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EFSD Early Warning System:

Developing Tools to Predict Currency Crises

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Abbreviations

ASEAN+3	ASEAN Member States and the People's Republic of China, Japan and the Republic of Korea.
ECB	European Central Bank
EFSD	Eurasian Fund for Stabilization and Development
ESM	European Stability Mechanism
EU	European Union
EWS	Early warning system
IMF	International Monetary Fund

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1. Introduction

Over the last five decades, the world has faced numerous financial upheavals and crises, often with devastating economic, social, and political consequences. In many cases, such crises were not limited to individual countries, spreading instead to other economies. In particular, the Latin American crisis of 1994–1995, the Asian crisis of 1997–1998, and the global financial crisis of 2008–2009 affected a broad range of countries, with a massive impact on the global financial system. Those dramatic developments in the global economy gave a strong impetus to research designed to examine the nature of crisis phenomena, develop tools enabling their prompt detection and understanding, and designing preventive measures to eliminate various macroeconomic imbalances. The body of empirical works dedicated to that issue has a heavy emphasis on the development of early warning systems (EWSs).

An EWS is currently one of the most widespread tools used to identify imbalances (crises) and stress situations in the economy (related, as a rule, to currency, banking, or debt crises, or corporate bankruptcies). The purpose of any EWS is not to forecast crisis phenomena as such (crises are usually caused by sudden adverse internal or external shocks), but instead to furnish enough information to assess the current situation and predict how it may evolve in the future. Accordingly, the EWS can be defined as a set of methods and mechanisms for collection, processing, and analysis of information about the evolution of the situation in the economy that can be used to identify risks and vulnerabilities. The aim of EWS-based monitoring is to identify the sources of threat to macroeconomic stability, with a view to developing and designing preventive actions to minimise possible effects of the adverse situation or crisis.

International best practices offer various approaches to building an EWS. However, any EWS generally relies on an analysis of a special set of indicators or aggregated indices acting as leading indicators. Probabilistic and econometric methods and models are traditionally used for quantitative estimation of imbalances and sustainability of the economic system. Despite the existence of general principles for EWS construction and application, practical implementation of known approaches and methods can be different subject to the unique features in the economy of each country. First and foremost, this applies to the emerging economies.

The EWSs used by international financial institutions and national agencies operate either as independent tools, or as components of complex analytical systems.

One of the leaders in the area of development and utilisation of EWSs is the IMF, which began to actively use toolsets for early detection of currency and banking crises at the beginning of the 1990s. The first and best known EWS models are the KLR model (the Kaminsky, Lizondo, and Reinhart model) and the DCSD model (Developing Country Studies Division model) (Kaminsky et al., 1998; Berg et al., 2004). In addition, the IMF, acting within the framework of its multilateral surveillance programme, engages in Vulnerability Exercises which cover developed countries, emerging market countries, and developing countries (IMF, 2007a; 2011). These procedures are part of confidential Early Warning Exercises (EWE) jointly performed by the IMF and the Financial Stability Board (IMF, 2010). Country surveillance is carried out by the IMF in the context of bilateral Article IV consultations, and discussed with the government of the relevant country.

Each EWE is based on a large body of empirical research undertaken to make an in-depth quantitative analysis of vulnerabilities in the economy, using a large number of tools. Expert surveys conducted with the participation of analysts, representatives of academia, and politicians to estimate the probability of potential risk scenarios constitute an important component of the EWE (IMF, 2010).

Other well-known IMF tools include the Global Financial Stability Map (GFSM), developed by the Monetary and Capital Markets Department of the IMF (IMF, 2007b). The GFSM uses macroeconomic variables to visualise changes in risks and conditions affecting global economic stability (Dattels et al., 2010), and assesses four types of risk (macroeconomic risks, emerging market risks, credit risks, and market and liquidity risks) and two conditions (risk appetite, and monetary and financial conditions) that affect financial stability.

The Country Financial Stability Map (CFSM) complements GFSM analyses. For CFSM purposes, IMF experts also developed a tool to automatically plot financial stability maps for individual countries, and perform cross-country comparisons of individual risks or conditions (Cervantes et al., 2014).

Assessment of the financial condition of European Union countries is conducted by the European Stability Mechanism (ESM) within the framework of post-programme monitoring performed jointly with the European Commission. The ESM performs quarterly analyses of debtor countries until they fully repay their debts. An early warning system procedure was approved by the ESM Board on 24 March 2014; it requires the ESM to continuously track cash flows of the debtor countries, their ability to borrow on the open market, the medium- to long-term sustainability of public debt, and banking system risks. This ESM monitoring complements the fiscal and debt sustainability analyses of the European Commission and the European Central Bank, with the ESM concentrating primarily on the loan repayment outlook (ESM, 2019).

The ASEAN+3 Macroeconomic Research Office (AMRO) uses an integrated analytical system to monitor the economies of its member countries, comprising such tools as global/country risk maps, the ERPD Matrix, ARTEMIS (regional ASEAN+3 tracker for ERPD Matrix indicators), financial programming models for macroeconomic forecasts, debt sustainability analysis (DSA) modules, global vector autoregression (GVAR) models to analyse trade effects, financial stress indices (FSIs), business and credit cycle analyses, and assessment of secondary effects for the developing markets using default correlation indicators.

In the Eurasian Fund for Stabilisation and Development (EFSD) member states, tools used to identify threats to macroeconomic stability are mainly designed and used by central (national) banks and a number of research centres.

Another task facing the EFSD, as a regional financial mechanism, is to design and develop an efficient analytical tool to enable detection and integrated assessment of threats to macroeconomic stability in the countries receiving the fund’s financing (Armenia, Belarus, Kyrgyzstan, Tajikistan) and, consequently, to their solvency (EFSD, 2022).

In the course of our work on building the EFSD EWS, we used conventional approaches and data analysis methods, including the signal approach, or the leading indicators model (Kaminsky and Reinhart, 1999; Kaminsky, 1998), and binary choice models, or logit/probit models (Frankel and Rose, 1996; Goldstein et al., 2000; Kumar et al., 2003).

Our choice of these approaches and analytical methods is explained by the following:

- in line with international practices, it is recommended that development of an EWS should start by using conventional statistical data analysis and processing methods;
- the relative simplicity of their algorithmic and programmatic realisation;
- lack of evidence that more structurally sophisticated models (machine learning methods based on decision trees, deep learning methods, etc.) are qualitatively superior to conventional models.

Furthermore, it was decided to use dynamic model averaging (DMA) and dynamic model selection (DMS) to account for uncertainty (Raftery et al., 2010). Due to the use of time-varying parameters in DMA/DMS realisations, those methods have certain advantages, and may replace a number of alternative tools to detect stress situations in the financial market (e.g., Markov switching models).

This report has the following structure. Section 2 presents a review of literature on theoretical and empirical research dedicated to currency and banking crises and relevant early warning methods. Methodological issues related to the modelling and estimation of EWS models are presented in Section 3. Section 4 describes the methodology used to identify stress periods for the economies of Armenia, Belarus, Kyrgyzstan, and Tajikistan. An explanation of methodological issues related to the collection and primary statistical processing and analysis of data used for EWS design is given in Section 5. Section 6 presents a detailed description of the algorithm used to select potential predictors. Section 7 explains the methodology employed to identify the principal components on the basis of the selected predictors, and elaborates on the choice of the number of the principal components and their relationship to the selected predictors. The last section presents the empirical results of the selection and testing of the EWS models used and, in particular, the estimated thresholds; it also describes experiments with forecasting models, analyses their properties, and offers retrospective forecasts for the principal components.

2. Literature Review

Starting in the 1970s, each wave of crises was accompanied by a spate of theoretical and empirical research seeking not only to explain the root causes of crisis phenomena, but also to design tools, including EWS models, to forecast the growth of risks to macrofinancial stability. Such research was usually focussed on the emergence of currency and banking crises, with individual papers differing in (1) their definition of what constitutes a crisis event; (2) methodology (the most widely used ones being the nonparametric signal approach and the multidimensional regression approach based on logit/probit models); (3) the set of indicators used; and (4) geographic and time horizon coverage.

