Findings of the Signal Approach for Financial Monitoring in Kazakhstan

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Abstract

This study concentrates on the signal approach for Kazakhstan. It focuses on the properties of individual indicators prior to observed currency crises. The indicators are used to build composite indicators. An advanced approach uses principal components analysis for the construction of composite indicators. Furthermore, the common signal approach is improved by robust statistical methods. The estimation period reaches from 1997 to 2007. It is shown that most of the composite indicators are able to flag the reported crises at an early stage. In a second step it is checked whether the most recent crisis in 2009 is signalled in advance.

JEL Code: E32, E37, E59.

Keywords: currency crises, leading economic indicators, signal approach, Kazakhstan.

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Forecasting currency crises is a challenging task. A well-known standard approach is the *signal approach* developed by Kaminsky, Lizondo and Reinhart (KLR).[1] Following this approach currency crises are identified by means of a foreign exchange market pressure index. This pressure index serves as a reference series for dating currency crises. In a second step KLR propose the monitoring of macroeconomic variables (*single indicators*) that may tend to show unusual behaviour in periods (one or two years) prior to currency turbulences. An indicator sends a crisis warning signal whenever it moves beyond a given critical threshold. Moreover, c*omposite indicators* can be constructed that encompass the signalling behaviour of the selected individual indicators. Finally, crises probabilities can be estimated. This procedure, which can be performed for each single country with reported currency crises, characterizes the signal approach.

From the statistical point of view the signal approach can be characterized as a non-parametric approach, since it does not require the assumption of a specific model (in contrast to logit models or Markov regime-switching models). Indeed the parametric models may be more efficient, when the models assumptions hold in reality. The signal approach on the other hand should be a quite versatile method. It should be especially advantageous when data quality is quite unsure and/or when dependencies between macroeconomic variables might not be stable. Dependencies could be time varying in developed countries, but this problem should be of especial importance in developing countries like Kazakhstan. In such cases the signal approach will be a rather robust method for monitoring currency crises. So, even when there are model based approaches working well within available samples, the signal approach has its own justification because it is a nonparametric method. In this study the signal approach is refined by outlier robust estimation methods, which further enhances the usefulness of the signal approach.

The following *empirical study* concentrates on the signal approach for *Kazakhstan*. It focuses on the signalling properties of several *individual macroeconomic indicators* prior to episodes of foreign exchange market turbulences in Kazakhstan, as indicated by

[1] See Kaminsky, Lizondo, Reinhart (1998),

the exchange market pressure index. The individual indicators are used to build *composite currency crises indicators* by exploiting the signal behaviour of each individual indicator. A more advanced approach uses *principal components analysis* of the individual indicators to construct composite indicators. The estimation period of the critical thresholds reaches from January 1997 to December 2007. For this time span it is shown that most of the composite indicators are able to flag the two reported currency crises in this time span at an early stage (in-sample analysis). In a second step it is checked whether the most recent crisis in February 2009 is signalled by the composite indicators in advance (out-of-sample analysis). In an annex, the model based parametric Markov regime-switching approach is briefly discussed[1]. All data was taken from the Agency of Statistics of the Republic of Kazakhstan, the National Bank of Kazakhstan and International Financial Statistics (IFS), published by the International Monetary Fond.

An important requirement for an early-warning system to function properly is *timeliness*. For this reason this study is based on monthly data or on quarterly data, which has been transformed into monthly data by means of *temporal disaggregation* techniques.

[1] The econometric appoach can be also based on *panel data* of a group of countries with observed currency crises. The disadvantage of the panel approach is that country specifics might be neglected (e.g. for the case of Kazakhstan the predominant importance of *oil prices*). See Knedlik, Scheufele (2007). Berg, Pattillo (1999), Abiad (2003).

1 The Signal Approach

1.1 Defining Currency Turbulences

Following the signal approach, currency turbulences should be defined using *definite criteria*. Currency crises are identified by means of a *foreign exchange market pressure index* relying on the known symptoms of such episodes of currency turbulences:[1]

- a sudden and sharp devaluation of a currency,
- a substantial decrease in foreign exchange reserves

It is quite important to focus on both aspects, because currency crises can break out that leads to a sharp devaluation of a currency. But sometimes monetary institutions try to avoid these devaluations. They intervene to avoid or soften the devaluation. Although no sharp devaluation occurred in these cases, they are also currency crises because the authorities were forced to intervene. Such hidden or sometimes avoided crises are visible in the foreign exchange reserves because they are used to intervene. For a method, that is used to give early warnings on currency crises it is important that visible and hidden or avoided crises are included in the calculations. Hence an index of pressure in the foreign exchange market IP_t at month t is constructed by using the monthly rates of change of the foreign exchange reserves and the real exchange rate.

$$IP_t = \gamma_1 \Delta wr_t - \gamma_2 \Delta rer_t$$

Δwr_t is the monthly rate of change of the foreign exchange reserves; Δrer_t is the monthly rate of change of the real exchange rate, which is given by the nominal exchange rate of the Tenge to the USD, adjusted for the trends in consumer prices in the United States and in Kazakhstan.[2] A rise in the real exchange rate corresponds to a real depreciation

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[1] See Kaminsky, Lizondo, Reinhart. (1998), Schnatz (1998, 1999a, 1999b), Deutsche Bundesbank (1999) and Nierhaus (2000).

[2] The real exchange rate rer_t is given by $rer_t = er_{CURRENCY|US\$,t} \bullet CPI_{US,t} / CPI_t$. It follows that $\Delta rer_{,t} \approx \Delta er_{CURRENCY|US\$,t} + \Delta CPI_{US,t} - \Delta CPI_t$. A real depreciation of the currency follows from a nominal depreciation of the currency and/or a rise in US consumer prices and/or a decline in domestic consumer prices.

of the currency. Since the variances of $\Delta rer_{,t}$ and Δwr_t are different, they are weighted (γ_1 and γ_2) by using the standard deviation of the variables.[1] The real exchange rate is used to avoid corrections for periods with high inflation differentials between home and abroad.[2]

Tensions in the foreign exchange market are identified for periods when the foreign exchange market index swings deeply into the negative. In the present study, for a currency turbulence, the pressure index IP_t must exceed its mean μ more than 3 times the standard deviation $\sigma = \sqrt{varIP_t}$.[3] The parameters μ and σ are unknown theoretical values, depending on the underlying distribution of IP_t.

Definition: month t with crisis event <=> $IP_t < \mu - 3\sigma$

From that point, a window of three quarters is drawn. If a new event occurs in this area, then the time in-between is defined as a *crisis episode*. Otherwise the last point in time of the event is fixed as the end of the episode.

In a normal distribution the probability for an observation smaller than $\mu - 3\sigma$ would be about 0.135%. So currency crises are very rare events, as they should be. Calculating respective probabilities from a distribution with heavy tails or an asymmetric distribution would indeed lead to larger values.

