predicts a crisis and the crisis occurs within four quarters (good 'on' signal)
B: the variable predicts a crisis, but no crisis occurs during the signaling period (false crisis signal)
C: the variable does not predict a crisis, but a crisis occurs (missed crisis signal or false calm signal)
D: The variable does not predict a crisis and no crisis occurs (good 'off' signal)

These four situations are summarized in the following matrix:

Indicator Performance		
	Crisis within four quarters	No crisis within four quarters
Signal issued by indicator	**A**	**B**
No signal issued by indicator	**C**	**D**

We define the following test:

$$\begin{cases} H_0 : a\ crisis\ occurs \\ \qquad against \\ H_1 : a\ crisis\ does\ not\ occur \end{cases}$$

or

$$\begin{cases} H_0 : A \cup C \\ \quad against \\ H_1 : B \cup D \end{cases}$$

A type I error of this test is the probability of rejecting H_0 when it is true and is defined as $P(C / A \cup C)$. A type II error is the probability of accepting H_0 when H_1 is true, that is $P(B / B \cup D)$. The noise-to-signal ratio is defined as the ratio of type II errors over 1 minus type I errors :

$$\alpha = \frac{P(B / B \cup D)}{1 - P(C / A \cup C)} = \frac{P(B / B \cup D)}{P(A / A \cup C)} \tag{5}$$

The noise-to-signal ratio is thus the ratio of false signals to good signals. A macroeconomic variable is considered as a good warning indicator of a currency crisis if this ratio has values near 0. Accordingly, the threshold $\overline{X}$, to be selected, must minimize the above ratio. To do this, we use the quantiles of the variable *X* and retain those yielding the lowest value of α. We also compute the probability of correctly predicting a crisis :

$$\beta = \frac{P(A)}{P(A \cup B)} \tag{6}$$

Performance of economic indicators

Tables 2-8 display the results for the six countries (pooling and individual countries). Column 1 reports the quantiles corresponding to the minimum noise-to-signal ratio for each indicator. In all cases, the quantiles chosen vary with the macroeconomic indicator under consideration. Generally, we could say that for the countries where the quantiles chosen are, in majority, situated below Q5, the proportion of observations corresponding to crises in higher in comparison with those of the periods considered as tranquil. As a consequence, the risk of emitting false signals of future calm periods (or missed signals) is low. When the majority of quantiles chosen is situated above Q5, the conclusion is the opposite. As a high value for the threshold increases the proportion of tranquil periods, the risk of emitting false signals of calm periods is increased.

Column 3 reports the noise-to-signal ratio. The indicators have a good explanatory power if the ratio is lower than 1. As seen, this is the case for a majority of variables for the six countries.

The pooling approach is the same as the country-specific approach, except that we pool together the data for all the countries in order to estimate the threshold for each indicator. The threshold chosen is that which minimizes the noise to signal ratio when we consider at the same time the number of As, Bs, Cs and Ds (see the above matrix and the method for the minimization of the NTS ratio) for all countries. These are calculated relative to the percentile distribution of the indicator, by country. In the end, the percentile threshold chosen will be the same for all countries for a given indicator, but the actual value will vary across countries (since the distributions are not the same).

As far as the pooling approach is concerned (see Table 2), we can observe that the best three indicators are the REER, with an NTS ratio of 0,11, the M2/Reserves, and the Exports of goods and services. The good performance of the REER indicator corroborates what is usually found in the literature, and is also in line with the findings for the country-specific approach. The worst-performing indicators are Imports, Growth and M2/GDP. Even in the country-specific approach, these indicators were not generally found to perform very well.

Generally speaking, the overall performance of the indicators from an NTS ratio point of view is not significantly improved, compared to the country-specific approach. But what we can observe is that the percentage of crises correctly called has even worsened. For example, the second-best indicator, the ratio of M2/Reserves, only calls correctly about 5% of crises. On the other hand, the growth indicator called more than 80% of crisis episodes, yet its performance is not very good from an NTS ratio point of view. This performance could possibly be attributed to the fact that the pooling approach is more restrictive, in that it privileges the avoidance of bad crisis signals over the possibility of having more signals indicating situations of increased vulnerability. This confirms that the country-specific approach might suit better the purposes of this study.

Let us now comment the results for individual countries (country-specific approach). For Russia, a bad score is reported by the indicator M2/GDP. This is understandable in a context where the degree of intermediation of the economy is very weak. A better score is obtained by the real exchange rate, a conclusion that is in line with the usual findings in the empirical literature, and the best scores are obtained by GDP, the ratio of the current account to GDP and commercial bank deposits. Though the ratio is lower than 1 for a majority of variables, it seems quite difficult to find indicators with a high degree of reliability in the prediction of financial crises in Russia. This is seen in the fourth column of Table 3, where the ratio of crises accurately predicted has a rather limited explanatory power for many variables, even some of those displaying the lowest noise-to-signal ratios. These findings for Russia corroborate what was observed historically, namely, the difficulty for multilateral international organizations to anticipate the 1998 crisis and to construct reliable forewarning systems.

For Hungary, the best indicators in terms of noise-to-signal ratios are imports and M2/Reserves, which also give satisfactory scores in terms of percentage of correctly called crises and probability of crisis when a warning signal is emitted by these indicators. As far as Poland is concerned, the best indicator is indisputably the ratio of the current account to GDP. This is not the case for the Slovak Republic, where the best results are given by the real effective exchange rate and the commercial bank deposits variable, a situation mirrored closely by Kazakhstan, as well as the Czech Republic, where the real effective exchange rate also scores high.

In general, good scores are often obtained by the real effective exchange rate (REER), as in most of the recent literature, and the commercial bank deposits variables (supporting the view that banking, financial and currency crises are closely related). However, unsatisfactory scores are usually obtained by M2-based variables and the growth rate variable. According to historical observations, one can explain these results as follows. On one hand, Hungary, Poland, Slovakia and the Czech Republic have experienced successful transitions through a liberalization of the foreign trade sector and a restructuring of their economy, which has increased their credibility *vis à vis* the financial markets. These reforms have contributed to attenuate the severity of speculative attacks on the local currencies. On the other hand, the economic growth that resulted from successful transition policies has been predominantly concentrated in services and the impact on the manufacturing sector has been limited. The bad performance of the GDP growth indicator might be due to the fact that an aggregate index of growth has an imperfect explanatory power. Further, the fact that ratios and growth rates have a lower explanatory power than variables expressed in nominal terms, may partly reflect the fact that the inflation rate has a high signaling role for the financial markets. It is the successful policy of inflation moderation that renders exports more competitive in the foreign trade markets. It is the liberalization of prices that reduces the difference between domestic and world prices, thereby limiting the negative pass-trough effects on imports and economic activity. These effects contribute to increase the level of foreign reserves, thereby preventing the risk of a financial crisis.

3. Composite indicator and the probability of a crisis

The next step is to combine the different macroeconomic indicators. This avoids placing too strong an emphasis on one variable in particular. Single indicators contain only partial information on forthcoming crises. In order to evaluate the forecasting performance of our indicators in tracking currency crises, we compute the following noise-to-signal ratio weighted indicator:

$$I_t = \sum_j (1/\alpha_j) * S_t^j \tag{7}$$

where the index j denotes a macroeconomic indicator, α_j is the noise-to-signal ratio obtained for the indicator j and s is the signal variable defined above. The signal variable is weighted by the inverse of the noise to signal ratio, thereby giving more weight to indicators that reported low scores. The performance of this composite indicator can be tested using several criteria. Here, it is used to compute the conditional probability of a currency crisis :

$$P(C_{t,t+h} / I_L < I_t < I_U) = \frac{\sum quarters \quad with \quad I_L < I_t < I_U \text{, } given \ that \ a \ crisis \ occurs \ within \ h \ quarters}{\sum quarters \quad with \quad I_L < I_t < I_U} \tag{8}$$

We evaluate the probability that a crisis will occur within h quarters (h=4 in this case), provided that the composite indicator is included within certain threshold values, I_L (lower bound) and I_U (upper bound). These bounds are determined exogenously and do not vary with time, but they do vary from country to country (according to specific characteristics and the values of the composite indicator), permitting the establishment of more custom-made intervals for each country considered.

Once the upper and lower bounds have been determined, we then proceed to the calculation of the empirical conditional probability that a crisis will occur within four quarters given that the composite indicator is included within a certain interval. Here, the main difference between the pooling and country-specific approaches occurs in the computation of the conditional probability of a crisis. As a first step in the pooling approach, the composite indicator for each country is calculated based on the results of the pooling estimation, and then all of the composite indicator values for all countries are taken into account for the computation of the conditional probabilities (this is in contrast to the country-specific approach, where the values of the composite indicator for each country are considered separately). The bounds of each interval for the composite indicator also remain the same for all countries.