Theoretical research on currency crises can be conventionally divided into several generations. First-generation theoretical models (e.g., Krugman, 1979) maintained that currency crises are caused by misalignment of domestic macroeconomic policies, usually excessively expansionist fiscal and monetary policies. In economies with fixed currency exchange rates — which are incapable of endlessly raising external debt financing — this generally leads to the loss of reserve assets and, ultimately, a fiscal policy crash.

Second-generation theoretical models of currency crises (e.g., Obstfeld, 1986, 1994) examine government behaviour: politicians assess the costs and benefits of ongoing domestic currency support, and at a certain point in time may be willing to discontinue exchange rate targeting if the costs exceed the benefits. In such models, doubts as to whether the government is ready to support its exchange rate target may give rise to multiple equilibria and, accordingly, a speculative currency attack has every chance to succeed, even if the current policy is consistent with exchange rate commitments.

Ozkan and Sutherland (1995) presented a theoretical model where the government's objective function with a positive sign depends on the benefits of maintaining a fixed nominal exchange rate, and the government's objective function with a negative sign — on deviation of output from the target level. If the exchange rate is fixed, an interest rate hike abroad results in higher domestic interest rates and lower output and, consequently, forces the government to spend more on maintaining its exchange rate policy. Therefore, if external interest rates exceed a certain critical level, the costs associated with further support of the fixed rate begin to exceed the benefits, and the government resolves to discontinue such support. Based on that model, we draw the conclusion that dynamics of output, and of domestic and foreign interest rates, may be a useful indicator of emergence of currency crises. In other words, the factors that have significant impact on the government's objective function may be potentially used as leading indicators.

Third-generation models have a wider coverage, and focus on the ways in which financial market distortions and banking system imbalances produce currency crises. For example, Aghion et al. (2001) examine a situation where currency devaluation increases the value of firms' debt obligations denominated in foreign currencies and reduces their profits, which, in turn, may restrict their ability to borrow. The subsequent decrease in investment and production associated with such borrowing limitations may curtail demand for the domestic currency, and spark a currency crisis.

Other third-generation theoretical models demonstrate how financial liberalisation and government guarantees for private sector obligations may give rise to the risk of moral hazard and an unstable budget deficit which, in turn, also leads to a crisis. For example, McKinnon and Pill (1995) suggest that financial liberalisation, in combination with deposit insurance, may encourage banks to start a credit boom (actively lending both in the domestic and foreign currencies), which ultimately leads to a banking and currency crisis. Chang and Velasco (2001) stress the possibility of international liquidity crises in an open economy with unrestricted access to capital markets, where banks attract deposits in the domestic and foreign currencies, but at the same time have longer-term illiquid investments which cannot be easily converted into cash in the event of a crisis and large-scale withdrawal of deposits. Dooley (2000) and Burnside et al. (2004) maintain that extension by the government of implicit or explicit guarantees to the banking system may prompt the banks to increase their external obligations, making the banking system vulnerable to attack. The weakening of the banking sector, in turn, makes it more difficult to fix the currency rate by hiking domestic interest rates, which may lead to a collapse of the domestic currency.

A huge body of research is dedicated to studying the causes of banking crises, and the impact produced on banking systems by shocks related, for example, to cyclic output declines, deterioration of terms of trade, drop of asset prices, etc. (Baron et al., 2018; Caprio and Klingebiel, 1996; Kaminsky and Reinhart, 1999; Laeven and Valencia, 2018; Lindgren et al., 1996; Reinhart and Rogoff, 2008a, 2008b; Romer and Romer, 2017; Schularick and Taylor, 2012).

G. Kaminsky and C. Reinhart (1999) presented a holistic view of the relationship between currency and banking crises, describing how countries deal with problems in the banking sector, and explaining whether a banking crisis can precipitate a currency crisis. They reviewed the behaviour of 16 macroeconomic and financial indicators selected on the basis of theoretical judgments and data availability. An analysis of crisis phenomena was conducted for 20 countries which had experienced a total of 76 currency crises and 26 banking crises from 1970 to 1995. Kaminsky and Reinhart identified certain patterns in the economic development of countries and their macroeconomic variables on the eve of periods of instability. It was established that banking and currency crises are closely linked to financial liberalisation in the countries under review, and that in most cases, upon completion of financial reforms, banking crises preceded currency crises. The economists also discovered reverse cycles, whereby currency crises undermined the already weakened banking sector. When currency and banking crises emerged simultaneously, the destructive impact on the national economy was much more powerful than when they evolved separately. In each type of crisis, the financial shock ensuing from financial liberalisation, or from gaining access to international capital markets, triggered the “rapid growth — abrupt contraction” cycle. One of the critical conclusions drawn by the authors is that currency and banking crises can hardly be described as “self-realising”, as in most cases their evolution could be attributed to the dynamics of multiple economic indicators.

Despite the assumption of several analysts that the 1997–1998 Asian crises belonged to a new type (in their opinion, they emerged despite the fact that all relevant financial and economic indicators were impeccable). Kaminsky and Reinhart, relying on their analysis of pre-crisis periods in the affected Asian countries, concluded that the trends prevailing at the time in the economies under review were rather similar to those typical for most crisis episodes in the countries of Latin America, Europe, and other regions. If an economy is characterised by low and stable inflation, acceptable economic growth, and a state budget surplus, but the government attempts a liberalisation of its capital account despite weak financial regulation and poor banking supervision, it prompts emergence and subsequent escalation in the banking sector of problems which, with time, undermine the ability of the central bank to honour its exchange rate commitments. That happened during the Asian crises and, for example, during the 1982 Chilean crisis (Diaz-Alejandro, 1985). In the opinion of Kaminsky and Reinhart, it was systemic banking sector problems that caused the collapse of domestic currencies in Thailand, South Korea, and Indonesia.

The defining characteristics of the economic environment causing instability of the banking sector and, ultimately, leading to a banking crisis received an in-depth treatment by A. Demirguc-Kunt and E. Detragiache (1998, 2005). The authors analysed market economies where instability of the banking sector was observed in 1980–1994. They established that, in the sample under review, low GDP growth rates, excessive interest rates, and high inflation significantly increased the probability of a systemic banking crisis. It was determined that terms-of-trade shocks also increased the probability of problems in the banking sector, but their contribution was not as forceful as that of the factors listed above. The budget deficit and the rate of devaluation of the domestic currency did not produce any independent impact in the economies under review. Another interesting result was that the existence of a deposit insurance scheme increased the risk of instability in the banking system. Even though bank deposit insurance may strengthen a bank by eliminating the possibility of self-fulfiling panic, it also creates stimuli for excessive risk-taking by its managers (moral hazard). Demirguc-Kunt and Detragiache found that, during the time interval under review, the moral hazard had made a significant contribution to the emergence and escalation of systemic banking crises, probably because the countries using insurance deposit schemes were generally not successful in enforcing robust prudential regulation and supervision measures, or the deposit insurance system was not organised in a proper way.

A comprehensive review of systemic banking crises was presented by Laeven and Valencia (2008, 2013, 2018). They compiled a database containing records of 151 crisis episodes around the world in 1970–2017, including information about banking crisis timeframes, as well as related policy measures and fiscal and macroeconomic costs. Their research makes it possible to form a holistic view of the causes and consequences of banking crises, and of the required remedial measures.

If we look at research papers through the prism of development and utilisation of tools for analysis and early detection of risk factors contributing to the emergence of crises, it is necessary, first and foremost, to distinguish the two basic — and most popular — methodological approaches: the leading indicator models (signal approach), and the discrete models.

In the models based on the signal approach, indicator behaviour is studied during the normal (non-crisis), pre-crisis, and crisis periods. The indicators are selected on the basis of data describing how their behaviour changes as the economy moves from normal operation into a crisis, subject to their ability to effectively signal the onset of a crisis. One of the first research papers based on the signal approach was published by Eichengreen et al. (1996), who conclude that a currency crisis begins when the index of exchange market pressure exceeds a certain threshold value.