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1 $\gamma_1 = \sqrt{var(\Delta rer_{,t})}/[\sqrt{var(\Delta wr_t)} + \sqrt{var(\Delta rer_t)}]$, $\gamma_2 = \sqrt{var(\Delta wr_t)}/[\sqrt{var(\Delta wr_t)} + \sqrt{var(\Delta rer_t)}]$.

2 See Schnatz (1999b).

3 See Kaminsky, Lizondo, Reinhart. (1998), p. 16.

The true σ is unknown and must be estimated from data at hand.[1] Since the analysis of currency crises means searching for extreme events in time series, the question arises as to how to measure scale. Empirical variance and empirical standard deviation are estimators, which are very sensitive against outliers. Data used for the analysis of currency crises contain extreme events or outliers, therefore robust estimation methods might be preferable. With non-robust estimators, outliers could mask themselves. One robust measure of scale is the median of absolute deviations from the median (MAD). This robust scale estimator is used in the study at hand. The MAD is adjusted by a factor for asymptotically normal consistency. It holds

$$E\left[1.4826 \bullet MAD(X_1, X_2, X_3, \ldots)\right] = \sigma$$

for $X_j, j = 1,2,3,\ldots,n,$ distributed as $N(\mu,\sigma^2)$ and large n.

1.2 Selecting Indicators

The signal approach uses indicators to detect currency crises in advance. Since currency crises are extreme events, they usually are preceded by extreme developments or imbalances. So they might be detected by leading indicators, showing exceptional values before the crises starts. With this conception in mind it is obvious to condense the information contained in leading indicators to a binary variable, which differentiates whether the indicator is in a normal or in a extreme range. This is an important feature of the signal approach. The indicators are transformed to binary variables and are not used in there original form

From the statistical point of view the signal approach can be characterized as a non-parametric approach, since it does not require the assumption of a specific model (in contrast to logit models or Markov-switching models). Indeed the parametric models

[1] Also unknown in μ, which is estimated by the arithmetic mean m of IP_t.

may be more efficient when the models assumptions hold in reality. The signal approach on the other hand should be a quite versatile method.

The signal approach proposes the monitoring of a quantity of macroeconomic variables (*indicators*) that may tend to show unusual patterns in periods prior to currency turbulences. Under the *signal approach*, a reasonable crises indicator should be systematically higher (or lower) prior to currency turbulences than in tranquil periods. Formally, an indicator is said to issue a warning signal if it exceeds (is below) a critical threshold level. This level has to be chosen appropriately to balance the risks of having numerous false signals and the risk of not registering crises.[1] For all calculations a 12-month crisis window is used.

To fix ideas, let S_t be a binary signal variable, depending on the value of the individual indicator V_t at time t, the critical cutoff value δ and the expected sign (+/-) before crises:

$$S^+_t = \begin{cases} 1 & \text{if } V_t > \delta \\ 0 & \text{if } V_t \leq \delta \end{cases} \qquad \text{or } S^-_t = \begin{cases} 1 & \text{if } V_t < \delta \\ 0 & \text{if } V_t \geq \delta \end{cases}$$

In this concept the informative content of an observation at time t is reduced to one of two possibilities: either the indicator exceeds (is below) the threshold δ and gives a crisis warning signal (S_t = 1), or it is below (exceeds) the threshold sending no signal (S_t = 0). However, there may be correct signals and false signals. An indicator sends a correct signal if

- S_t = 1 and a crisis happens within 12 months
- S_t = 0 and no crisis happens within 12 months.

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[1] See Kaminsky, Lizondo, Reinhart (1998).

In the first case the indicator sends a signal and is followed within 12 months by a currency crisis. In the second case the indicator does not send a signal and is not followed by a crisis. By contrast, the indicator issues a false signal if

- $S_t = 1$ and no crisis happens within 12 months
- $S_t = 0$ and a crisis happens within 12 months.

In the third case the indicator sends a signal and is not followed by a crisis. In the last case the indicator does not send a signal and is followed by currency turbulence. Altogether, the performance of an indicator can be measured in terms of Table 1.

Table 1

Classification Table

Classification Table	**Crisis within 12 months**	**No crisis within 12 months**	**Total**
Signal is sent: $S_t = 1$	A (= number of signals)	B (= number of signals)	A+B
No signal is sent: $S_t = 0$	C (= number of signals)	D (= number of signals)	C+D
Total	A+ C	B+D	A+B+C+D
Correct	A	D	A+D
Correct as % of total	A/(A+C)	D/(B+D)	(A+D)/(A+B+C+D)
Incorrect as % of total	C/(A+C)	B/(B+D)	(B+C)/(A+B+C+D)

Following KLR, a perfect indicator would only produce signals that belong to the north-west and south-east cells of the inner matrix (see shadowed area). It would issue a signal in every month that is followed by a crisis (A > 0), so that the number of missing warning signals C equals zero, and it would not send a signal in every month that is not followed by a crisis (D > 0), so that the number of wrong warning signals B equals zero.

On the basis of this concept, the *overall performance* of an indicator V_t (that is the ability to issue correct signals and to avoid false signals) can be measured by the *(adjusted) noise-to-signal ratio ω.* This figure is defined as the ratio of

- the number of false warning signals (= noise) divided by the number of observations in tranquil periods B/(B+D) and
- the number of correct warning signals divided by the number observations in the run-up period A/(A+C).

Indicators with $\omega > 1$ are excluded from the analysis. Following KLR,[1] another way of interpreting the results of noisiness of the indicators is by comparing the probability of a crisis *conditional* on a warning signal from the indicator P(Crisis | warning signal) = A/(A+B) with the *unconditional* probability of a crisis P(Crisis) = (A+C)/(A+B+C+D). If the indicator has useful information, then the conditional probability of a crisis should be higher than the unconditional one.

Another measure for the quality of an indicator V_t is the *odds ratio* ζ. The odds ratio describes the strength of association between two binary data values. The *odds* for a currency crisis within 12 months (or not), given a signal S_t (that is warning signal or not) can be defined in terms of conditional probabilities (Table 2). The *odds* for a crisis conditional on a warning signal is [A/(A+B)]/[B/(A+B)] =A/B. The odds for a crisis conditional on a missing warning signal is C/(C+D)]/[D/(C+D)= C/D. Then the odds ratio ζ is defined as

$$\zeta = (A/B)/(C/D) = (A \bullet D)/(B \bullet C)$$

An odds ratio of 1 indicates that the event of a currency crisis is equally likely if we observe a crisis warning signal or not. An odds ratio greater than 1 indicates that the crisis is more likely if the indicator has sent a warning signal. And an odds ratio less than 1 indicates that the crisis is even less likely if the indicator has sent a warning signal. Obviously, reasonable indicators have odds ratios greater than 1.[2]

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[1] See Kaminsky, Lizondo, Reinhart (1998).