The results for these calculations are given in Table 9. For example, the conditional probability that a crisis will occur in Russia within $t+3$, quarters given that the composite indicator at $t=1$ takes the value 12, is 0.6 (country-specific approach).

When the composite indicators stemming from the pooling and country-specific approaches are compared, it is possible to observe that the pooling one gives higher conditional probabilities of crises at lower interval values, in other words, lower values of the composite indicator point to increased vulnerability (compare the graphs representing the composite indicators and conditional probabilities from the pooling and country-specific approaches in Figures 8 to 19). This result might seem contradictory to what was mentioned earlier, namely, that the pooling method is more restrictive than the country-specific approach. This, however, can be attributed to the fact that the situation in one country affects that of the entire group (as the probabilities are calculated for all countries at the same time), making these results less reliable. Conversely, with the country-specific approach we see that the calculations give reasonable and coherent results, in that in most cases the conditional probability of a crisis tends to increase monotonically with the value of the composite indicator, and tends towards 1 (certainty of a crisis) at very high indicator values.

Tables 10 (pooling) and 11 (country-specific) display simultaneously the value of the composite indicator for each period, the conditional probability associated with it, and the incidence of crises, for each country studied. Analyzing the behavior of the composite indicator in the case of the country-specific approach, we clearly distinguish two situations. In the cases of Hungary (columns 4-6) and Poland (columns 7-9), the highest probabilities of crises are obtained when a crisis is imminent, or when a crisis actually occurs. During the periods of non-crisis, the probability values remain relatively small. For the remaining countries, the conclusion is slightly different. The probabilities are high for a longer period before a crisis (especially at the beginning of the nineties), and in the case of the Czech Republic are relatively high for the majority of the period under study. The warning system thus seems to perform rather well for these countries.

4. Conclusion

The warning system presented here could be refined by adopting approaches recently suggested in the empirical literature, for instance regime switching Markovian early warning systems (Arias and Erlandsson (2004)). However, defining an agenda whereby more sophisticated models have to be constructed, seems a difficult task in the case of Russia, given the degree of the spread and detrimental economic repercussions of the 1998 crisis. The current state of the macroeconomic fundamentals does not exclude a repetition of such a crisis in the future. A more promising approach would be to complete our early warning system with other standard approaches : value at risk analysis, logit/probit analysis, and event analysis. The greatest difficulty is to obtain reliable data over the period of the nineties, which reduces the number of potential indicators that can be used in the analysis.

A general conclusion that emerges from this paper is the following. We have proposed a measure of the probability of crises associated to an aggregate indicator, where the percentage of false alarms and the proportion of missed signals can be combined to give an appreciation of the vulnerability of an economy. In this perspective, the important problem is not only whether a system produces true predictions of a crisis, but also whether there are forewarning signs of a forthcoming crisis prior its actual occurrence. For purposes of prevention, policymakers need to have advance warnings in the medium/long-term rather than just a few periods prior to a crisis. Our system seems to perform rather well in this respect for most of the countries studied, but a future venue of research might seek to integrate an indicator for contagion effects to further improve the performance of an early warning system.

APPENDIX

Table 1 : Data Description

Indicators	Definition and units
1. Real exchange rates	Real effective exchange rate (CPI-based) – Index number
2. M2	Quasi-money – National currency – Millions, Billions
3. Credit	Domestic credit – National currency – Millions, Billions
4. Reserves	Total reserves minus gold – US Dollars – Millions, Billions
5. GDP	GDP, production – National currency – Millions, Billions
6. Commercial bank deposits	Demand deposits + Government deposits – National currency – Millions, Billions
7. Imports	Imports of goods and services – Millions, Billions
8. Exports	Exports of goods and services – Millions, Billions.

Source : International Financial Statistics (IFS), International Monetary Fund

Table 2 : Performance of Single Indicators (Pooling)

Advance Indicator	Threshold Quantile	Number of Crises Called (per country)	Noise to Signal Ratio	% of Crises Correctly Called	P(Crisis/Signal)
REER	Q1	4	0,11	22,22%	0,92
M2 / GDP	Q10	1	0,78	3,03%	0,60
M2 / Reserves	Q10	1	0,23	5,05%	0,83
Domestic Credit / GDP	Q10	1	0,38	3,03%	0,75
Exports of Goods and Services	Q1	4	0,31	19,19%	0,79
Imports of Goods and Services	Q9	4	0,93	5,05%	0,56
GDP	Q1	4	0,48	17,17%	0,71
Growth	Q8	25	0,90	81,82%	0,60
(EXP-IMP)*100 / GDP	Q2	7	0,51	30,30%	0,75
Commercial Bank Deposits	Q1	4	0,40	19,19%	0,79

Source : Author's Calculations

Table 3 : Performance of Single Indicators : Russia

Advance Indicator	Threshold Quantile	Number of Crises Called	Noise to Signal Ratio	% of Crises Correctly Called[6]	P(Crisis/Signal)[7]
REER	Q1	4	0,31	21,43%	0,75
M2 / GDP	Q8	7	0,93	14,29%	0,50
M2 / Reserves	Q9	4	0,31	21,43%	0,75
Domestic Credit / GDP	Q9	7	0,31	21,43%	0,75
Exports of Goods and Services	Q3	10	0,23	57,14%	0,80
Imports of Goods and Services	Q8	7	0,93	14,29%	0,50
GDP	Q2	7	0,16	42,86%	0,86
Growth	Q4	13	0,67	50,00%	0,58
(EXP-IMP)*100 / GDP	Q2	7	0,16	42,86%	0,86
Commercial Bank Deposits	Q4	13	0,28	71,43%	0,77

Source : Authors' Calculations

Table 4 : Performance of Single Indicators : Hungary

Advance Indicator	Threshold Quantile	Number of Crises Called	Noise to Signal Ratio	% of Crises Correctly Called	P(Crisis/Signal)
REER	Q3	10	0,48	42,11%	0,80
M2 / GDP	Q8	7	0,63	15,79%	0,75
M2 / Reserves	Q6	13	0,21	47,37%	0,90
Domestic Credit / GDP	Q8	7	0,32	31,58%	0,86
Exports of Goods and Services	Q2	7	0,76	26,32%	0,71
Imports of Goods and Services	Q6	13	0,21	47,37%	0,90
GDP	Q2	7	0,76	26,32%	0,71
Growth	Q8	27	0,71	84,21%	0,73
(EXP-IMP)*100 / GDP	Q1	4	0,63	15,79%	0,75
Commercial Bank Deposits	Q2	7	0,76	26,32%	0,71

Source : Authors' Calculations

[6] This percentage can be computed as (A/A+C).
[7] This probability corresponds to β, and is calculated as (A/A+B).

Table 5 : Performance of Single Indicators : Poland

Advance Indicator	Threshold Quantile	Number of Crises Called	Noise to Signal Ratio	% of Crises Correctly Called	P(Crisis/Signal)
REER	Q1	4	0,55	16,67%	0,75
M2 / GDP	Q5	16	0,73	50,00%	0,69
M2 / Reserves	Q4	19	0,74	61,11%	0,69
Domestic Credit / GDP	Q5	16	0,73	50,00%	0,69
Exports of Goods and Services	Q7	22	0,76	83,33%	0,68
Imports of Goods and Services	Q3	22	0,58	77,78%	0,74
GDP	Q1	4	0,55	16,67%	0,75
Growth	Q1	4	0,55	16,67%	0,75
(EXP-IMP)*100 / GDP	Q3	10	0,18	50,00%	0,90
Commercial Bank Deposits	Q1	4	0,55	16,67%	0,75

Source : Authors' Calculations

Table 6 : Performance of Single Indicators : Slovak Republic

Advance Indicator	Threshold Quantile	Number of Crises Called	Noise to Signal Ratio	% of Crises Correctly Called	P(Crisis/Signal)
REER	Q2	7	0,16	42,86%	0,86
M2 / GDP	Q7	10	0,93	35,71%	0,50
M2 / Reserves	Q9	4	0,31	21,43%	0,75
Domestic Credit / GDP	Q5	16	0,73	64,29%	0,56
Exports of Goods and Services	Q5	16	0,42	78,57%	0,69
Imports of Goods and Services	Q2	25	0,93	78,57%	0,50
GDP	Q5	16	0,42	78,57%	0,69
Growth	Q1	4	0,31	21,43%	0,75
(EXP-IMP)*100 / GDP	Q3	10	0,62	42,86%	0,60
Commercial Bank Deposits	Q3	10	0,23	57,14%	0,80