The methodological basis for much of the research using the signal approach was provided by Kaminsky (1998), Kaminsky et al. (1998), and Kaminsky and Reinhart (1999). The authors presented a simple and transparent methodology enabling economists to study the causes of crises, assess economic vulnerabilities during the period preceding their onset, and draw conclusions as to the probability of their occurrence, on the basis of anomalous economic trend changes. Kaminsky et al. (1998) and Kaminsky and Reinhart (1999) also identified a number of indicators which have the power to predict imminent crises, and can be used by researchers as the initial sample of indicators for analytical purposes.

Despite their simplicity and popularity, the leading indicator models have a number of drawbacks. First, transformation of variables into a binary system results in loss of information about the relative significance of variable values. The loss of information problem becomes more evident where a composite indicator is used for analysis (Vlaar, 2000). Second, the signal approach ignores the correlation between independent variables, which may have an adverse effect on the construction of a composite index (Krznar, 2004). Third, the signal approach does not permit the use of certain statistical tests.

A large body of research is made up of papers using dependency models with discrete endogenous variables, known as binary and ordered multiple choice logit/probit models for spatial and panel data measured on nominal (qualitative) binary or ordered scales (Malyughin and Pytlyak, 2007). Models of that type define the probability distribution of discrete dependent variables as a function of independent variables and unknown parameters — i.e., enable an estimation of the formal model of interrelations between various indicators and discrete manifestations of crises. Econometric discrete choice models are rather convenient from the standpoint of interpreting estimation results in terms of crisis occurrence probabilities. In addition, the impact produced by all predictors is examined simultaneously. Also, unlike in the signal approach, predictors may produce a non-linear impact on the probability of a crisis.

Below we list several early — and the most interesting — models used to study currency and banking crises on the basis of discrete choice models. Frankel and Rose (1996) used a probit model to analyse data from 105 emerging countries for 1971–1992. Klein and Marion (1997) developed specifications for a logit model to analyse the collapse of exchange rate regimes in Latin America. Bussièr and Fratzscher (2002) estimated crisis phenomena using an ordered multiple choice logit model. Demirguc-Kunt and Detragiache (2005) studied the probabilities of occurrence of banking crises on the basis of a multiple choice logit model. It should be noted that empirical research papers differ by their selection of potential predictors, countries, time horizons, and data used.

At the same time, research papers on the development of early warning models are not limited to conventional approaches and methods (signal approach and discrete choice models). Some researchers analyse crisis phenomena using Markov switching models, which forecast crises through determination of switching points between various equilibrium states (Abiad, 2003; Abdelsalam and Abdel-Latif, 2020). The main advantage of Markov switching models is that they do not involve the need to define crisis criteria (provide definitions) and, accordingly, detect crisis episodes, as crisis situations are identified endogenously on the basis of model estimates.

Taking into consideration the fact that EWSs are characterised by uncertainty related to model specifications, it is objectively necessary to apply approaches which are capable of accounting for that gap. Such approaches include dynamic model averaging (DMA) and Bayesian model averaging (BMA). The DMA method was developed by Raftery et al. (2010), and used to solve an engineering problem. The BMA method is a special case of the DMA method. Koop and Korobilis (2012) were the first to apply the DMA method to perform economic modelling, as they used it, in particular, to analyse and forecast inflation dynamics. Abdelsalam and Abdel-Latif (2020) adapted the method to design an EWS for Egypt.

The use of machine learning algorithms is a relatively new direction of evolution of early warning systems. For example, Ponomarenko and Tatarintsev (2023) used the Random Forest algorithm to describe a non-linear dependence between financial development, financial imbalances, and probability of a financial crisis. The ESM economist Gabriele (2019) presented an early warning model for predicting systemic banking crises; the model combines the Regression Trees technology and the CRAGGING statistical algorithm (Savona and Vezzoli, 2015) to improve estimation accuracy and offset the deficiencies inherent in other models.

3. Model Toolset for Detection of Crisis Periods

The following methods and models were used (tested) to design the tools that will subsequently comprise the EFSD EWS: signal approach, discrete choice models (logit/probit models), dynamic model averaging (DMA), and dynamic model selection (DMS). We will now present the key features and algorithmic steps of that toolset.

1. Signal approach. In terms of algorithmic realisation, this approach is the simplest when compared to the other models. It essentially means that it is necessary to compute, for each indicator included in the analysis, the critical boundary which, if crossed, will "signal" the occurrence of a currency (banking) crisis (Kaminsky, 1998; Kaminsky et al., 1998).

Suppose *n* potential indicators for identification of a currency (banking) crisis are included in the analysis. The indicator X_t^j "signals" a crisis during the period of time *t*, if during that time interval it goes beyond the critical boundary $\overline{X}_t^j$, which can be formally written as follows:

$$\left\{S_t^j = 1\right\} = \left\{S_t^j, \left|X_t^j\right| > \left|\overline{X}_t^j\right|\right\}. \tag{1}$$

The indicator X_t^j is taken in modulus, as it can be both positive and negative — i.e., for some potential indicators with critical boundary $\overline{X}_t^j$ the state $S_t^j = 1$ when $X_t^j < \overline{X}_t^j$.

In the same way, it is possible to write a case where there is no crisis:

$$\left\{S_t^j = 0\right\} = \left\{S_t^j, \left|X_t^j\right| < \left|\overline{X}_t^j\right|\right\}. \tag{2}$$

The critical boundary $\overline{X}_t^j$ is determined as described below. According to Kaminsky et al. (1998), it is necessary to compute the noise-to-signal ratio (*NSR*), and then use optimisation to determine the minimal *NSR* value (a detailed description of the algorithm used to compute the noise-to-signal ratio is provided in Section 6).

Then the composite crisis occurrence indicator is computed on the basis of *NSR* values obtained separately for each indicator. Kaminsky (1998) presents four possible approaches to the computation of the composite indicator:

a) The idea behind the first approach is that if, during the period of time *t*, for most of *n* indicators the signal $S_t^j = 1$, then the probability of a crisis is relatively high. Under this approach, the composite indicator is computed as follows:

$$I_t^1 = \sum_{j=1}^{n} S_t^j, \tag{3}$$

where $S_t^j = 1$, if the indicator X_t^j crosses the critical boundary during the time period *t*, while in all other cases $S_t^j = 0$. The key drawback of this approach is that it does not differentiate between strong and weak signals, while strong signals can predict a crisis more correctly than weak signals. To account for the difference in the amplitude of signals, we can use the second composite indicator computation method.

b) Under the second approach, two critical boundaries are introduced for computation of the composite indicator: one for a weak signal ($\bar{X}_m^j$), and one for a strong signal ($\bar{X}_e^j$). According to this approach, the weak signal $SM_t^j = 1$ when $\left|\bar{X}_m^j\right| < \left|X_t^j\right| < \left|\bar{X}_e^j\right|$, and the strong signal $SE_t^j = 1$ when $\left|\bar{X}_e^j\right| < \left|X_t^j\right|$. Subject to that, the composite indicator can be written as follows:

$$I_t^2 = \sum_{j=1}^{n} \left(SM_t^j + 2SE_t^j \right). \tag{4}$$

The composite indicator I_t^2 varies between 0 and 2*n*. The closer to 2*n*, the higher the probability of a crisis.

c) The logic behind the third approach used to compute the composite indicator is that indicators may produce signals not simultaneously, but during different time periods. Accordingly, we suggest that the composite indicator should be computed as follows:

$$I_t^3 = \sum_{j=1}^{n} S_{t-s,t}^j . \tag{5}$$

According to this indicator, $S_{t-s,t}^j = 1$, if the indicator X_t^j at least once crosses the critical boundary during the period from *t* – *s* to *t*.

d) The fourth approach, unlike the three approaches described above, accounts for the predictive power of the indicators. Accordingly, the suggestion is to compute a weighted composite indicator, where inverse *NSR* values are used as weights:

$$I_t^4 = \sum_{j=1}^{n} \frac{S_t^j}{NSR^j}. \tag{6}$$

Based on the above composite indicators, it is possible to compute the probability of a crisis during the period [*t, t* + *h*]. We suggest that the following formula should be used:

$$P\left(C_{t,t+h} \mid I_l^k < I_t^k < I_u^k\right) = \frac{\text{number of months with } I_l^k < I_t^k < I_u^k \text{ at which the crisis occures within } h \text{ months}}{\text{total number of months with } I_l^k < I_t^k < I_u^k}, \tag{7}$$

where *P* is probability, and $C_{t,t+h}$ is crisis manifestation during the time interval [*t, t* + *h*], *k* = 1, 2, 3, 4. The numerator of the formula shows the number of months when the value of the composite indicator falls within the interval $I_l^k < I_t^k < I_u^k$, and the crisis occurs within the next *h* months (I_l^k — lower boundary, I_u^k — upper boundary). The denominator of the formula shows the total number of months when the value of the composite indicator falls within the interval $I_l^k < I_t^k < I_u^k$. In this paper, the fourth approach was used to compute the composite indicator — i.e., I_t^4 was computed (Equation 6).