[2] However, odds-ratios are not symmetric with respect to the ordering of variables. The logarithm of the odds ratio, the difference of the logits of the probabilities, makes the measure symmetric.

Table 2

Conditional Crisis Probabilities

	Crisis within 12 months	**No crisis within 12 months**
Signal is sent: $S_t = 1$	A/(A+B)	B/(A+B)
No signal is sent: $S_t = 0$	C/(C+D)	D/(C+D)

Finally, in order to discriminate between 'normal' and 'abnormal' behaviour of an individual indicator, the threshold δ has to be defined. If the cutoff value is set at a rather high level, the indicator is likely to miss all but the most severe crises. In contrast, if the threshold is set very low, the indicator is likely to catch all crises but is also likely to send many false warning signals in tranquil periods. A commonly used way is to set the cut-off value δ in relation to α-percentiles of the distribution of indicator observations, that is $\delta = F^{-1}(\alpha)$. For example, a possible threshold for the rate of growth of exports would be the set of rates of growth that would leave 75 % of the observations above the cut-off value. This set of growth rates is determined by the first quartile of the frequency distribution (i.e. the 25 % percentile).

A more sophisticated approach is to choose a *specific* percentile of the frequency distribution. The threshold value can be derived by taking the distribution of the predicted values and the number of turbulences for each country into account. The α-percentile might be calculated as the maximum possible number of correct signals prior to currency crisis (here generally 12) in relation to the total number of available observations. Subtracting this value from 1 puts the threshold in the area of the frequency distribution with the high values:[1]

α = 1 - (Max possible no. of alarms / Total no. of observations)

[1] See Schnatz, (1999a).

For indicators with an expected sign (-) the expression has to be modified:

α = (Max possible no. of alarms / Total no. of observations)

In this case the threshold is put in the area of the distribution with low values.[1]

1.3 Composite Indicators

Based on the assumption that the greater the number of leading indicators signalling a crisis, the higher the probability that such a crisis would actually occur, KLR proposed a number of composite leading indices. Composite indicators are constructed by weighting together the signals $S_{r,,t}$ of *k* individual indicators $V_{r,t}$.[2]

$S_t = \sum_{r=1,\ldots,k} S_{r,,t}\, w_r$ and $\sum_{r=1,\ldots,k} w_r = 1.$

Similar to individual crises indicators, the composite indicator gives a warning signal if it exceeds a critical value δ_S. Once again, the threshold δ_S is defined in relation to percentiles of the frequency distribution of observations. The percentile is calculated as the maximum possible number of correct signals prior to a currency crisis as a percentage of the total number of available observations. Subtracting this value from 1 puts the threshold in the area of the distribution with high values.

Obviously there are two rules for determining the weights of the specific indicator signals. One approach focuses on equal weights; the other would exploit the observed forecasting performance of the individual indicators before past crises. The latter approach is clearly favourable if future crises are driven by the same economic factors as the past crises, whereas the equal weight approach is neutral.

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1 Another specific approach, proposed by KLR, suggests that a grid of reference percentiles (for example percentiles between 10 and 20 percent) should be defined for each individual indicator. Then an ‘optimal’ rank is found by determining the critical cutoff value (associated with the pre-selected grid) that minimizes the adjusted noise-to-signal ratio

2 See Kaminsky (1998) for a detailed discussion of combining individual indicators.

1.4 Calculating Crisis Probabilities

While composite currency crises indicators show changes in the strength or weakness of crisis warning signals, the index *levels* cannot be directly interpreted. However, it is possible to assign a particular estimated *crisis probability* to any value of a composite crisis indicator by dividing the entire sample into several groups, each corresponding to a particular range of the composite indicator, and calculating the proportion of months associated with crises for each group, using the formula

$$P(\text{crisis} \mid a<S_t<b) = \frac{\text{Number of months with } a < S_t < b \text{ and a crisis following within 12 months}}{\text{Number of months with } a < S_t < b}$$

where S_t is the value of the composite indicator at time t, a is the lower bound of a particular range of the index, b is the upper bound of the range, and $P(\text{crisis} \mid a< S_t< b)$ is the estimated probability of a crisis occurring within 12 months conditional on S_t lying in the range between the lower and upper bounds a and b.[1] In the present study, the entire sample was divided, ranked by the value of the composite indicator, into five groups. The groups are classified in intervals as follows: 0, 0-30, 30-40, 40-50, 50-100. The estimated probabilities are non-linear transformations of the indicators.

2. Results for Kazakhstan

2.1 Observed Currency Crises

Figure 1 illustrates the conduct of the exchange market pressure index for Kazakhstan. As said before, tensions in the foreign exchange market are identified for periods when the pressure index swings sharply into the negative. For dating a currency crisis, the pressure index IP_t must exceed its *mean* 3 times the *adjusted MAD* (see dotted line).

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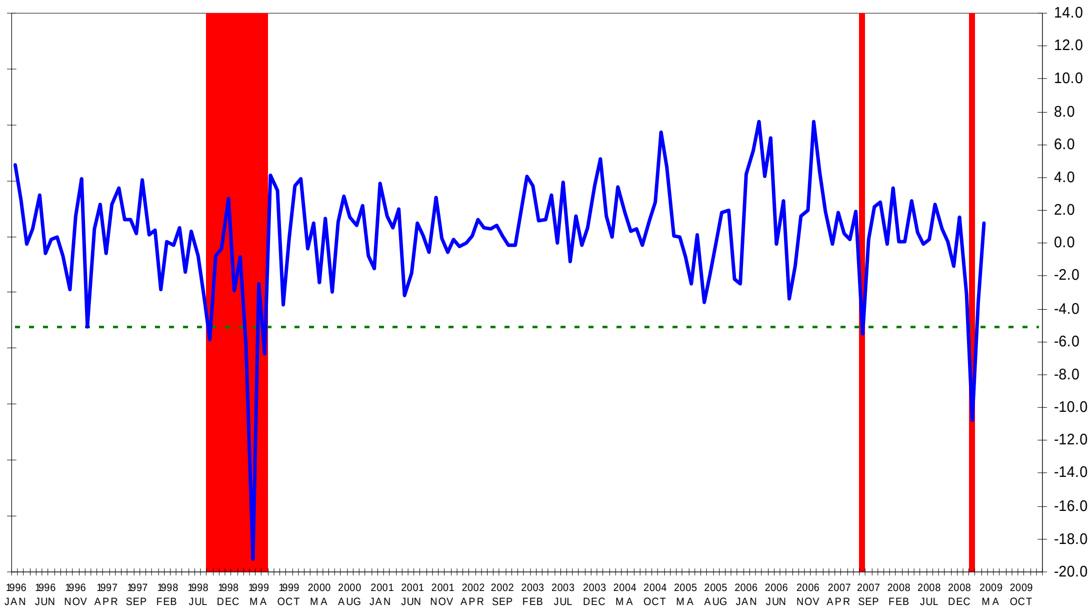
[1] See Zhuang, Dowling (2002) and Knedlik, Scheufele (2007).