Source : Authors' Calculations

Table 7 : Performance of Single Indicators : Czech Republic

Advance Indicator	Threshold Quantile	Number of Crises Called	Noise to Signal Ratio	% of Crises Correctly Called	P(Crisis/Signal)
REER	Q3	10	0,29	42,86%	0,90
M2 / GDP	Q2	25	0,77	80,95%	0,77
M2 / Reserves	Q7	10	0,29	42,86%	0,90
Domestic Credit / GDP	Q8	7	0,45	28,57%	0,86
Exports of Goods and Services	Q2	7	0,45	28,57%	0,86
Imports of Goods and Services	Q8	7	0,88	14,29%	0,95
GDP	Q2	7	0,44	28,57%	0,86
Growth	Q3	10	0,66	38,10%	0,80
(EXP-IMP)*100 / GDP	Q7	23	0,46	80,95%	0,85
Commercial Bank Deposits	Q8	25	0,50	100,00%	0,84

Source : Authors' Calculations

Table 8 : Performance of Single Indicators : Kazakhstan

Advance Indicator	Threshold Quantile	Number of Crises Called	Noise to Signal Ratio	% of Crises Correctly Called	P(Crisis/Signal)
REER	Q2	7	0,14	46,15%	0,86
M2 / GDP	Q1	28	1,03	84,62%	0,44
M2 / Reserves	Q1	28	1,03	84,62%	0,44
Domestic Credit / GDP	Q2	25	0,98	76,92%	0,45
Exports of Goods and Services	Q4	13	0,51	61,54%	0,62
Imports of Goods and Services	Q2	25	0,81	84,62%	0,50
GDP	Q4	13	0,51	61,54%	0,62
Growth	Q8	25	0,74	92,31%	0,52
(EXP-IMP)*100 / GDP	Q2	7	0,14	46,15%	0,86
Commercial Bank Deposits	Q2	7	0,14	46,15%	0,86

Source : Authors' Calculations

Table 9 : Conditional probabilities of financial crises

Pooling	
Value of composite index	Probability of crisis
0 – 2	0.2727
2 – 6	0.4706
6 – 10	0.6364
10 13	0.6538
Over 13	0.9200
Russia	
Value of composite index	Probability of crisis
0 – 2	0.0000
2 – 6	0.4286
6 – 10	0.5000
10 13	0.6000
Over 13	1.000
Hungary	
Value of composite index	Probability of crisis
0 – 2	0.1667
2 – 6	0.6000
6 – 10	0.6667
10 13	1.000
Over 13	0.8333
Poland	
Value of composite index	Probability of crisis
0 – 2	0.0000
2 – 6	0.6250
6 – 10	0.6364
10 13	1.000
Over 13	1.000
Slovak Republic	
Value of composite index	Probability of crisis
0 – 2	0.0000
2 – 6	0.2000
6 – 10	0.3333
10 13	0.7500
Over 13	0.8333
Czech Republic	
Value of composite index	Probability of crisis
0 – 2	0.0000
2 – 6	0.1667
6 – 10	0.9000
10 13	0.8571
Over 13	1.000
Kazakhstan	
Value of composite index	Probability of crisis
0 – 2	0.0000
2 – 6	0.3571
6 – 10	0.6667
10 13	0.8000
Over 13	1.000

Source : Authors' Calculations

Table 10 : Summary Table : Composite Indicator, Conditional Probability and Incidence of Crises - Pooling

	RUSSIA			HUNGARY			POLAND			SLOVAK REPUBLIC			CZECH REPUBLIC			KAZAKHSTAN		
	Composite Indicator	Conditional Probability	Incidence of Crises	Composite Indicator	Conditional Probability	Incidence of Crises	Composite Indicator	Conditional Probability	Incidence of Crises	Composite Indicator	Conditional Probability	Incidence of Crises	Composite Indicator	Conditional Probability	Incidence of Crises	Composite Indicator	Conditional Probability	Incidence of Crises
1996Q1	10,9185	0,9200	0	**20,9993**	**0,9200**	**1**	18,3932	0,9200	0	8,4235	0,6538	0	**15,8983**	**0,9200**	**1**	6,4538	0,6538	0
1996Q2	**10,9185**	**0,9200**	**1**	**18,3932**	**0,9200**	**1**	18,3932	0,9200	0	5,3478	0,6538	0	**16,7619**	**0,9200**	**1**	3,1912	0,6364	0
1996Q3	4,5801	0,6538	0	18,3932	0,9200	0	18,3932	0,9200	0	6,4538	0,6538	0	**8,4235**	**0,6538**	**1**	0,0000	0,2727	0
1996Q4	3,6010	0,6364	0	11,5296	0,9200	0	12,7071	0,9200	0	15,7828	0,9200	0	3,0758	0,6364	0	4,3687	0,6538	0
1997Q1	6,4538	0,6538	0	**6,8636**	**0,6538**	**1**	**5,6861**	**0,6538**	**1**	7,7670	0,6538	0	**11,0296**	**0,9200**	**1**	5,6861	0,6538	0
1997Q2	3,0758	0,6364	0	0,0000	0,2727	0	1,1061	0,4706	0	**0,0000**	**0,2727**	**1**	4,4646	0,6538	0	7,6558	0,6538	0
1997Q3	**3,0758**	**0,6364**	**1**	1,1061	0,4706	0	1,1061	0,4706	0	1,1061	0,4706	0	10,5505	0,9200	0	11,9394	0,9200	0
1997Q4	**3,0758**	**0,6364**	**1**	0,0000	0,2727	0	1,9697	0,4706	0	1,1061	0,4706	0	14,8939	0,9200	0	12,5202	0,9200	0
1998Q1	**6,3384**	**0,6538**	**1**	1,1061	0,4706	0	1,1061	0,4706	0	3,0758	0,6364	0	3,6010	0,6364	0	**10,5505**	**0,9200**	**1**
1998Q2	3,0758	0,6364	0	1,1061	0,4706	0	1,1061	0,4706	0	1,9697	0,4706	0	**2,4949**	**0,6364**	**1**	12,5202	0,9200	0
1998Q3	3,7121	0,6364	0	1,1061	0,4706	0	1,1061	0,4706	0	1,1061	0,4706	0	**1,1061**	**0,4706**	**1**	**3,0758**	**0,6364**	**1**
1998Q4	9,4444	0,6538	0	1,1061	0,4706	0	1,9697	0,4706	0	12,5202	0,9200	0	**1,1061**	**0,4706**	**1**	6,3384	0,6538	0
1999Q1	10,5505	0,9200	0	**2,3939**	**0,6364**	**1**	3,0758	0,6364	0	**17,3889**	**0,9200**	**1**	3,6010	0,6364	0	**8,8333**	**0,6538**	**1**
1999Q2	9,4444	0,6538	0	0,0000	0,2727	0	**3,0758**	**0,6364**	**1**	11,9394	0,9200	0	0,0000	0,2727	0	**1,1061**	**0,4706**	**1**
1999Q3	**4,3434**	**0,6538**	**1**	1,1061	0,4706	0	1,1061	0,4706	0	**3,6010**	**0,6364**	**1**	1,1061	0,4706	0	0,0000	0,2727	0
1999Q4	1,1061	0,4706	0	0,0000	0,2727	0	0,0000	0,2727	0	1,1061	0,4706	0	1,1061	0,4706	0	1,1061	0,4706	0
2000Q1	10,5505	0,9200	0	3,0758	0,6364	0	**3,0758**	**0,6364**	**1**	**3,6010**	**0,6364**	**1**	1,1061	0,4706	0	1,1061	0,4706	0
2000Q2	1,1061	0,4706	0	1,1061	0,4706	0	3,0758	0,6364	0	0,0000	0,2727	0	0,0000	0,2727	0	0,0000	0,2727	0
2000Q3	0,0000	0,2727	0	1,1061	0,4706	0	**1,1061**	**0,4706**	**1**	1,1061	0,4706	0	**1,1061**	**0,4706**	**1**	1,1061	0,4706	0
2000Q4	1,1061	0,4706	0	4,1490	0,6538	0	1,9697	0,4706	0	1,1061	0,4706	0	4,1490	0,6538	0	1,1061	0,4706	0
2001Q1	1,1061	0,4706	0	3,0758	0,6364	0	**1,1061**	**0,4706**	**1**	1,1061	0,4706	0	**1,1061**	**0,4706**	**1**	1,1061	0,4706	0
2001Q2	1,1061	0,4706	0	**0,0000**	**0,2727**	**1**	**1,1061**	**0,4706**	**1**	0,0000	0,2727	0	0,0000	0,2727	0	**1,1061**	**0,4706**	**1**
2001Q3	0,0000	0,2727	0	**1,1061**	**0,4706**	**1**	1,1061	0,4706	0	1,1061	0,4706	0	1,1061	0,4706	0	0,0000	0,2727	0
2001Q4	1,1061	0,4706	0	1,1061	0,4706	0	**5,4495**	**0,6538**	**1**	3,0758	0,6364	0	2,1793	0,6364	0	3,0758	0,6364	0
2002Q1	1,1061	0,4706	0	**1,1061**	**0,4706**	**1**	2,3939	0,6364	0	1,1061	0,4706	0	**2,3939**	**0,6364**	**1**	1,1061	0,4706	0
2002Q2	1,1061	0,4706	0	0,0000	0,2727	0	1,1061	0,4706	0	0,0000	0,2727	0	1,1061	0,4706	0	0,0000	0,2727	0
2002Q3	0,0000	0,2727	0	1,1061	0,4706	0	1,1061	0,4706	0	1,1061	0,4706	0	1,1061	0,4706	0	2,1793	0,6364	0
2002Q4	2,1793	0,6364	0	**7,4192**	**0,6538**	**1**	1,0732	0,4706	0	2,1793	0,6364	0	4,1490	0,6538	0	6,5227	0,6538	0
2003Q1	1,1061	0,4706	0	3,0758	0,6364	0	1,1061	0,4706	0	2,3939	0,6364	0	1,1061	0,4706	0	2,3939	0,6364	0
2003Q2	2,1793	X	0	4,1490	X	0	2,1793	X	0	2,1793	X	0	0,0000	X	0	0,0000	X	0
2003Q3	**2,1793**	**X**	**1**	2,1793	X	0	4,7854	X	0	**2,1793**	**X**	**1**	1,1061	X	0	4,7854	X	0
2003Q4	3,4672	X	0	4,1490	X	0	1,0732	X	0	2,1793	X	0	2,1793	X	0	2,1793	X	0