2. Binary choice models (logit/probit models). In these models, the dependent variable takes two values: 0 or 1 (where 0 = tranquil period, 1 = crisis period). Predictors can be both continuous and discrete (Greene, 2012). Compared to the signal approach, the binary choice models have a number of advantages. First, the impact produced by all predictors is examined simultaneously. Second, unlike in the signal approach, predictors may produce a non-linear impact on the probability of a crisis (Bussiere, 2007).

Let us assume that the probability of a crisis is a linear function of potential predictors:

$$\begin{aligned} Pr(y = 1|x) &= F(x, \beta), \\ Pr(y = 0|x) &= 1 - F(x, \beta), \end{aligned} \tag{8}$$

where F is a continuous, strictly increasing function whose range varies from 0 to 1.

If the probability of a crisis is modelled on the basis of a linear functional relationship assumption, then

$$F(x, \beta) = x'\beta. \tag{9}$$

Inasmuch as mathematical expectation $E(y|x) = F(x, \beta)$, we can write the following regression equation:

$$y = E(y|x) + (1 - E(y|x)) = x'\beta + \varepsilon, \tag{10}$$

where E stands for mathematical expectation.

As a rule, logistic and standard normal distributions are used as the probability distribution function $F(x, \beta)$ (Greene, 2012). Logit and probit models are distinguished depending on which distribution function is used.

Those probability distribution functions, accordingly, have the following form:

$$Pr(y = 1|x) = \frac{e^{x'\beta}}{1 + e^{x'\beta}} = \Lambda(x'\beta) \quad \text{(logit model)} \tag{11}$$

$$Pr(y = 1|x) = \int_{-\infty}^{x'\beta} \varphi(t)dt = \Phi(x'\beta) \quad \text{(probit model)} \tag{12}$$

Inasmuch as logit and probit models are binary choice models, the likelihood function can be modelled using binomial distribution which can be presented as follows:

$$L(\beta|x) = \prod_{i=1}^{n} \left[F(x_i'\beta)^{y_i} (1 - F(x_i'\beta)^{(1-y_i)} \right]. \tag{13}$$

Then the log likelihood function takes the following form:

$$lnL = \sum_{i=1}^{n} [y_i \, lnF(x_i'\beta) + (1 - y_i) ln(1 - F(x_i'\beta))]. \tag{14}$$

Having the general form of the log likelihood function, likelihood functions for the logit and probit models, respectively, can be written as follows:

- logit model:

$$lnL = \sum_{i=1}^{n}\left(y_i \, ln\left(\frac{exp(x_i'\beta)}{1+exp(x_i'\beta)}\right) + (1-y_i)\, ln\left(1-\frac{exp(x_i'\beta)}{1+exp(x_i'\beta)}\right)\right); \tag{15}$$

- probit model:

$$lnL = \sum_{i=1}^{n}\left(y_i \, ln\left(\Phi(x_i'\beta)\right) + (1-y_i) ln\left(1-\Phi(x_i'\beta)\right)\right). \tag{16}$$

The task is to compute β values that will maximise the value of the likelihood function. As we equate the first derivative to zero, we find the optimal value of β. Taking into consideration that the above functions are twice differentiable, we also compute the second derivatives matrix, and then use the Newton-Raphson iterative procedure to determine the optimal values of β (Greene, 2012).

3. Dynamic model averaging (DMA). In our paper, this method is used to model and forecast pressure in the exchange market. Computed *empi* values are used as the dependent variable (the *empi* computation mechanism is described in Section 4).

The idea behind the method is described below. Let us assume that z_t is the number of explanatory potential predictors. Based on various combinations of those predictors, it is possible to build K various models. Then for the k^{th} model we can write:

$$y_t = z_t^{(k)}\theta_t^{(k)} + \varepsilon_t^{(k)}, \quad \varepsilon_t^{(k)} \sim N(0, H_t^{(k)}), \tag{17a}$$

$$\theta_{t+1}^{(k)} = \theta_t^{(k)} + \eta_{t+1}^{(k)}, \quad \eta_t^{(k)} \sim N(0, Q_t^{(k)}). \tag{17b}$$

Suppose that $L_t \in \{1,2, \ldots, K\}$ indicates which model is used at the point of time t; $\Theta_t = (\theta_t^{(1)'}, \ldots, \theta_t^{(k)'})'$ is the vector of unobservable parameters at the point of time t, $y^t = (y_1, \ldots, y_t)'$. The choice of the name "dynamic model averaging" can be attributed to the fact that different models are estimated at each point of time, and the results of their estimation are then averaged. For example, to estimate model parameters at the point of time t using data as of the point of time $t-1$, the DMA computes probabilities $Pr(L_t = (k|y^{t-1}))$ for $k = 1, \ldots, K$, and then averages model estimations by applying those probabilities (*dynamic model averaging*). Another variant is possible where the model with the highest probability is selected for forecasting based on computed probabilities $Pr(L_t = (k|y^{t-1}))$ (*dynamic model selection*).

The DMA presents great interest for applied macroeconomics, as the method assumes that model specifications and their parameters are not fixed in time, and that the forecast is built on a combination of forecasts generated by multiple models weighted by their historical accuracy. At the same time, the DMA has certain drawbacks. Thus, the number of models required to estimate a large number of parameters is many times higher. Let us consider a situation where we have m potential predictors, and the choice of models is determined by whether each of those predictors is included in the given model. Then the total number of individual models is $K = 2^m$. Huge computational capacity is required to enable concurrent processing of such a large number of models. This drawback becomes particularly noticeable when computations are performed in real time (Koop and Korobilis, 2012; Styrin, 2019).

To reduce the DMA computation times, it is suggested to use approximation which is reduced to application of the so-called "forgetting factors" for the parameters (λ) and for the model (α). Those factors take values slightly below one. The role of the factors λ and α is explained below.

For given values of H_t and Q_t, it is possible to use standard filtration results to perform recursive estimation or forecasting. In other words, the use of the Kalman filter starts with the following:

$$\left(\theta_{t-1} \,|\, y^{t-1}\right) \sim N(\hat{\theta}_{t-1}, \Sigma_{(t-1|t-1)}). \tag{18}$$

Then the Kalman filter uses the following scheme:

$$\left(\theta_t \,|\, y^{t-1}\right) \sim N(\hat{\theta}_{t-1}, \Sigma_{(t|t-1)}), \tag{19}$$

where $\Sigma_{(t|t-1)} = \Sigma_{(t-1|t-1)} + Q_t$. Notably, Raftery et al. (2010) maintain that things are greatly simplified, if this equation is substituted with

$$\Sigma_{(t|t-1)} = \frac{1}{\lambda} \Sigma_{(t-1|t-1)}, \tag{20}$$

which is equivalent to $Q_t = (1 - \lambda^{-1})\Sigma_{(t-1|t-1)}$, where $0 < \lambda \leq 1$.