Figure 1

Pressure Index for Dating Currency Crises in Kazakhstan (1996-2009)



Following these rules, three crisis periods were detected for Kazakhstan (shaded areas). The most prominent observation is the 1998/99 turbulence. The exchange rate devalued from 79.4 Tenge per USD (September 1998) to 130.4 Tenge per USD (June 1999), and the currency reserves dropped in September 1998 by 12.8 % and in March 1999 by 15.4 %. In August 2007 the Banking Crisis took place, accompanied by a remarkable decrease in foreign exchange reserves (Table 3). In February 2009, the National Bank of Kazakhstan defined a new level of exchange rate of the national currency, 150 Tenge per USD ±3% or ±5 Tenge (before: band within 117-123 Tenge per USD or 120 Tenge ±2%). Starting from the fourth quarter of 2008 until February, the NBK spent USD 6 bn. (including USD 2.7 bn. in January 2009) to maintain stability in the foreign exchange market.[1]

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[1] See National Bank of Kazakhstan, press release No. 3, February 4, 2009.

Table 3

Overview of Currency Crises in Kazakhstan

Period	Description
Sep. 1998 – June 1999	· Exchange rate of the Tenge was devalued from 79.4 (Sept 1998) to 130.4 (June 1999) (-40 %). · Foreign exchange reserves dropped by 12.8 % (Sept. 1998) and 15.4 % (March 1999) respectively.
August 2007	· Foreign exchange reserves dropped by 15.3 %.
February 2009	· Exchange rate of the Tenge was devalued from 121.3 (Jan. 2009) to 144.9 (Feb. 2009).

2.2 Identifying Individual Indicators for Kazakhstan

The signal approach proposes the monitoring of a quantity of macroeconomic variables (*single indicators*) that may tend to show unusual patterns in periods prior to currency turbulences. The following list of individual indicators[1] with noise-to-signal ratios below unity[2] displayed a conspicuous behaviour in the year prior to currency turbulences in Kazakhstan, and will be used in this study for that reason.

– *Deviation of the real exchange rate from its least absolute deviations trend (LAD trend).* A negative value indicates an overvaluation. A multi-country comparison of real exchange rates shows that currencies often tend to be overvalued prior to speculative attacks. The LAD trend minimizes the sum of absolute values of deviations (errors) from the trend line. The least absolute deviations trend is robust in that it is resistant to outliers in the data.

– *Export growth*. The overvaluation of a currency should have repercussions on trade flows. Export growth often declines in the run-up to currency crises, including the

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1 For a detailed discussion see Schnatz (1998) and Ahec-Šonje and Babić (2003).

2 Individual indicators with noise-to-signal ratios of above one were excluded from the analyses.

period prior to the outbreak of the crises.

- *Balance on current account as a share of GDP*. Current account deficits (as a percentage of GDP) were typically higher prior to speculative attacks than in tranquil periods. Not only the loss of international competitiveness, which should show up already in a deterioration of the trade account, but also the funds necessary to service international debts, which is reflected in the current account position, may have been important for assessing a country's vulnerability to speculative attacks.

- *Growth of domestic credit as a share of GDP*. The growth of domestic credit as a percentage of GDP could indicate that a country is conducting an excessively expansionary economic policy. Moreover, a large level of domestic credit growth could also indicate excessive lending financed by an exchange-rate-orientated monetary policy.

- *Change of oil price (Brent).* Energy (production of crude oil and natural gas) is the leading economic sector in Kazakhstan.

- *Real interest rate.* An increase of real interest rates could mean shrinking liquidity in the financial system of a country.

- *Growth of real GDP.* The overvaluation of a currency should dampen economic activity.

- *Money Supply*. An increase in M1 means that the monetary policy is expansionary, causing pressure for the domestic currency.

- *Lending/deposit interest rates differential.* A widening lending to deposit rate differential can signal a risk increase and deterioration of bank portfolios, as well as lack of competition and supervisory and regulatory weaknesses.

- *External debt as a share of GDP*. A growing external dept to GDP ratio often signals an increasing external vulnerability.

The ten individual indicators for Kazakhstan were analysed according to the methods of KLR. The results are summarised in Table 4. Thresholds were calculated for the time span January 1997 to December 2007. Table 4 also shows the *expected sign* (+ high values; - low values) of the individual indicators in periods prior to currency turbulences.

Table 4

Performance of Individual Currency Crises Indicators

	Expected sign before crises (1)	Good signals as percentage of possible good signals (2)	Bad signals as percentage of possible bad signals (3)	Adjusted noise-to-signal-ratio (4)	Odds-Ratio (5)	P(Crisis | signal) (6)	P(Crisis | signal) - P(crises) (7)
In terms of the classification table 2		A/(A+C)	B/(B+D)	[B/(B+D)]/ [A/(A+C)]	(A*D)/(B*C)	A/(A+B)	A/(A+B) - (A+C)/(A+B+C+D)
Real exchange rate (dev. from LAD trend)	-	0.50	0.12	0.25	7.08	0.50	0.30
Export	-	0.33	0.16	0.49	2.53	0.33	0.13
CAB/GDP	-	0.42	0.14	0.35	4.23	0.42	0.22
Credits to economy/GDP	+	0.63	0.09	0.15	16.30	0.63	0.43
External debt/GDP	+	0.38	0.15	0.41	3.28	0.38	0.18
Oil price (Brent)	-	0.54	0.11	0.21	9.24	0.54	0.34
Real GDP	-	0.33	0.16	0.49	2.53	0.33	0.13
Lending /deposit interest rates differencial	+	0.38	0.16	0.44	3.04	0.36	0.16
Money supply	+	0.38	0.15	0.41	3.28	0.38	0.18
Real interest rate	+	0.42	0.14	0.35	4.23	0.42	0.22

3 Conduct of Composite Indicators

3.1. Signal Approach

As composite leading indices contain more information and are in general more reliable than single indicators, they are used for predicting crises. The first approach focuses on the traditional signal method. Under the signal approach, composite indicators are constructed by weighting together the signals of individual indicators. Indicator S1 gives equal weights (=1/10) to all individual signal variables S_r

$$S1_t = \sum_{r=1,\dots,10} S_{r,t}\ 1/10$$

In any month, we can observe between zero and ten warning signals, so $0 \geq S1_t \leq 1$.

A second indicator uses the information on the forecasting accuracy of each single indicator S_r by exploiting the specific noise-to-signal ratios $\omega_r = [B_r/(B_r+D_r)]/[A_r/(A_r+C_r)]$:

$$S2_t = \Sigma_{r=1,\ldots,10} S_{r,t} [(1/\omega_r)/\Sigma_{r=1,\ldots,10} 1/\omega_r]$$

Here the signals of the individual indicators are weighted by the inverse of their adjusted noise-to-signal ratios, which were divided by the sum of the inverse noise-to-signal ratios to add up to unity. Composite indicator 2 gives more weight to the signalling behaviour of individual indicators with low noise-to-signal ratios.