Source : Authors' Calculations

Table 11 : Summary Table : Composite Indicator, Conditional Probability and Incidence of Crises

	RUSSIA			HUNGARY			POLAND			SLOVAK REPUBLIC			CZECH REPUBLIC			KAZAKHSTAN		
	Composite Indicator	Conditional Probability	Incidence of Crises	Composite Indicator	Conditional Probability	Incidence of Crises	Composite Indicator	Conditional Probability	Incidence of Crises	Composite Indicator	Conditional Probability	Incidence of Crises	Composite Indicator	Conditional Probability	Incidence of Crises	Composite Indicator	Conditional Probability	Incidence of Crises
1996Q1	22,2143	1,0000	0	**10,6140**	**1,0000**	**1**	6,8095	0,6364	0	10,6071	0,7500	0	**15,7397**	**1,0000**	**1**	7,2738	0,3571	0
1996Q2	**20,7143**	**1,0000**	**1**	**10,6140**	**1,0000**	**1**	6,8095	0,6364	0	11,1429	0,7500	0	**15,7397**	**1,0000**	**1**	6,2482	0,3571	0
1996Q3	14,2857	0,6000	0	12,1930	0,8333	0	6,8095	0,6364	0	11,1429	0,7500	0	**15,7397**	**1,0000**	**1**	4,9055	0,0000	0
1996Q4	15,7857	1,0000	0	9,2105	0,6667	0	3,1429	0,6250	0	12,7500	0,7500	0	15,7397	1,0000	0	7,2152	0,3571	0
1997Q1	15,7857	1,0000	0	**10,6140**	**1,0000**	**1**	**4,9762**	**0,6250**	**1**	18,4133	0,8333	0	**17,2635**	**1,0000**	**1**	21,9844	0,8000	0
1997Q2	20,7143	1,0000	0	6,0526	0,6667	0	1,3095	0,0000	0	**8,7704**	**0,3333**	**1**	14,4444	0,8571	0	29,6328	0,8000	0
1997Q3	**14,2857**	**0,6000**	**1**	7,4561	0,6667	0	1,3095	0,0000	0	6,0918	0,3333	0	9,8730	0,9000	0	17,9692	0,6667	0
1997Q4	**15,7857**	**1,0000**	**1**	0,0000	0,1667	0	6,8095	0,6364	0	6,0918	0,3333	0	14,5968	0,8571	0	23,2152	0,8000	0
1998Q1	**25,4286**	**1,0000**	**1**	4,5614	0,6000	0	1,3095	0,0000	0	13,0561	0,8333	0	10,5333	0,8571	0	**15,6254**	**0,6667**	**1**
1998Q2	14,2857	0,6000	0	1,4035	0,1667	0	1,3095	0,0000	0	13,0561	0,8333	0	**5,4286**	**0,9000**	**1**	31,6254	1,0000	0
1998Q3	6,7857	0,5000	0	3,5088	0,6000	0	3,0206	0,6250	0	11,4490	0,7500	0	**2,0000**	**0,1667**	**1**	**30,6584**	**1,0000**	**1**
1998Q4	10,0000	0,6000	0	3,5088	0,6000	0	8,5206	0,6364	0	22,6990	0,8333	0	**6,9778**	**0,9000**	**1**	24,2408	0,8000	0
1999Q1	13,2143	0,6000	0	**8,2456**	**0,6667**	**1**	13,1040	1,0000	0	**22,1633**	**0,8333**	**1**	4,8190	0,1667	0	**23,0101**	**0,8000**	**1**
1999Q2	6,4286	0,5000	0	0,0000	0,1667	0	**12,6151**	**1,0000**	**1**	21,0918	0,8333	0	5,4286	0,9000	0	**7,5024**	**0,3571**	**1**
1999Q3	**3,2143**	**0,4286**	**1**	1,4035	0,1667	0	11,2401	1,0000	0	**10,9286**	**0,7500**	**1**	2,0000	0,1667	0	3,2234	0,0000	0
1999Q4	4,7143	0,4286	0	0,0000	0,1667	0	9,8651	0,6364	0	11,4490	0,7500	0	5,6825	0,9000	0	5,5331	0,3571	0
2000Q1	3,2143	0,4286	0	2,9825	0,6000	0	**14,4484**	**1,0000**	**1**	**10,1633**	**0,7500**	**1**	6,9778	0,9000	0	5,5331	0,3571	0
2000Q2	0,0000	0,0000	0	1,4035	0,1667	0	12,6151	1,0000	0	5,3571	0,3333	0	8,8825	0,9000	0	4,1905	0,0000	0
2000Q3	0,0000	0,0000	0	6,1404	0,6667	0	**12,6151**	**1,0000**	**1**	1,0714	0,0000	0	**8,8825**	**0,9000**	**1**	5,5331	0,3571	0
2000Q4	1,5000	0,0000	0	12,4561	0,8333	0	8,5556	0,6364	0	3,7500	0,2000	0	11,5492	0,8571	0	5,5331	0,3571	0
2001Q1	1,5000	0,0000	0	12,4561	0,8333	0	**8,9484**	**0,6364**	**1**	3,5204	0,2000	0	**10,4063**	**0,8571**	**1**	5,5331	0,3571	0
2001Q2	0,0000	0,0000	0	**4,7368**	**0,6000**	**1**	**7,1151**	**0,6364**	**1**	4,2857	0,2000	0	10,0254	0,8571	0	**5,5331**	**0,3571**	**1**
2001Q3	0,0000	0,0000	0	**10,8772**	**1,0000**	**1**	5,8056	0,6250	0	2,4490	0,0000	0	8,8825	0,9000	0	4,1905	0,0000	0
2001Q4	1,5000	0,0000	0	10,8772	1,0000	0	**4,4306**	**0,6250**	**1**	5,1276	0,3333	0	10,0254	0,8571	0	12,9177	0,6667	0
2002Q1	2,5714	0,4286	0	**12,4561**	**0,8333**	**1**	7,1151	0,6364	0	3,5204	0,2000	0	**8,2476**	**0,9000**	**1**	5,5331	0,3571	0
2002Q2	2,1429	0,4286	0	9,4737	0,6667	0	5,8056	0,6250	0	1,0714	0,0000	0	1,2952	0,0000	0	4,1905	0,0000	0
2002Q3	1,0714	0,0000	0	10,8772	1,0000	0	5,8056	0,6250	0	1,0714	0,0000	0	3,4540	0,1667	0	5,5331	0,3571	0
2002Q4	3,6429	0,4286	0	**12,4561**	**0,8333**	**1**	3,0556	0,6250	0	3,7500	0,2000	0	4,5968	0,1667	0	5,5331	0,3571	0
2003Q1	3,6429	0,4286	0	12,4561	0,8333	0	7,6389	0,6364	0	5,3571	0,3333	0	2,8190	0,1667	0	5,5331	0,3571	0
2003Q2	2,1429	X	0	12,4561	X	0	5,8056	X	0	1,0714	X	0	2,4381	X	0	4,1905	X	0
2003Q3	**2,1429**	**X**	**1**	12,4561	X	0	5,8056	X	0	**1,0714**	**X**	**1**	4,5968	X	0	5,5331	X	0
2003Q4	3,6429	X	0	12,4561	X	0	5,8056	X	0	1,0714	X	0	4,5968	X	0	5,5331	X	0