Raftery et al. (2010) suggest that $\lambda = 0.99$. Let us clarify the use of the forgetting factor λ. From Equation (20) and the nature of the factor λ, we may conclude that the weight for a new $\Sigma_{(t-1|t-1)}$ will be higher than for the later ones. For example, if we consider five years (20 quarters), the weight of the very first matrix $\Sigma_{(t-1|t-1)}$ at $\lambda = 0.99$ will be approximately 0.82 (0.99^(20)), and at $\lambda = 0.99$ — approximately 0.36 (0.95^(20)). Then during the time period t there emerge actual y^t, and the parameters are adjusted in accordance with the following rule:

$$\theta_t \,|\, y^t \sim N(\hat{\theta}_t, \Sigma_{t|t}),$$

$$\hat{\theta}_{t|t} = \hat{\theta}_{t|t-1} + \Sigma_{t|t-1} z_t' (H_t + z_t \Sigma_{t|t-1} z_t')^{-1} (y_t - z_t \hat{\theta}_{t-1}),$$

$$\Sigma_{t|t} = \Sigma_{t|t-1} - \Sigma_{t|t-1} z_t' (H_t + z_t \Sigma_{t|t-1} z_t')^{-1} z_t \Sigma_{t|t-1}.$$

Recursive computations are performed on the basis of the following distribution:

$$y_t \,|\, y^{t-1} \sim N(z_t \hat{\theta}_{t-1}, H_t + z_t \Sigma_{t|t-1} z_t'). \tag{21}$$

For the case with multiple parameters $(\theta_{t-1} | y^{t-1})$, $(\theta_t | y^{t-1})$, $\theta_t | y^t$, accordingly:

$$\Theta_{t-1} \,|\, L_{t-1} = k,\; y^{t-1} \sim N\left(\hat{\Theta}_{t-1}^{(k)}, \Sigma_{t-1|t-1}^{(k)}\right),$$

$$\Theta_{t-1}|L_t = k,\ y^{t-1} \sim N\left(\Theta_{t-1}^{(k)},\ \Sigma_{t|t-1}^{(k)}\right),$$
$$\Theta_t\ |L_t = k,\ y^t \sim N\left(\hat{\Theta}_{t|t}^{(k)},\ \Sigma_{t|t}^{(k)}\right),$$

where $\hat{\Theta}_{t|t}^{(k)}$, $\Sigma_{t|t}^{(k)}$, $\Sigma_{t|t-1}^{(k)}$ are estimated on the basis of the Kalman filter. It should be noted that all of the above formulas are based on conditional estimation where $L_t = k$.

Koop and Korobilis (2012) also present a method for unconditional estimation of the DMA. That method is also described in Raftery et al. (2010), using the forgetting factor α. However, unlike in the case with λ, the factor α is used for the model, not for the parameters. Then the idea behind the application of the Kalman filter is as described below.

At the first step, probability density is computed for all models using the following formula:

$$p(\Theta_{t-1}\,|\,y^{t-1}) = \Sigma_{k=1}^{K}\, p\left(\theta_{t-1}^{(k)}\,|L_{t-1} = k\,, y^{t-1}\right) Pr\,(L_{t-1} = k\,|\,y^{t-1}). \tag{22}$$

Let us make certain designations to simplify Formula (22). Suppose, $\pi_{t|s,l} = Pr(L_t = l|y^s)$, then $p\,(\Theta_{t-1}|y^{t-1})$ can be presented as

$$\pi_{t|t-1,k} = \sum_{l=1}^{K} \pi_{t-1|t-1,l}\, p_{kl}\,. \tag{23}$$

However, in Raftery et al. (2010), Expression (23) is substituted with

$$\pi_{t|t-1,k} = \frac{\pi^{\alpha}_{t-1|t-1,k}}{\Sigma_{l=1}^{K} \pi^{\alpha}_{t-1|t-1,l}}, \tag{24}$$

where $0 < \alpha \leq 1$. Besides, α is only slightly different from “one”, and is also interpreted as factor λ. Adjustment of $\pi_{t|t-1,k}$ is made in accordance with the following rule:

$$\pi_{t|t,k} = \frac{\pi_{t|t-1,k}\, p_k\,(y_t\,|\,y^{t-1})}{\Sigma_{k=1}^{K} \pi_{t|t-1,l}\, p_l\,(y_t\,|\,y^{t-1})}, \tag{25}$$

where $p_l(y_t|y^{t-1})$ is probability density for model l.

Recursive forecasting can be performed by averaging forecast results for each model:

$$E\,(y_t\,|\,y^{t-1}) = \sum_{k=1}^{K} \pi_{t|t-1,k}\, z_t^{(k)} \hat{\theta}_{t-1}^{(k)}. \tag{26}$$

The value $E(y_t|y^{t-1})$ is the averaged forecast for all possible models. If we take the model with the largest $\pi_{t|t-1,k}$, the forecasting can be carried out using a model with the highest density value. Summing up, we can say that, to begin estimation, it is necessary to select the initial values $\pi_{0|0,k}$ and $\theta_0^{(k)}$, $k = 1,\ldots, K$. The computation technique depends on the selection of H_t. Raftery et al. (2010) suggest a simple substitution $H_t^{(k)} = H^{(k)}$, where $H^{(k)}$ is replaced with consistent estimation — i.e., $H_t^{(k)} \rightarrow H^{(k)}$, when $t \rightarrow \infty$. It is also desirable for the variation matrix $H^{(k)}$ to change itself depending on time. To that end, Koop and Korobilis (2012) suggest a formula which makes it possible to adjust the values of $H^{(k)}$ depending on time. That change occurs in accordance with the following formula:

$$\hat{H}^{(k)}_{t+1|t} = k\hat{H}^{(k)}_{t|t-1} + (1-k)\left(y_t - z^k_t \hat{\theta}^{(k)}_t\right)^2, \tag{27}$$

where k is the same coefficient as α and λ. As a rule, coefficient $k = 0.95$.

4. Definition of Stress (Crisis) Periods

Financial crises are so diverse in nature that, even though the academic community has been actively researching the cause-and-effect relations leading to their emergence and manifestation, no established view on critical issues has been adopted over the last three decades. Today there is no commonly accepted definition of what constitutes a financial crisis, nor are there unified criteria that could be used to determine whether a financial crisis has, in fact, occurred. As a result, even if researchers use the same time periods, country samples, and statistical data, the number of crises they count can be different, and in some cases that difference can be quite substantial.

In our opinion, the most frequently used set of currency crisis definition criteria is that proposed by Kaminsky and Reinhart (1999) and Frankel and Rose (1996) (either in the original form or with some modifications). As for banking crises, more researchers rely on the definitions and criteria proposed by Kaminsky and Reinhart (1999) and Demirguc-Kunt and Detragiache (1998, 2005). Those and other currency and banking crisis definitions (criteria) are presented in Appendix 1.

In this paper, it was decided to use for detection of stress periods in the exchange markets of Armenia, Belarus, Kyrgyzstan, and Tajikistan the so-called exchange market pressure indices (*empi*), which, to a certain degree, can also serve as coincident indicators. That decision eliminates the need to either design exchange market stress criteria that uniformly apply to all four countries, or formulate a unique set of criteria and parameters for each country.

To compute *empi* values, we used the following formula proposed by Kaminsky et al. (1998) and Patnaik et al. (2017):

$$empi_t = \frac{\Delta e_t}{e_t} - \left(\frac{\sigma_e}{\sigma_r}\frac{\Delta r_t}{r_t}\right) + \left(\frac{\sigma_e}{\sigma_i}\Delta i_t\right), \tag{28}$$

where e_t is the average nominal exchange rate for the period (domestic currency to US dollar), r_t is gross international reserve assets (in US dollars), i_t is the nominal interest rate on loans denominated in US dollars, Δ is the first difference, σ_e is the standard deviation of currency exchange rate changes $\left(\frac{\Delta e_t}{e_t}\right)$, σ_r is the standard deviation of international reserve assets changes $\left(\frac{\Delta r_t}{r_t}\right)$, and σ_i is the standard deviation of nominal interest rate changes Δi_t.

We used Formula (28) and the appropriate time series to compute *empi* values. Notably, the higher the *empi* value, the higher the pressure sustained by the exchange market, which may in turn lead to significant devaluation of the domestic currency, reduction of international reserves, and an increase in interest rates.