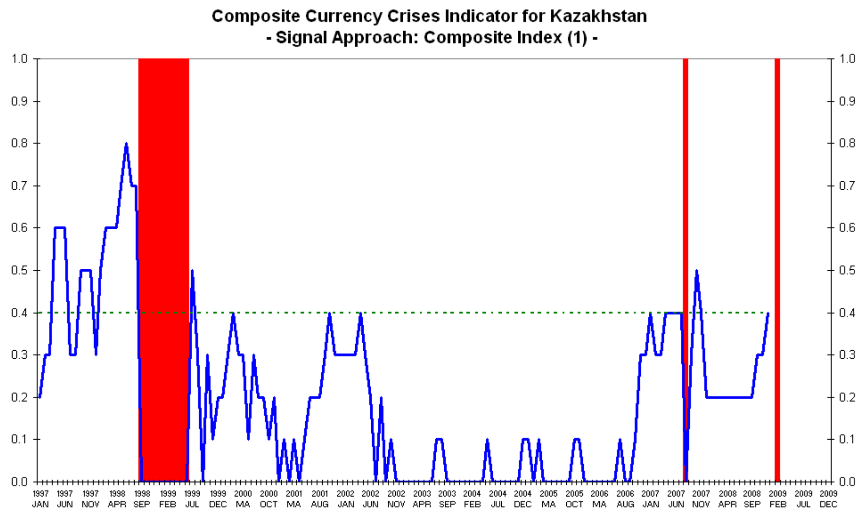
Composite indicator 3 uses the information coming from the specific odds-ratios $\zeta_r = (A_r \bullet D_r)/(B_r \bullet C_r)$ of the single indicators S_r:

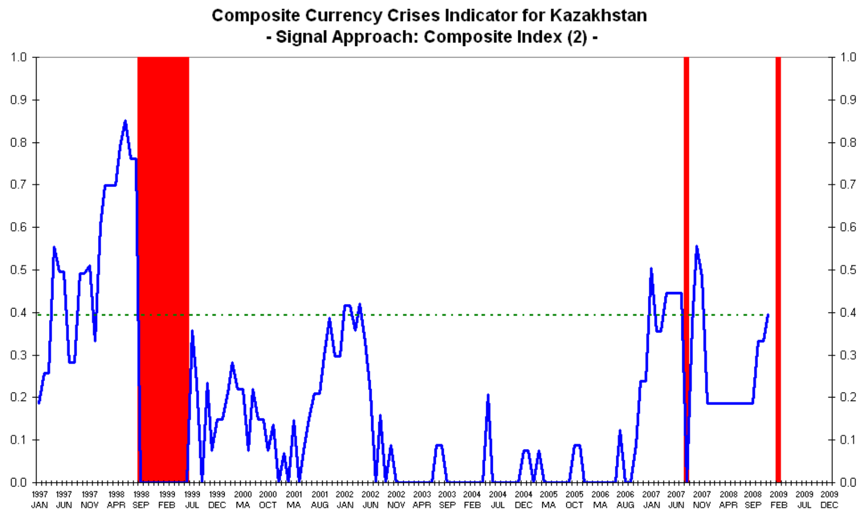
$$S3_t = \Sigma_{r=1,\ldots,10} S_{r,t} \bullet [\zeta_r / \Sigma_{r=1,\ldots,10} \zeta_r]$$

This indicator gives more weight to the signalling behaviour of individual indicators with high odds-ratios.

Figures 2a-2c shows the conduct of the three composite indicators in Kazakhstan. Crises periods are represented by shaded areas. The dotted line shows the specific indicator thresholds δ_S. The composite indicators send a warning signal whenever they move above the critical value. As said before, the estimation period for the critical thresholds reaches from January 1997 to December 2007, thus allowing an out-of-sample test with the most recent crisis in Kazakhstan, which happened in February 2009. In addition, the estimated crises probabilities are shown in figures 3a-3c. Here the dotted lines mark the 50 % probability for a currency crisis.

Fig. 2a-2c


Composite Currency Crises Indicator for Kazakhstan
- Signal Approach: Composite Index (1) -


Composite Currency Crises Indicator for Kazakhstan
- Signal Approach: Composite Index (2) -