Source : Authors' Calculations

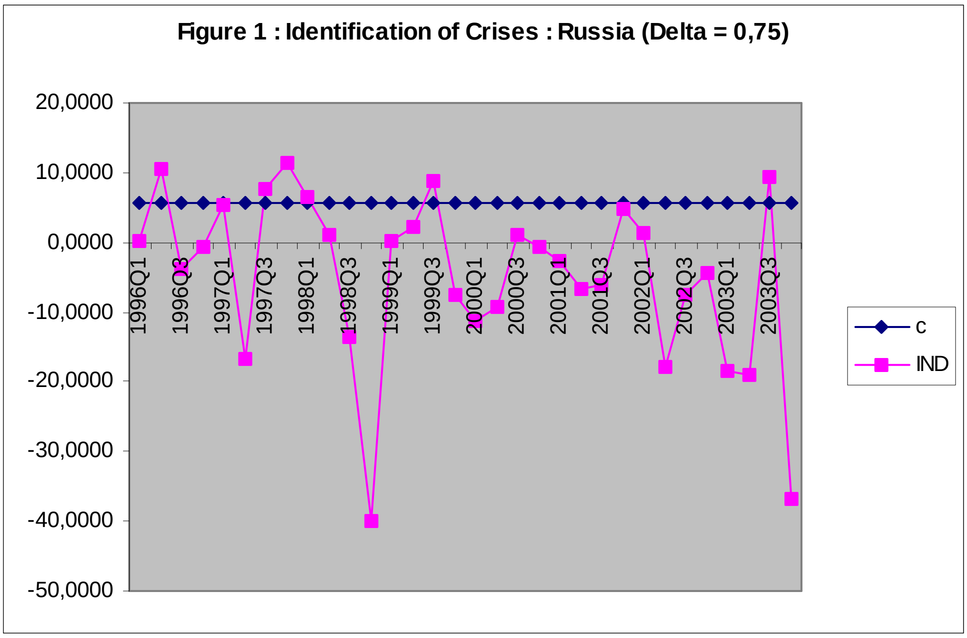


Figure 1 : Identification of Crises : Russia (Delta = 0,75)
20,0000
10,0000
0,0000
-10,0000
-20,0000
-30,0000
-40,0000
-50,0000
1996Q1
1996Q3
1997Q1
1997Q3
1998Q1
1998Q3
1999Q1
1999Q3
2000Q1
2000Q3
2001Q1
2001Q3
2002Q1
2002Q3
2003Q1
2003Q3
c
IND

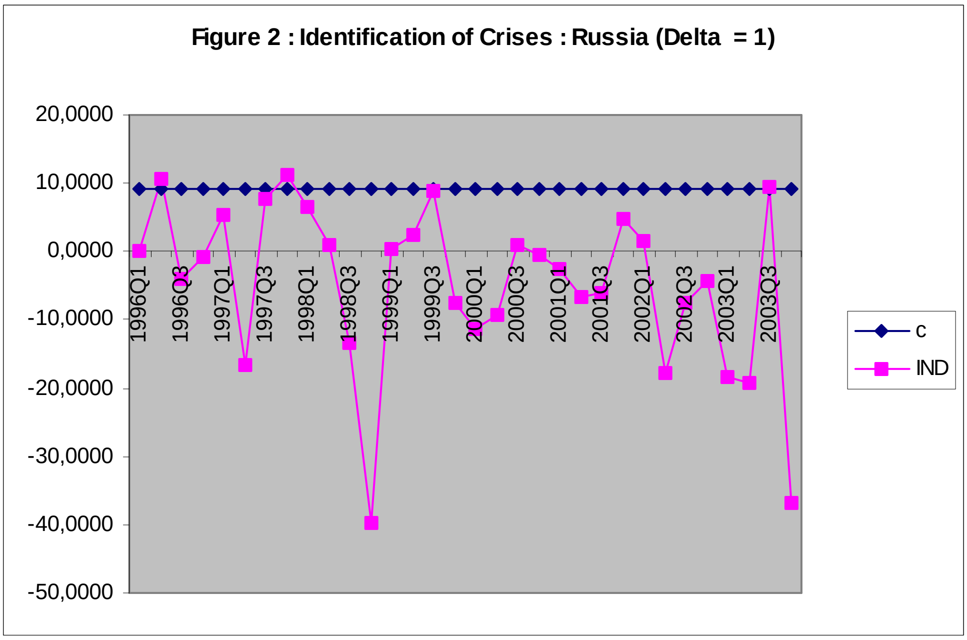


Figure 2 : Identification of Crises : Russia (Delta = 1)
20,0000
10,0000
0,0000
-10,0000
-20,0000
-30,0000
-40,0000
-50,0000
1996Q1
1996Q3
1997Q1
1997Q3
1998Q1
1998Q3
1999Q1
1999Q3
2000Q1
2000Q3
2001Q1
2001Q3
2002Q1
2002Q3
2003Q1
2003Q3
c
IND

Figure 3 : Identification of Crises : Hungary (Delta = 0,75)

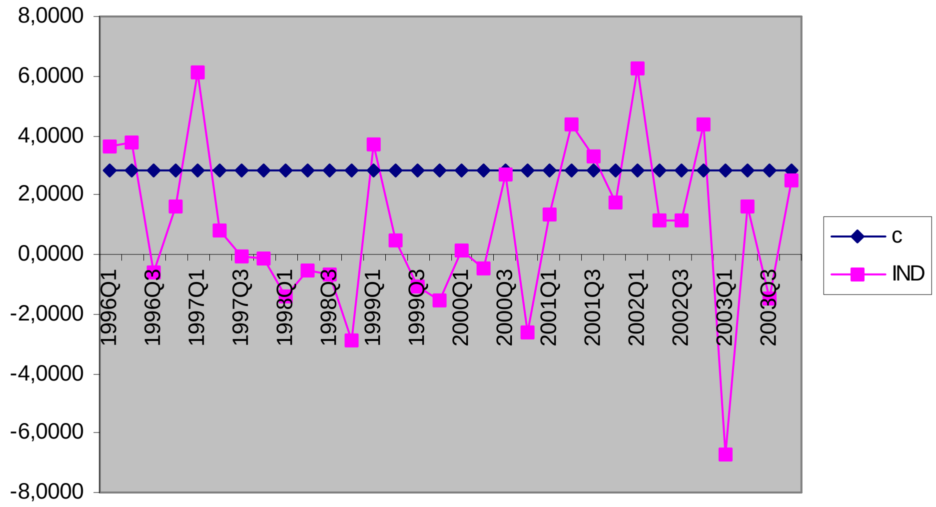


Figure 4 : Identification of Crises : Poland (Delta = 0,75)

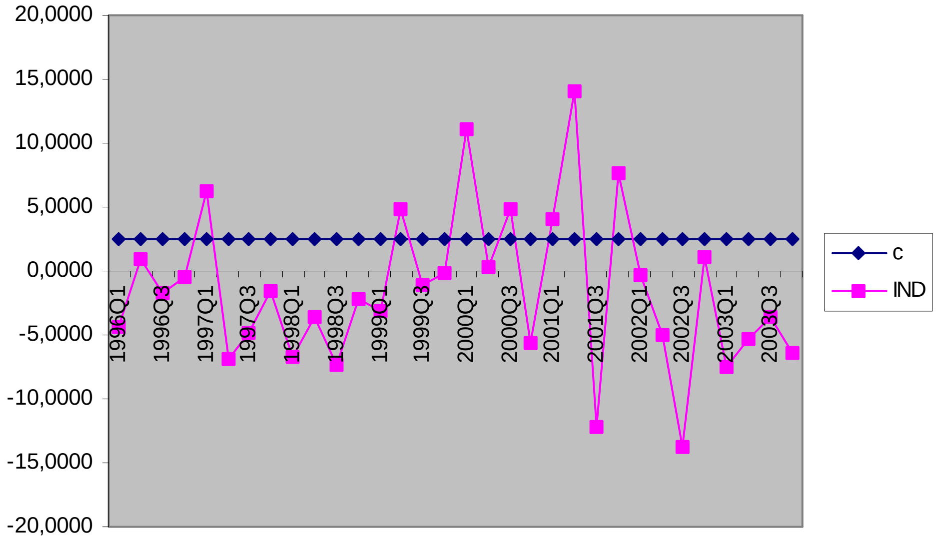


Figure 5 : Identification of Crises : Slovak Republic (Delta = 0,75)