A pressure threshold is computed to make a judgment regarding the level of pressure in the exchange market:

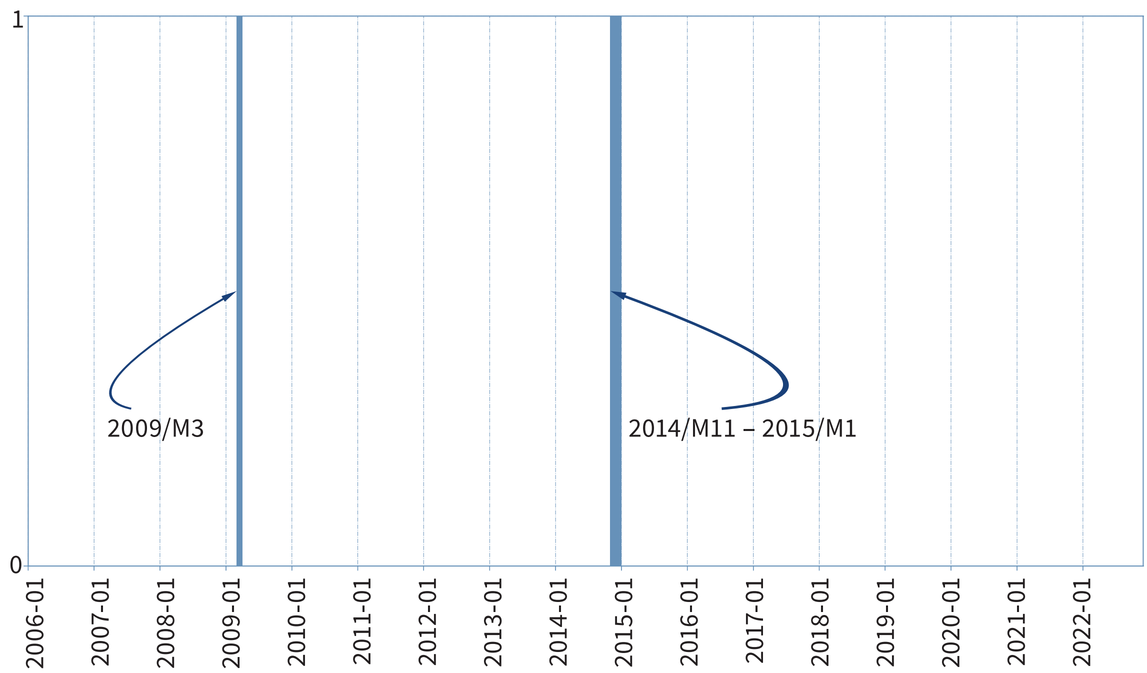
$$\overline{empi} + k \times \sigma_{empi}, \qquad (29)$$

where k is a coefficient which varies from 1 to 3[1] (Abdelsalam and Abdel-Latif, 2020). If *empi* exceeded the threshold, a stress was recorded in the exchange market.

As a result, the following stress periods were recorded in the exchange markets of the economies under review:

Two stress periods were detected in Armenia in 2006/M1–2023/M6: 2009/M3, and 2014/M11–2015/M1 (Figure 1a).

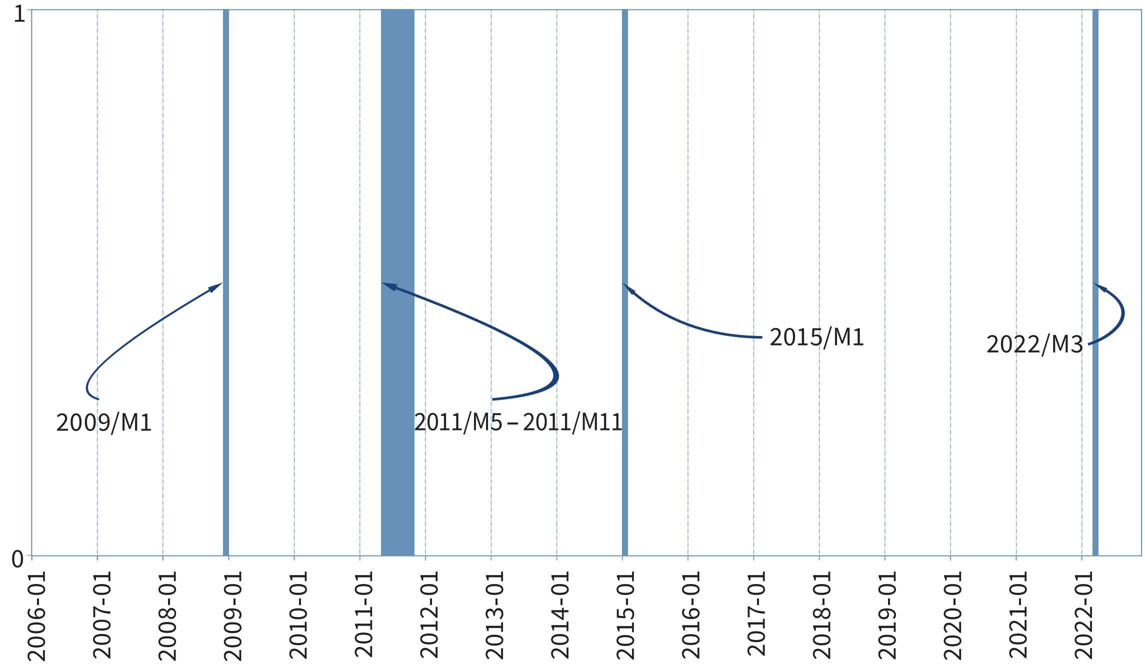
Figure 1a. Identification of stress periods in the exchange market of Armenia (1 — pressure is present, 0 — pressure is absent)



Four stress periods were recorded in Belarus in 2006/M1–2023/M6: 2008/M12–2009/M1, 2011/M5–2011/M11, 2015/M1, and 2022/M3 (Figure 1b).

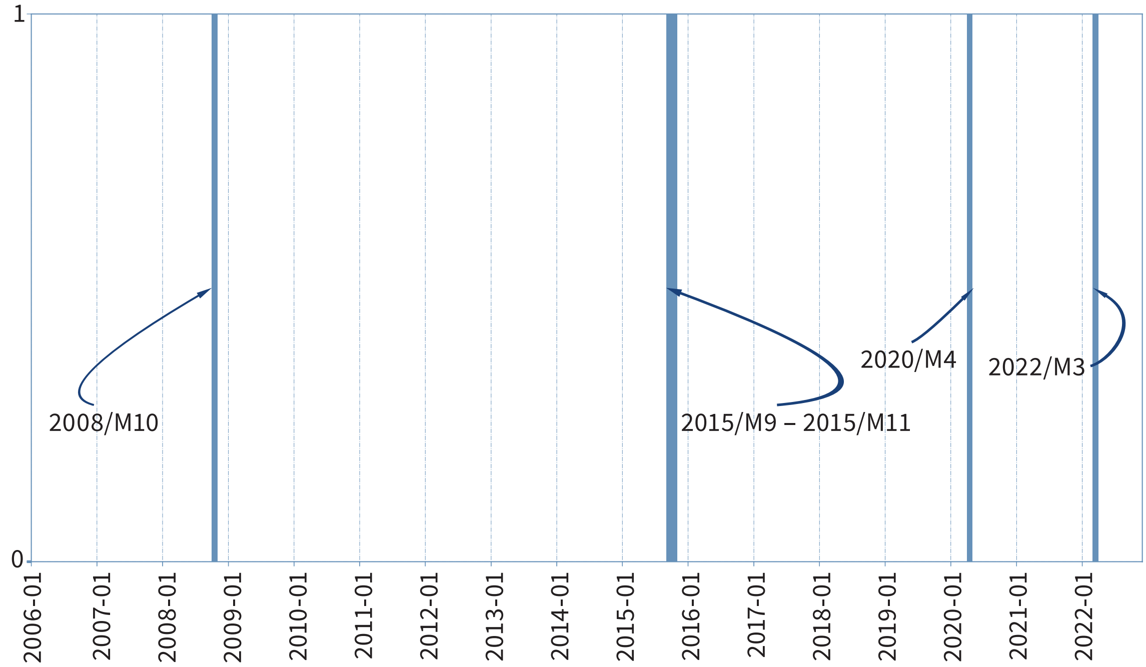
[1] The value of the coefficient k for Armenia is 1.645, which corresponds to 90% of standard normal distribution, for Belarus — 1.645 (90% of standard normal distribution), for Kyrgyzstan — 2 (97.5% of standard normal distribution), and for Tajikistan — 2 (97.5% of standard normal distribution).