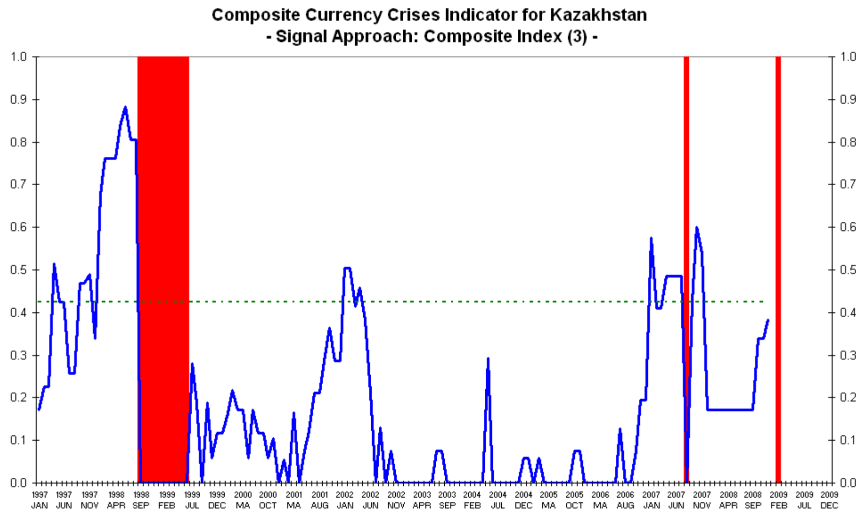
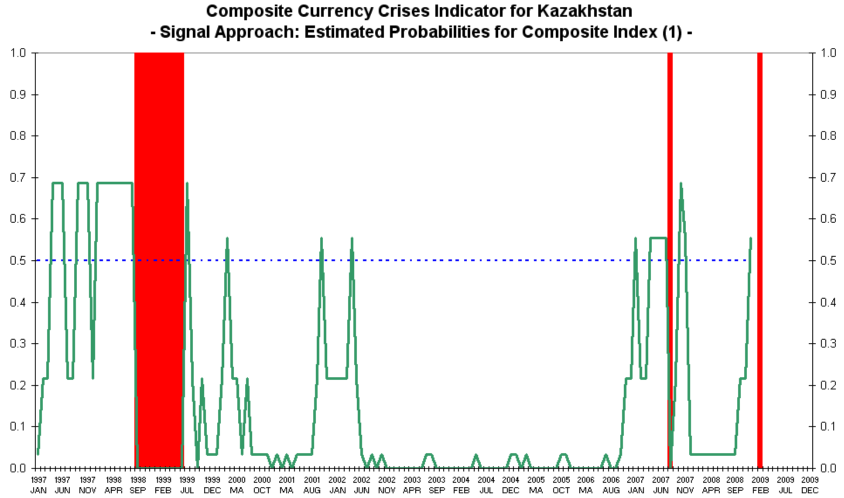
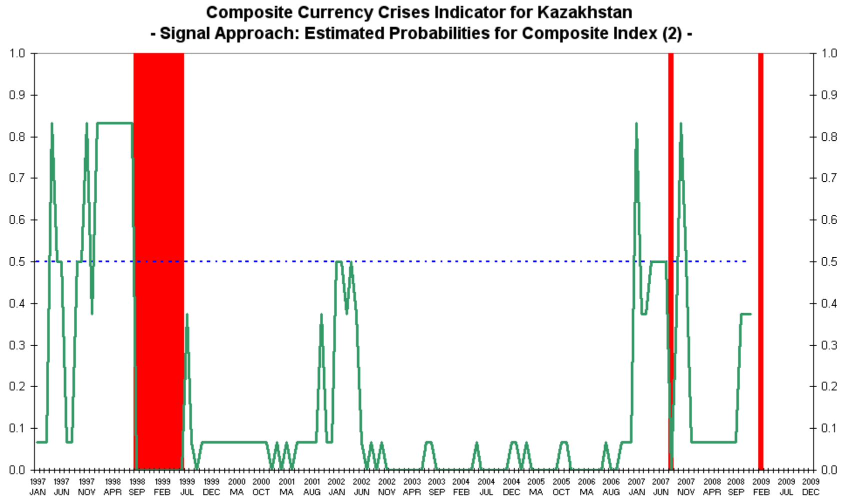
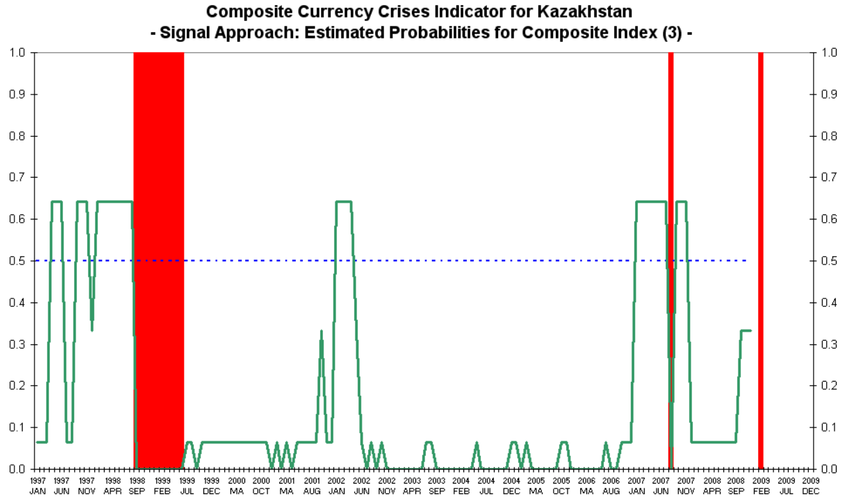

Composite Currency Crises Indicator for Kazakhstan
- Signal Approach: Composite Index (3) -

Fig. 3a-3c


Composite Currency Crises Indicator for Kazakhstan
- Signal Approach: Estimated Probabilities for Composite Index (1) -


Composite Currency Crises Indicator for Kazakhstan
- Signal Approach: Estimated Probabilities for Composite Index (2) -


Composite Currency Crises Indicator for Kazakhstan
- Signal Approach: Estimated Probabilities for Composite Index (3) -

3.2 Mixed approach: Principal Components and Single Indicators

A larger number of indicators can be firstly condensed with the help of principal component analysis (PCA).[1] PCA involves a mathematical procedure that transforms a number of possibly correlated variables into a smaller number of uncorrelated variables called principal components. The first principal component accounts for as much variability (measured by variance) in the data as possible. Each succeeding component accounts for as much of the remaining variability as possible, under the constraint that every principal component is uncorrelated with the preceding ones. Mathematically, PCA leads to a eigenvalue decomposition of the covariance or, as in this analysis of the correlation matrix of the leading indicators. The eigenvectors give the weighting scheme of the indicators, and the corresponding eigenvalues are equal to the variance, explained by the corresponding principal component. From the eigenvalue decomposition as many eigenvectors as indicators results. To condense the information contained in the whole indicator set, only a few principal components are extracted and used in the signal approach. So the question is how many components are needed to provide an adequate summary of a given data set? Here a relative ad hoc procedure is used. Only principal components with eigenvalues greater than one are chosen. This simple procedure is called Kaiser criterion. In a second step the components are examined for plausibility.

Here a *mixed approach* is pursued. On the one hand two predominant individual indicators, namely the *real exchange rate (deviation from LAD trend)*[2] and the *change of oil price,* are used as input for the composite indicator; on the other hand the *principal components with eigenvalues greater than one* of the remaining eight indicators. For the identification of the "expected sign" of the principal components before currency crises, a cross-correlation analysis with the pressure index for the time-span January 1997 to

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[1] See Jolliffe I.T. (2002).

[2] A multi-country comparison of real exchange rates shows that currencies often tend to be overvalued prior to speculative attacks.

December 2000 was carried out. The inverse direction of the observed largest cross-correlation was taken for the expected sign of the principal component.
Indicator S4 gives equal weights to the warning signals of the five individual input series. Indicator S5 uses the information on the forecasting accuracy of each input series by exploiting the specific noise-to-signal ratios. Once again the warning signals are weighted by the inverse of their adjusted noise-to-signal ratios. Finally indicator S6 uses the odd-ratios of the input series as a weighting scheme. Figures 4a-4c present the composite indicators, figures 5a-5c the estimated crises probabilities.