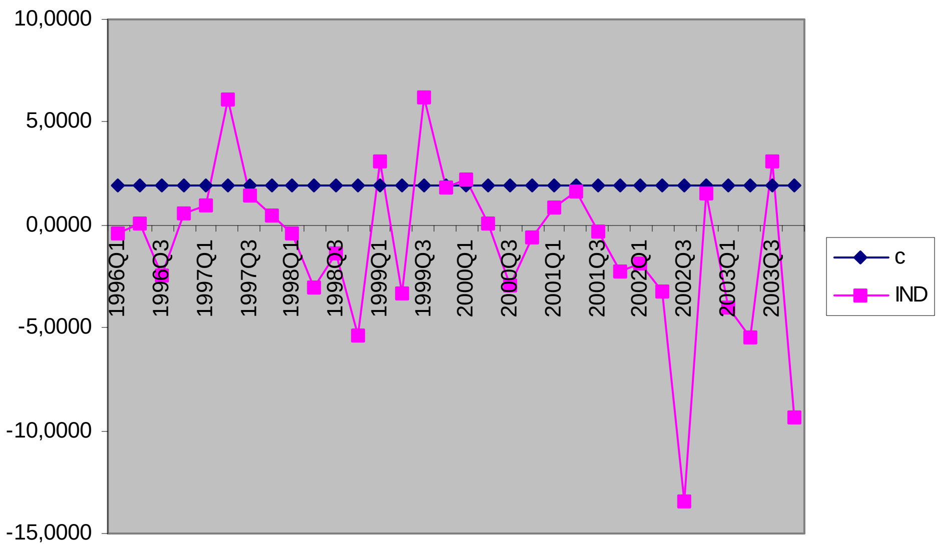
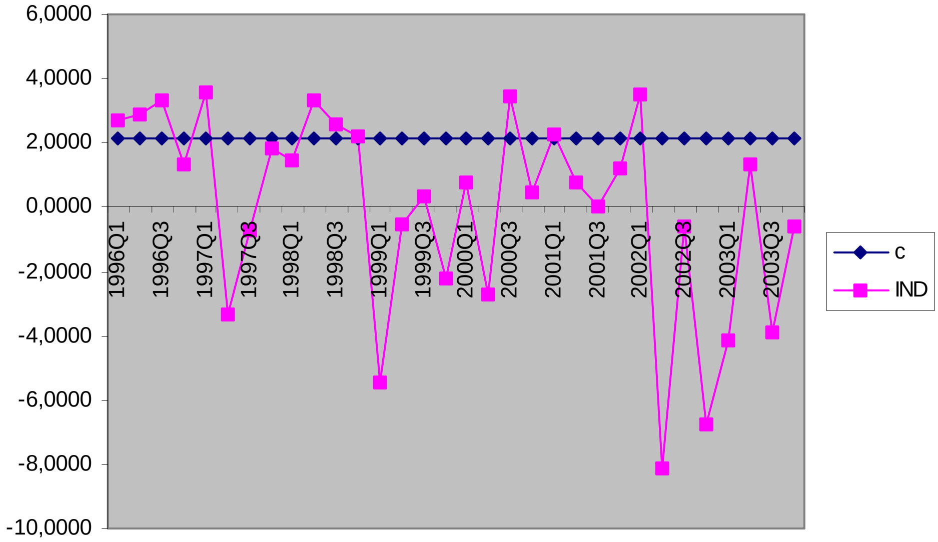


Figure 6 : Identification of Crises : Czech Republic (Delta = 0,75)



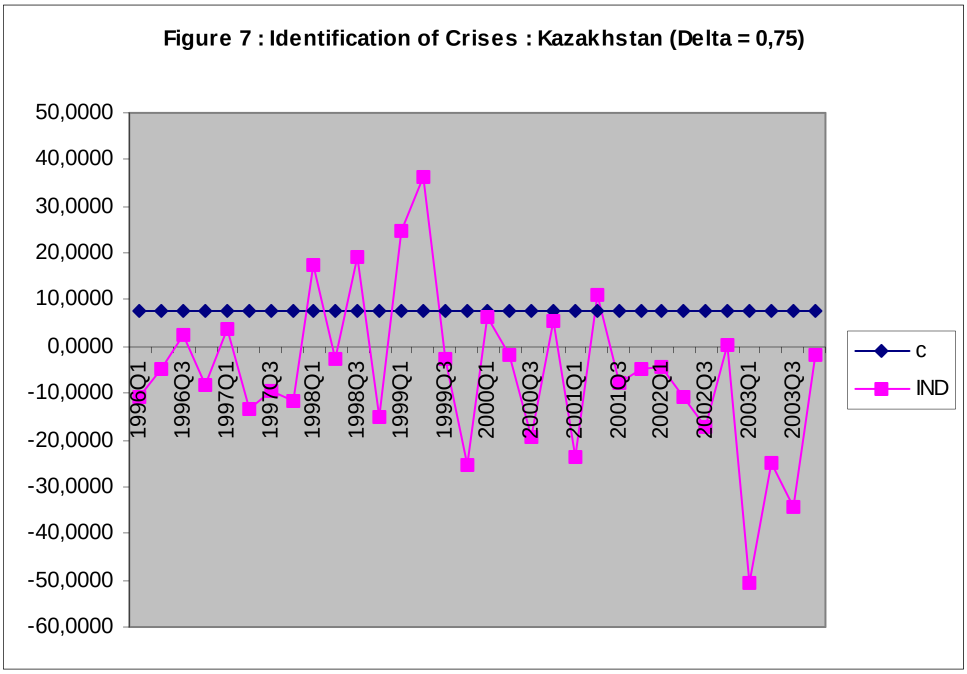


Figure 7 : Identification of Crises : Kazakhstan (Delta = 0,75)
50,0000
40,0000
30,0000
20,0000
10,0000
0,0000
-10,0000
-20,0000
-30,0000
-40,0000
-50,0000
-60,0000
1996Q1
1996Q3
1997Q1
1997Q3
1998Q1
1998Q3
1999Q1
1999Q3
2000Q1
2000Q3
2001Q1
2001Q3
2002Q1
2002Q3
2003Q1
2003Q3
c
IND

Figure 8 : Composite Indicator and Conditional Probability : Russia (Pooling)

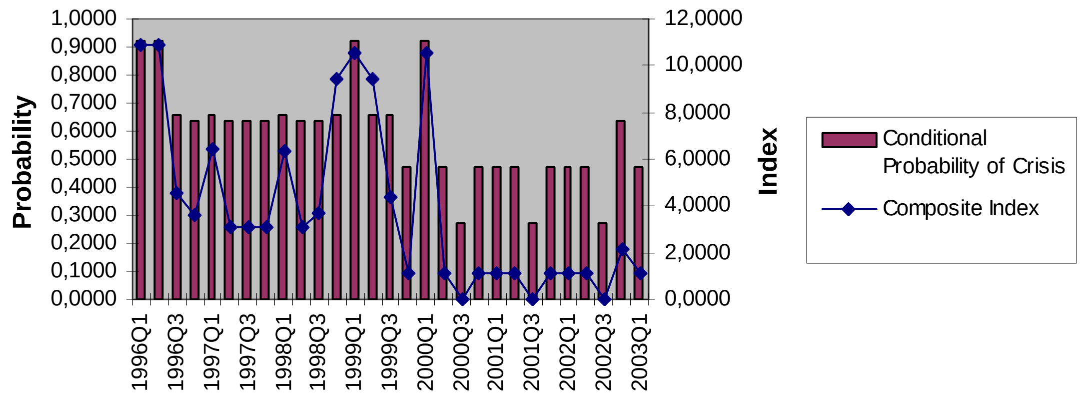


Figure 9 : Composite Indicator and Conditional Probability : Russia (Individual Country Approach)

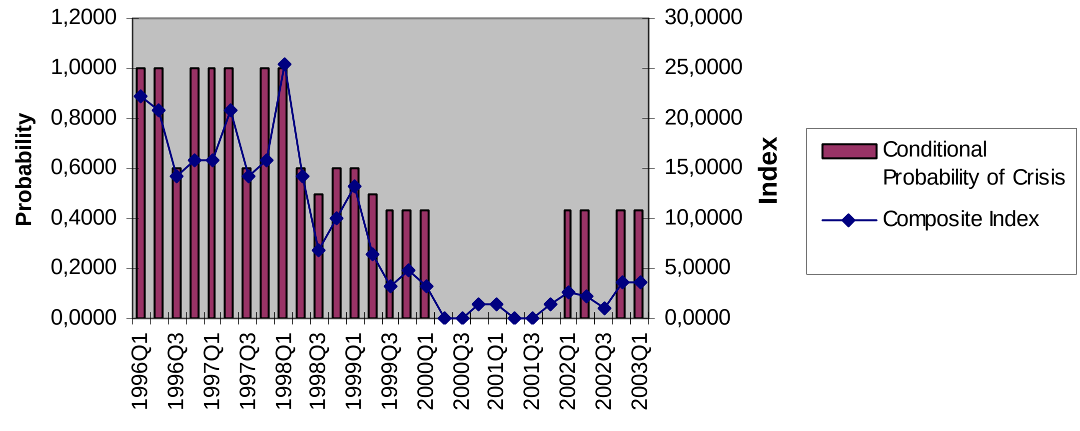


Figure 10 : Composite Indicator and Conditional Probability : Hungary (Pooling)