Figure 1b. Identification of stress periods in the exchange market of Belarus (1 — pressure is present, 0 — pressure is absent)



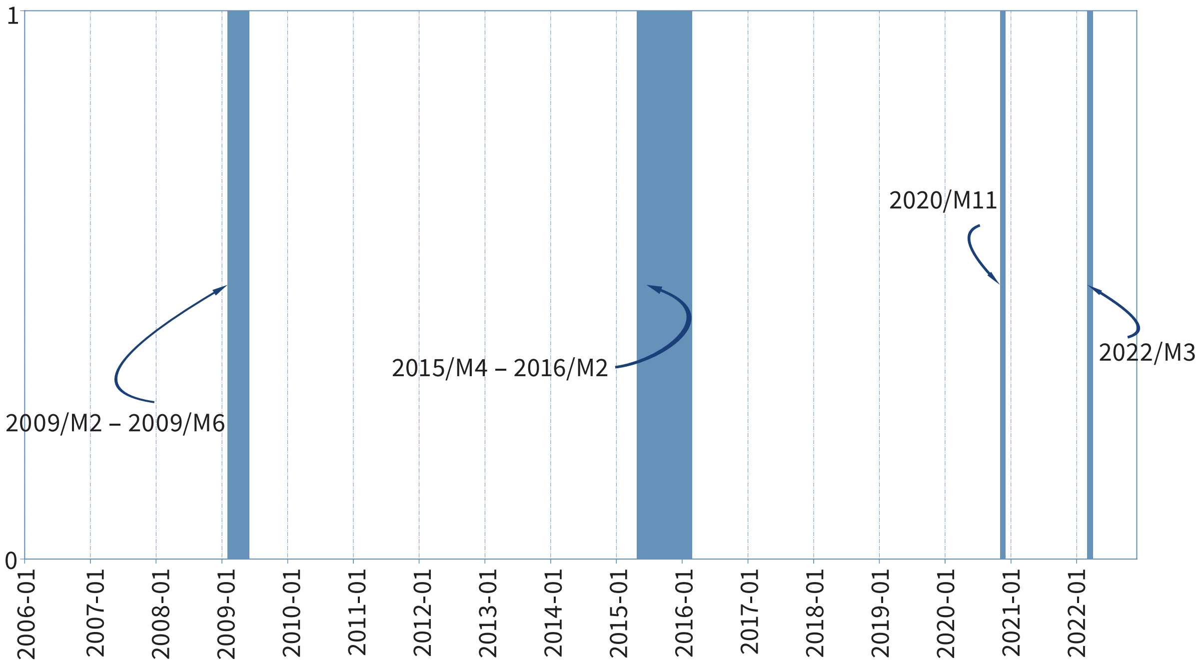
Four stress periods were recorded in the exchange market of Kyrgyzstan in 2006/M1–2023/M6: 2008/M10, 2015/M9–2015/M11, 2020/M4, and 2022/M3 (Figure 1c).

Figure 1c. Identification of stress periods in the exchange market of Kyrgyzstan (1 — pressure is present, 0 — pressure is absent)



Four stress periods were recorded in the exchange market of Tajikistan based on *empi* dynamics: 2009/M2–2009/M6, 2015/M4–2016/M2, 2020/M11, and 2022/M3 (Figure 1d).

Figure 1d. Identification of stress periods in the exchange market of Tajikistan (1 — pressure is present, 0 — pressure is absent)



No systemic banking crises were identified in Armenia, Belarus, Kyrgyzstan, and Tajikistan over the time horizon under review (2006/M1–2023/M6).

It should be noted that the stress period in the exchange market of Tajikistan (2015/M4–2016/M2) coincided with a stress period in the country's banking sector. Starting in 2014, the unstable economic situation in Tajikistan's key partner countries and the impact produced by external shocks led to the banking sector of Tajikistan being threatened with a systemic crisis. By the end of 2014, the share of nonperforming loans exceeded 10%. Several credit institutions of Tajikistan, including Agroinvestbank OJSC, Tajiksodirotbank OJSC (both systemically-important banks), Tajprombank CJSC, and Fononbank CJSC faced liquidity shortages. To revitalise the financial system and minimise the negative impact on the other sectors of the economy, the Government of Tajikistan resolved to recapitalise the banks. By the end of 2016, the scope of support offered to just two banks (Agroinvestbank OJSC and Tajiksodirotbank OJSC) amounted to about 6% of the country's GDP. The Government and the National Bank of the Republic of Tajikistan managed to keep the situation in the financial market under control (they prevented bank runs, performed bailouts and liquidated the most troubled credit institutions, and commenced realisation of several policy documents designed to strengthen the financial market). As a result, we classified the situation in the banking sector of Tajikistan in 2015–2016 as a major stress, rather than a systemic banking crisis. Although some of the indicators characterising the banking sector of Tajikistan exceeded threshold values associated with banking crisis criteria as defined by Demirguc-Kunt and Detragiache (2005), we believe that, all things considered, there was no systemic banking crisis in Tajikistan in 2015–2016.

Our conclusions regarding the stress periods identified in the financial markets of Armenia, Belarus, Kyrgyzstan, and Tajikistan are generally consistent with those presented by Laeven and Valencia (2008, 2013, 2018).

5. Data and Primary Data Processing

Data selection and primary processing were done in several stages.

At Stage 1, we used, for the purposes of development of EWS models and testing of data, a list of 20 macroeconomic indicators which had been suggested by Kaminsky and Reinhart (1999) and Kaminsky (1998), and could potentially be used as predictors of stress periods in the economy.

At Stage 2, the initially selected set of macroeconomic variables was expanded by adding indicators that are essentially similar, but more disaggregated. We used, as our main sources of information, materials published by central (national) banks and national statistical agencies, IMF databases, and other public information resources. The expanded indicator base covered the real, monetary, fiscal, budgetary, and external sectors of the economy, and included additionally computed indicators. Table 1 presents the number of initial data time series analysed for each of the four countries.

Table 1. Number of Analysed Data Time Series by Country

Country	Number of Indicators
Armenia	231
Belarus	236
Kyrgyzstan	301
Tajikistan	138

Periodicity and depth of statistical data: monthly data from January 2006 to June 2023. The use of data prior to 2006 is difficult due to inferior quality or absence.

The time series under analysis were subjected to primary statistical processing, including logarithmic transformation, seasonal adjustment, trend extraction using the Hodrick–Prescott filter, and gap estimation (difference between seasonally adjusted and extracted trend of the time series).

Gaps need to be used in the analysis because time series in emerging economies are subject to substantial fluctuations (Bloom, 2013). Therefore, the use of first differences may add an artificial upward bias to the threshold level compared to when gaps are used. In addition, we followed in the footsteps of other authors who also used data in gaps (Csortos and Szalai, 2014; Borio and Lowe, 2002a, 2002b).

Special software written in the object-oriented programming language Python was used to perform primary statistical processing of data, and to support a large part of the EWS computation cycle. To perform the DMA estimation, we used the eDMA package designed in the R environment using the Rcpp and RccpArmadillo libraries (Catania and Nonejad, 2018), and code written in the MATLAB environment (Koop and Korobilis, 2012).

6. Selection of Potential Signal Variables

Potential signal variables are indicators whose dynamics can be interpreted as early signals of stress or a crisis. The process of selection of such variables is described below.

Upon completion of primary statistical processing of data, it is necessary to select variables signalling a crisis in subsequent periods. This is done by measuring the ratio of the share of false signals during tranquil periods to the share of true signals within signal windows (noise-to-signal ratio, or *NSR*) using a popular signal variables search algorithm proposed by Kaminsky and Reinhart (1999) and Kaminsky (1998).