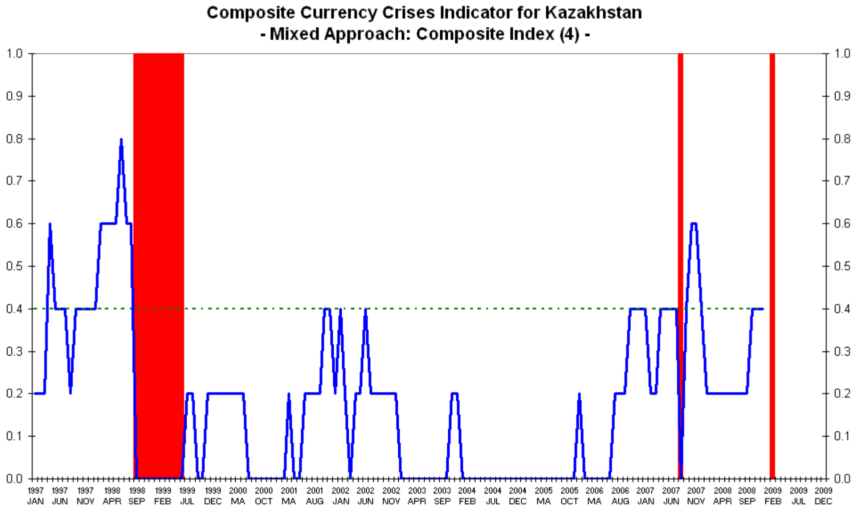
Obviously, there is no unambiguous composite indicator that shows best results for Kazakhstan (see table 5). This finding is not very astonishing, taking into account that all time-series are relatively short and that there are only two observed currency turbulences in the in-sample-period 1997 to 2007. However, the *noise-to-signal ratios* of all composite crises indicators are well below unity. Consequently, all indicators exhibit useful information (see columns five to seven in table 5). The estimated *conditional probability* for a currency crisis P(Crisis | signal) is in all cases higher than the unconditional probability for a crisis. Furthermore, the *odds ratios* are clearly above one. An odds ratio greater than one indicates, that a crisis is more likely if the indicator has sent a warning signal.

Table 5

Performance of Composite Currency Crises Indicators

	In-sample Percentage of crises signalled (1a)	Out-of-sample Percentage of crises signalled (1b)	Good signals as percentage of possible good signals (2)	Bad signals as percentage of possible bad signals (3)	Adjusted noise-to-signal-ratio (4)	Odds-Ratio (5)	P(Crisis | signal) (6)	P(Crisis | signal) - P(crises) (7)
In terms of the classification table			A/(A+C)	B/(B+D)	[B/(B+D)]/ [A/(A+C)]	(A*D)/(B*C)	A/(A+B)	A/(A+B)- (A+C)/(A+B+C+D)
Signal Approach								
Composite Indicator (1)	50	0	0.46	0.05	0.11	15.57	0.69	0.49
Composite Indicator (2)	100	0	0.67	0.08	0.12	22.25	0.67	0.47
Composite Indicator (3)	100	0	0.67	0.07	0.11	25.71	0.70	0.50
Mixed Approach								
Composite Indicator (4)	50	0	0.29	0.03	0.11	12.90	0.70	0.50
Composite Indicator (5)	100	100	0.54	0.08	0.15	13.15	0.62	0.42
Composite Indicator (6)	100	100	0.54	0.05	0.10	21.75	0.72	0.52

Fig.4a-4c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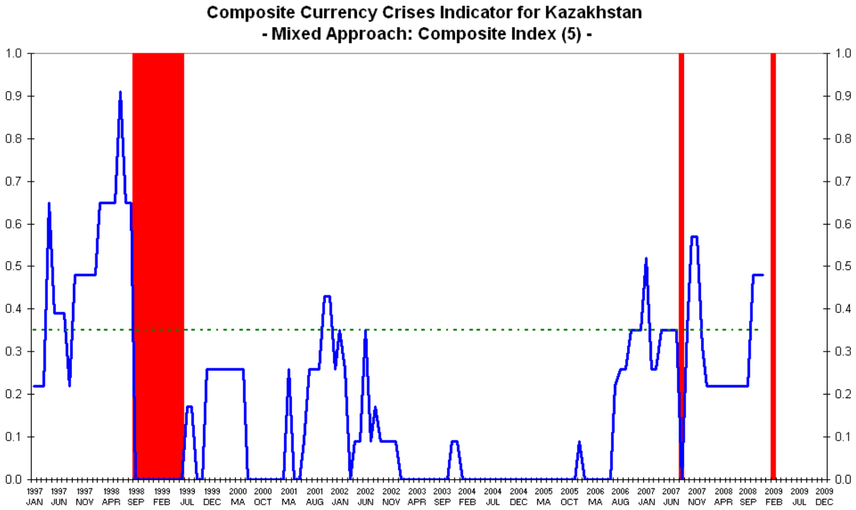
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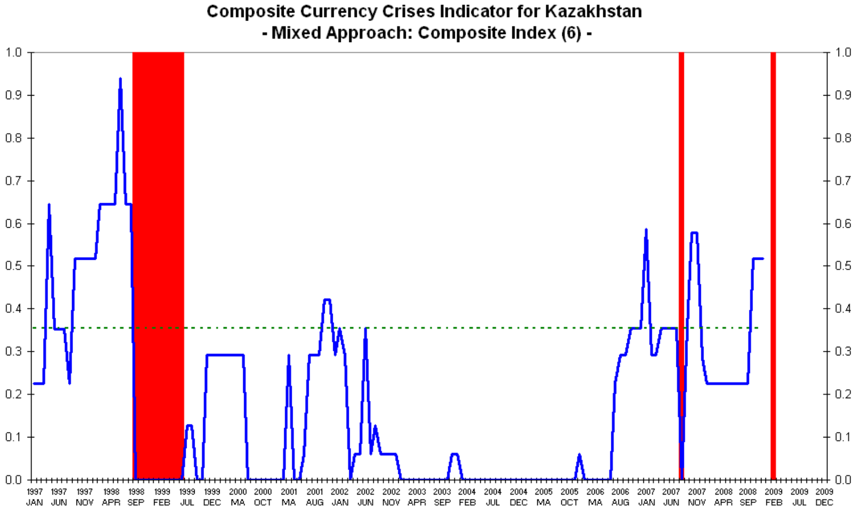
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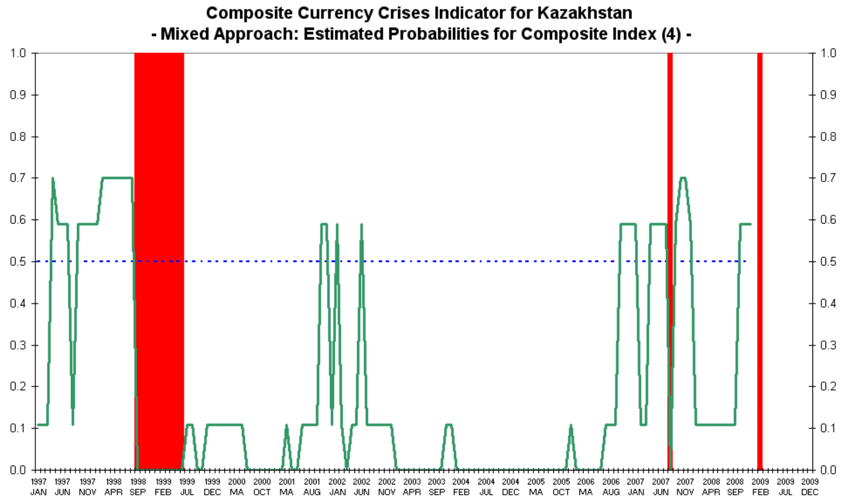
Fig. 5a-5c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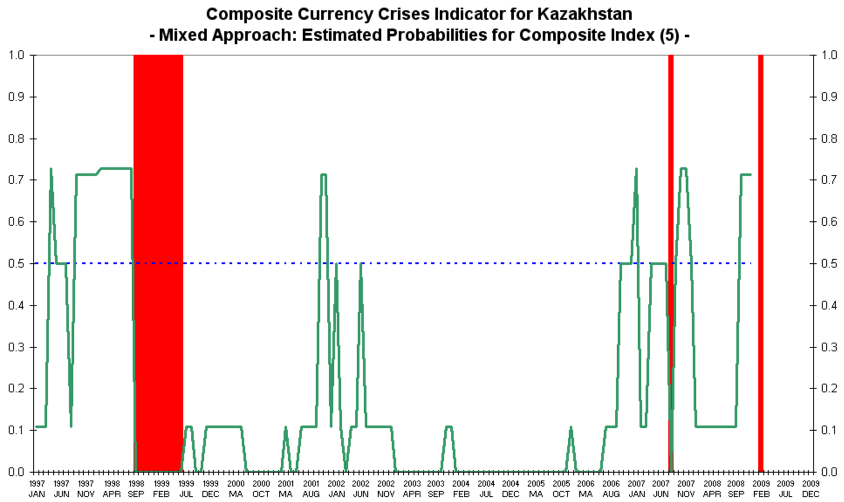
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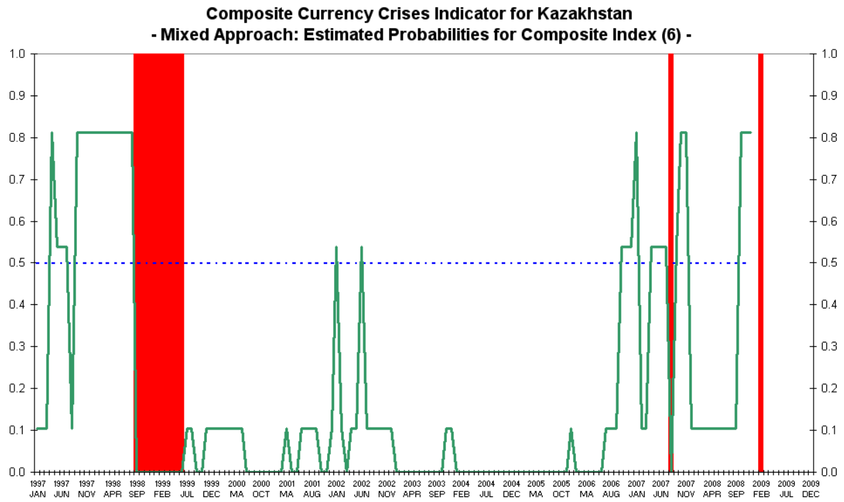
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Indicator 1 as well as indicator 4 miss the 2007 crisis, the remaining four indicators signal all crises in the in-sample-period 1997 to 2007. Concerning the out-of-sample-crisis 2009, only indicators 5 and 6 from the mixed approach gave correct warning signals in the preceding year 2008. Finally, indicators 2 and 3 as well as indicators 5 and 6 showed some false alarms in 2001/2002.