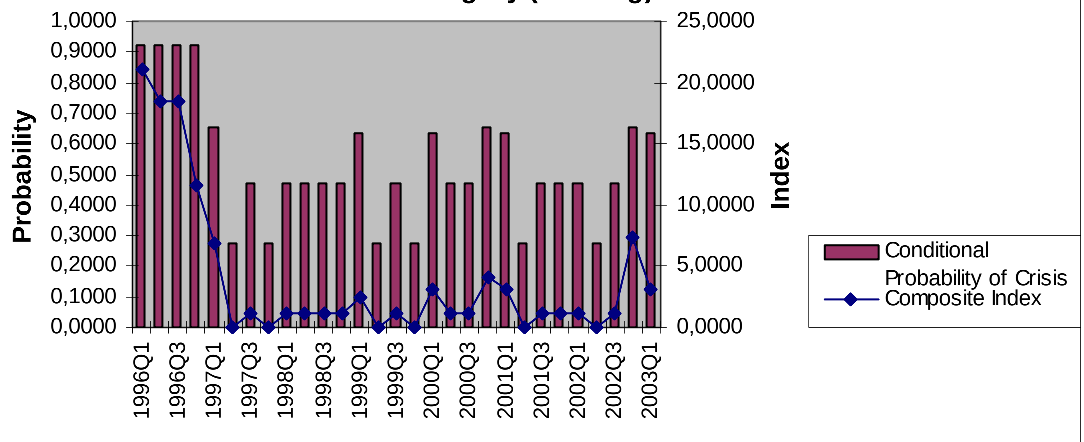


Figure 11 : Composite Indicator and Conditional Probability : Hungary (Individual Country Approach)

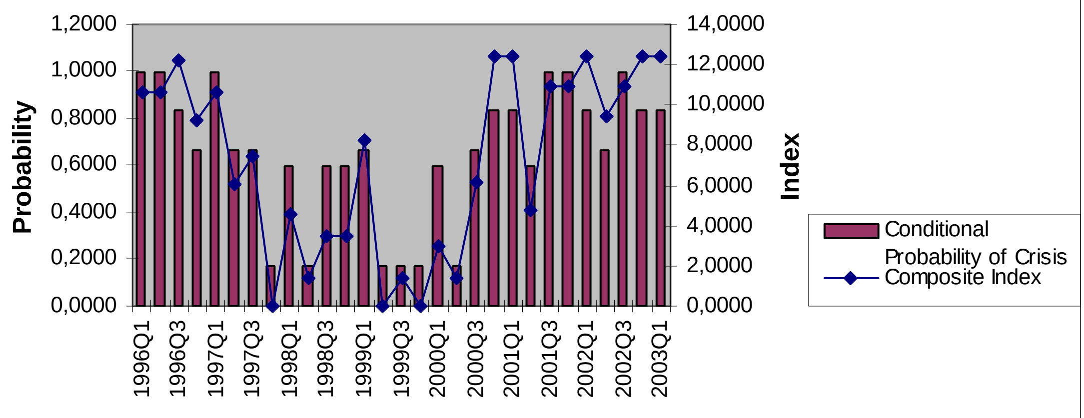


Figure 12 : Composite Indicator and Conditional Probability : Poland (Pooling)

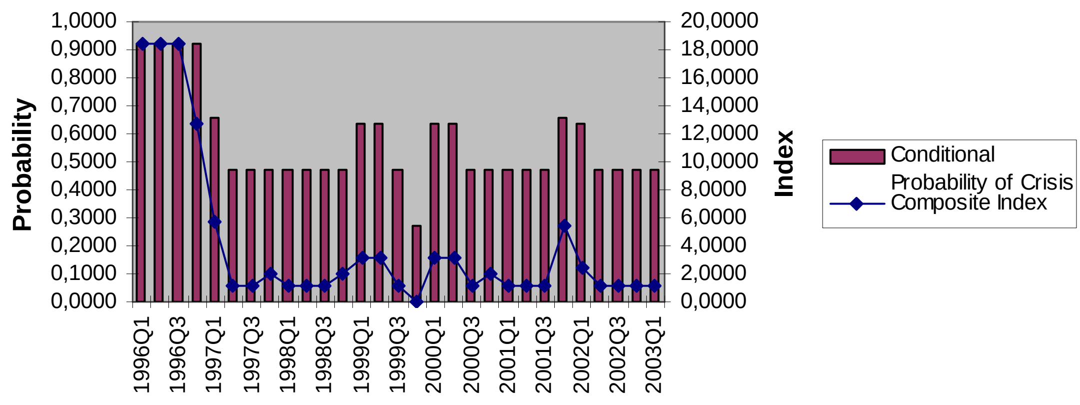
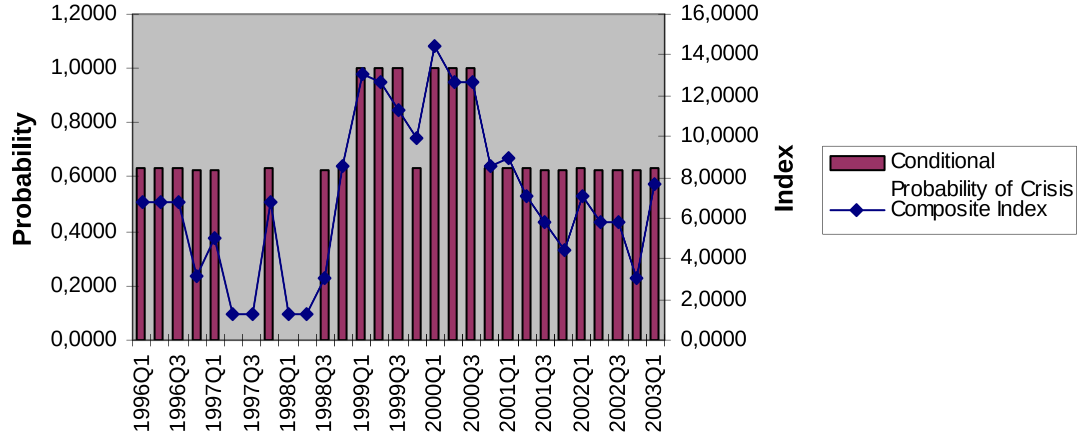


Figure 13 : Composite Indicator and Conditional Probability : Poland (Individual Country Approach)



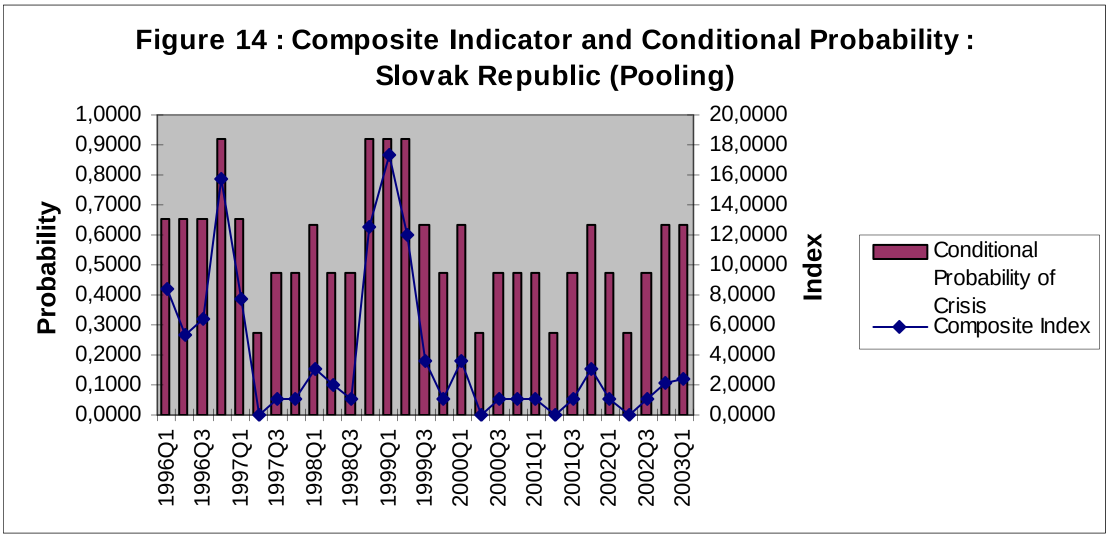


Figure 14 : Composite Indicator and Conditional Probability :
Slovak Republic (Pooling)
Probability
Index
Conditional Probability of Crisis
Composite Index