Annex

Annotation: Model Based Approaches

For the analysis of currency crises besides the signal approach also model based parametric methods are applied in the literature. These approaches include nonlinear regression models like logit regressions. Another model based approach is Markov regime-switching (MRS). This is briefly discussed in the sequel.

In modern statistics, non-linear time series methods are increasingly being used for the modeling of structural breaks and regime-dependent dynamics. Markov regime-switching models are prominent examples in which the model parameters depend on stochastic regime variables. With this approach a model that is in itself linear becomes more flexible because the parameters can take on different values, depending on the regime in which the time series is found. In this way in the modeling process it can be taken into consideration that the dynamics vary over time. Since the time points of the regime change do not need to be provided in advance but can be estimated during the calculations, this model type can also be used for the dating of currency crises.

Concretely, the foreign exchange market index IP_t is assumed to depend on a non-observable status variable s_t, which is designated as the status or regime at point-of-time t. The number of cyclical regimes in this study is limited to two. For $s_t = 1$, status 1 (*crisis period*) applies; for $s_t = 2$, status 2 applies (*tranquil period*). The probability with which the regime changes from one period to the other period (or remains in one) is assumed to be time-invariant and depends only on the state of the previous period s_{t-1}

$p(s_t = i \mid s_{t-1} = j) = p_{ij}; \quad i, j = 1,2$

With a Markov process with two states, there are a total of four transition probabilities. For these $p_1 + p_{12} = p_{22} + p_{21} = 1$ applies; the status variable s_t thus follows a Markov process of the first degree. The distribution of IP_t (with a given state of i) is described by the density function f

$$f(IP_t \mid s_t = i, \mu_i, \mathbf{ß}, \sigma^2) = 1/(2\pi\, \sigma^2)^{1/2} \exp[-(1/2)(IP_t - \mu_i - \mathbf{Z}_t\, \mathbf{ß})^2/\sigma^2]$$

i.e., IP_t is normally distributed with a state-dependent mean value $\mu_i + \mathbf{Z}_t\mathbf{ß}$ and constant variance σ^2. $\mathbf{Z}_t$ is a vector of indicators at time t and **ß** is a vector of non-switching regression parameters. For state 1, μ_1 applies, otherwise μ_2. The vector of parameters to be estimated (p_{11}, p_{22}, μ_1, μ_2, **ß**, σ^2) of the MS model is designated with the symbol $\boldsymbol{\theta}$.[1] The MRS model can be estimated with the maximum-likelihood method, in which in the calculation practice numeric optimisation methods are employed due to non-linearities.[2]

At the same time, the procedure supplies, in addition to estimations of the parameter vector $\boldsymbol{\theta}$, also a quantification of *regime probabilities* depending on amount the of information considered in each case: The probability $p(s_t = i \mid I_T)$ designates the conditional probability of being at point t in regime i, in the case that the entire amount of information is conditioned (smoothed probability) in estimation period [1,…,T] of the MRS model. The probability $p(s_t = i \mid I_t)$, on the other hand, describes the conditional probability for state i, in the case that the focus is only on the amount of information available up to the calculating period t (filtered probability). For the final point-of-time T, the filtered value corresponds to the smoothed value. Both regime probabilities may serve as composite currency crisis indicators.

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1 The probability p_{12}, which is also unknown and to be estimated, follows from the relationship $1 - p_{11}$; the probability p_{21} from $1 - p_{22}$.

2 For a time-varying specification of transition probabilities p_{ij} and variance σ^2, see Abiad (2003) and Knedlik, Scheufele (2007).

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