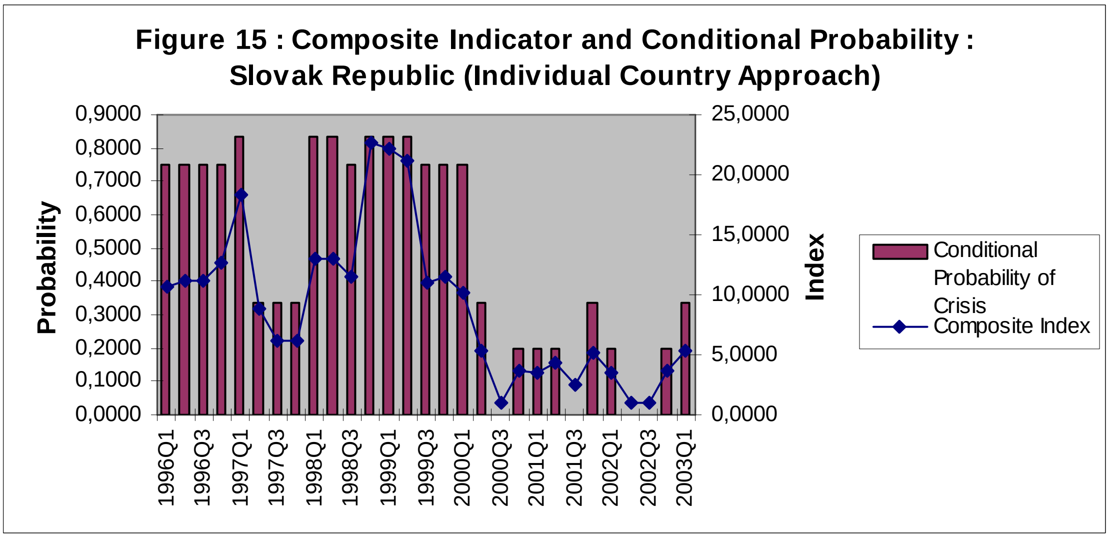


Figure 15 : Composite Indicator and Conditional Probability :
Slovak Republic (Individual Country Approach)
Probability
Index
Conditional Probability of Crisis
Composite Index

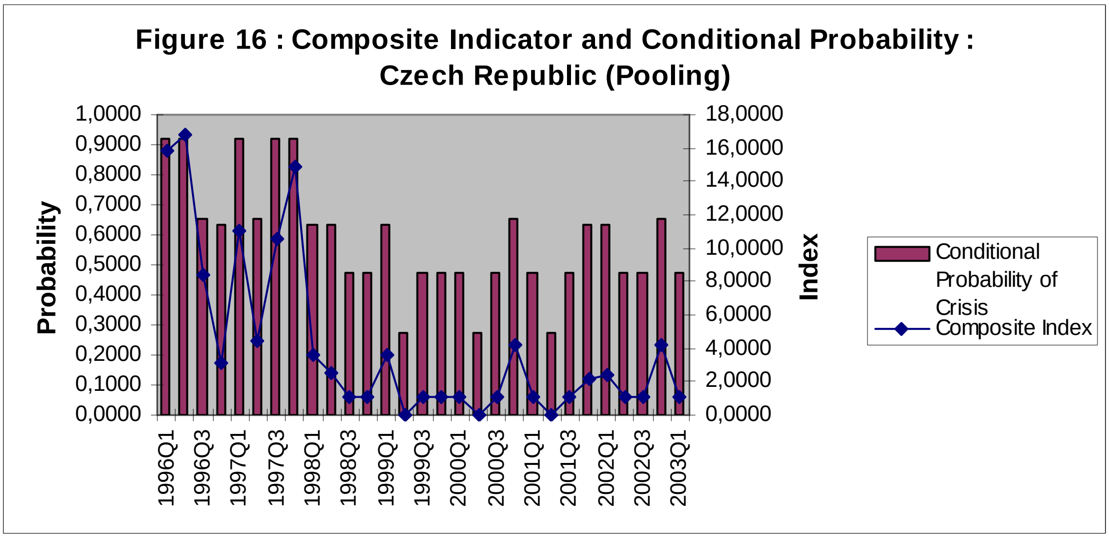


Figure 16 : Composite Indicator and Conditional Probability :
Czech Republic (Pooling)
Probability
Index
Conditional Probability of Crisis
Composite Index

Figure 17 : Composite Indicator and Conditional Probability : Czech Republic (Individual Country Approach)

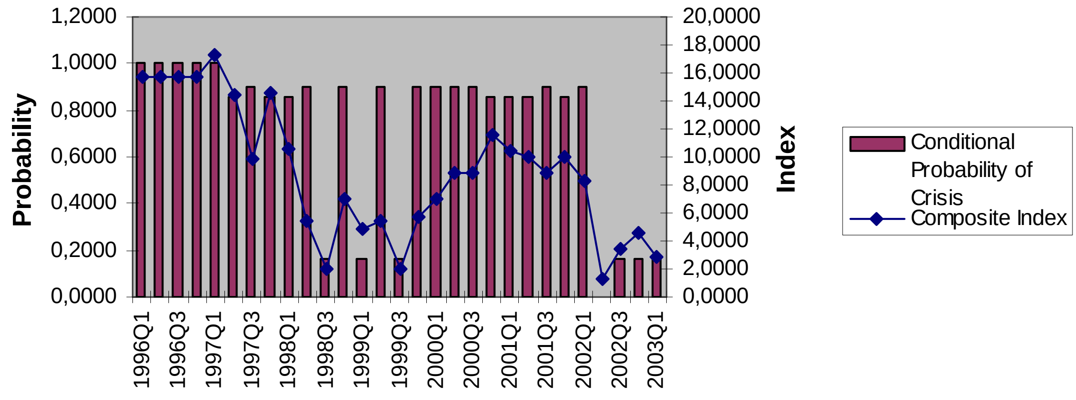


Figure 18 : Composite Indicator and Conditional Probability : Kazakhstan (Pooling)

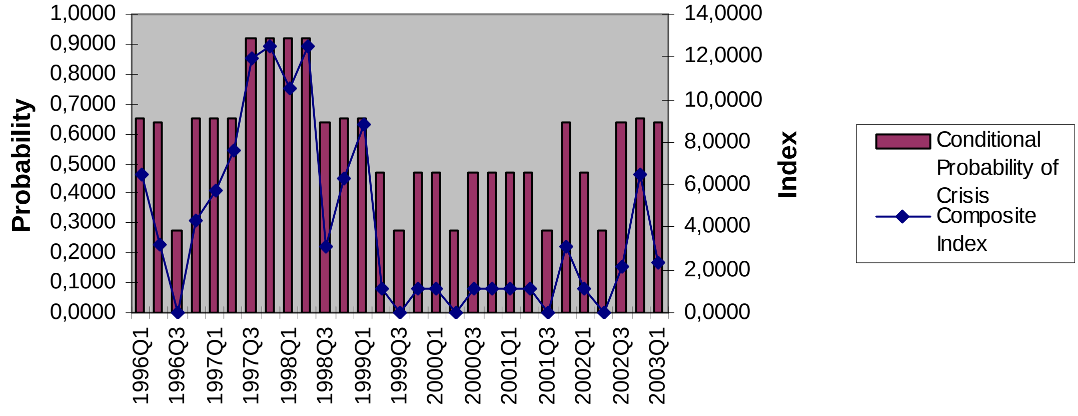
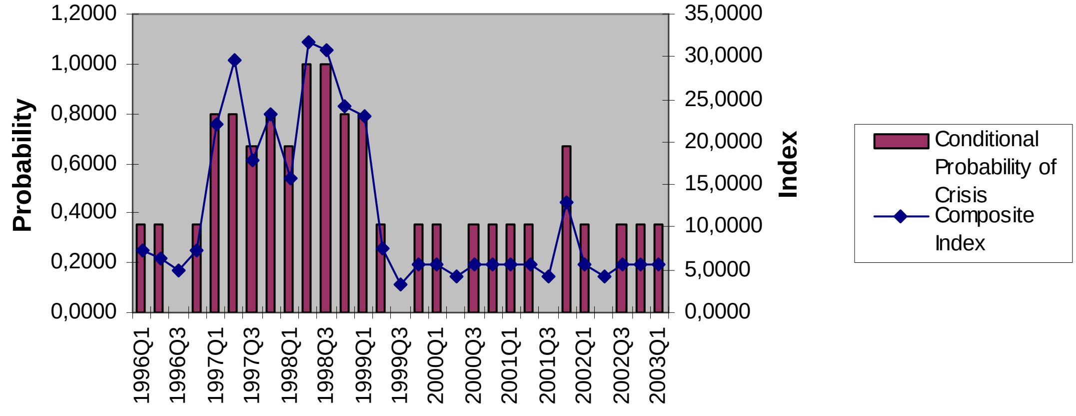


Figure 19 : Composite Indicator and Conditional Probability : Kazakhstan (Individual Country Approach)



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