This indicator is measured in several steps:

1. Arithmetic mean and standard deviation are computed for each transformed time series (see Section 5).
2. Six-month signal windows preceding stress periods are determined for each such period. It should be noted that experiments were conducted for different values of the signal window, including 12 and 18 months, but the list of potential predictors remained practically the same as for the range of six months. A number of studies take the range of the signal window to be 24 months (Kaminsky, 1998; El-Shazly, 2002). In this study, a signal window range of 24 months was not applied, because the time series starts mainly from 2002. Based on this, it was concluded that six months is the optimal signal window range for the analysed countries.
3. A threshold value is computed for each time series. The optimal threshold is defined as the value of the indicator which maximises the ability of that indicator to accurately forecast a crisis. The threshold value is computed as follows:

$$\hat{x} \pm k\sigma_x , \tag{30}$$

   where $\hat{x}$ is arithmetic mean, σ_x is standard deviation, k is estimated coefficient (Abdelsalam, Abdel-Latif, 2020). The ± sign depends on the specific indicator and the significance of its dynamics for the economy. For example, growth of imports can create a current account deficit, and may precipitate stress or a crisis in the exchange market.

4. Optimisation methods are used to compute the coefficient k (measure of threshold level limitation) to determine the threshold value of each time series. The coefficient k is a randomly selected positive number. Optimisation is performed to find the global minimum. The selected coefficients k serve approximately the same purpose as the threshold area used to determine the confidence interval or to test statistical hypotheses.
5. The coefficients k are selected for each time series so as to minimise the desired noise-to-signal ratio (*NSR*) computed as the ratio of the share of false signals during tranquil periods to the share of true signals within signal windows.

$$NSR = \frac{FP\ /(FP + TN)}{TP\ /(TP + FN)}, \tag{31}$$

where *TP* (true positive) means that the indicator gave a signal inside the signal window, and the crisis occurred; *FP* (false positive) means that the indicator gave a signal outside the signal window, and the crisis did not occur; *FN* (false negative) means that the indicator did not give a signal inside the signal window, but the crisis did occur; *TN* (true negative) means that the indicator did not give a signal outside the signal window, and there was no crisis.

6. Upon completion of the optimisation process, minimal *NSR* values (Table 2) are determined for each country sample (the indicator depends on the dataset used, and on expert judgment). Time series with *NSR* values in excess of the minimums so determined are excluded from further analysis.

However, it is not enough to select potential predictors based only on *NSR* values, especially when the number of identified crises or stress periods is relatively small. This statement is substantiated below.

For example, two stress periods were recorded in the exchange market of Armenia in 2006/M1–2023/M6 (see Section 4). Let us assume that the potential indicator gave a true signal of the occurrence of stress only for one period, but failed to respond to pressure in another situation. Consequently, for this indicator, $TP/(TP + FN) = 0.5$ (*NSR* denominator, see Equation 31). Let us also assume that, based on actual computations, we determined that the share of false signals $FP/(FP + TN) = 0.1$. Therefore, for this indicator, $NSR = 0.2$, which means that, in line with the approach described above, the indicator should be included in the list of potential predictors. However, its predictive power will evidently be low, as it responded to only one of the two stress periods.

In that connection, for those indicators whose *NSR* is below the pre-set minimal value, it is also necessary to compute coefficients of correlation between the actual stress periods and the lagging (by 1–12 months) signal values (in this case, all series under analysis have binary values — i.e., correlation coefficients are computed on the basis of binary variables). Subsequent selection of indicators is performed in accordance with the following scheme. Signals whose correlation coefficient values for all lags are less than the value specified in Table 2 are excluded from analysis, and vice versa.

Table 2. Minimal *NSR* Values and Coefficients of Correlation between Stress Periods and Lagging Signal Values

Country	Minimal *NSR* Value	Lag Correlation Coefficient
Armenia	0.2	0.3
Belarus	0.2	0.5
Kyrgyzstan	0.2	0.25
Tajikistan	0.2	0.25

The distribution of analysed indicators by *NSR* and lag correlation coefficient values for each country is presented in Appendix 2.

Upon completion of selection in accordance with the above scheme, we received, for each country, a list of potential predictors of stress (crisis) in the exchange market (see Appendix 3).

It should be noted that most indicators from the list proposed by Kaminsky and Reinhart (1999) and Kaminsky (1998) failed to meet the selection criteria.

As noted above, to estimate the efficiency of predictors, we used a six-month signal window. To determine the optimal width of the window, correlation coefficient values for various lags (1–12 months) were computed for each country-specific group of potential predictors (Appendix 4). Based on an analysis of estimation results for each country, the conclusion was drawn that in most cases maximum lag correlation coefficients lie within the range from 1 up to and including 6 lags. Therefore, the largest correlations occur within the range between the 1st and the 6th lags — i.e., it is expedient to set the maximum signal window width at 6 months.

7. Construction of Principal Components on the Basis of Selected Predictors

From Appendix 3, it can be seen that the list of selected potential predictors includes essentially similar time series (for example, various types of deposits, interest rates, global price indices, exchange rates). One of the possible ways to proceed in this situation would be to select several critical predictors on the basis of expert judgments — i.e., to leave, say, one price index or one deposit indicator. However, we were concerned that this might result in the loss of potentially important information. That gave rise to the need to aggregate the selected potential predictors into mutually independent and cumulatively complementary groups (principal components). We resolved to analyse the whole set of potential predictors separately for each country, using the principal components method, which is well-known in applied statistics (Ayvazyan et al., 1989; Soshnikova et al., 1999; Jolliffe, 2002)[2].

The principal components method makes it possible to explain a substantial part of variance of the initial variables using a smaller number of mutually uncorrelated variables. Before we can construct the principal components, the following equality should be satisfied:

$$\Sigma_{i=1}^{n} var\,(X_i) = \Sigma_{j=1}^{n} var\,(F_j), \tag{32}$$

where X_i is vector of initial variables (i = 1, 2, …, n), F_j is vector of principal components (j = 1, 2, …, n). The equality shows that the number of principal components is equal to the number of initial variables. However, the following inequality is satisfied for the principal components (but not for the initial variables):

$$var\,(F_1) \geq var\,(F_2) \ldots \geq var\,(F_n), \tag{33}$$

— i.e., the first principal component has the highest variance, the second principal components has lower variance compared to the first principal component, but higher variance compared to the subsequent principal components, etc. It is due to this property that several first principal components are capable of explaining a substantial part of variance of the initial variables.

The principal components are computed as linear combinations of initial variables — i.e., $F = XB$, where B is the weight coefficients matrix where $B'B = 1$. The task is to select for matrix B the values which maximise variance of the appropriate principal components. In other words, it is necessary to solve a maximum optimisation problem.

To find such matrix B, we need to construct the Lagrange function. To do that, Equality (32) is presented in matrix form:

$$var\,(X) = var\,(XB), \text{ or } var\,(X) = B'SB, \tag{34}$$

[2] The principal components method is only one of the possible statistical analysis variants. The decision regarding the selection of the method, or the approach to be used for analysis, is made by the researcher based on his or her personal judgment.

where S is the variance-covariance matrix of initial variables X.

Then the Lagrange function can be presented in the following form:

$$L = B'SB - \lambda(B'B - 1). \tag{35}$$

By differentiating on B and equating the result to zero, we receive $|S - \lambda I|\, B = 0$. To obtain a non-zero solution, we find the roots of the matrix equation $|S - \lambda I| = 0$. As we solve that equation, we determine eigenvalues (λ) and eigenvectors (B) of the matrix S. Then, having the values of matrix B elements, we compute the dynamics of the principal components using the formula $F = XB$.

Therefore, the first step in using the principal components method is to compute the coefficients of correlation (covariance) comprising the correlation (covariance) matrix S. That matrix is used to compute variance of the principal components, and principal component loadings on the selected predictors. That problem is solved by identifying eigenvalues and the related eigenvectors.

Computed shares of the selected principal components in total variance of the initial indicators for each of the four countries are presented in Appendix 5, and visualisation of the structure of the selected principal components, complete with the shares of predictors in principal component variance, is shown in Appendix 6.

The decision regarding the number of the principal components retained for subsequent analysis and modelling is made on the basis of the Kaiser criterion, according to which only principal components with eigenvalues of more than 1 should be retained (Nunnally and Bernstein, 1994). Subject to the foregoing, subsequent computations for Armenia involve the first five principal components (explaining 64.82% of the variance of the initial predictors), computations for Belarus — the first five principal components (explaining 73.15% of the variance of the initial predictors), computations for Kyrgyzstan — the first five principal components (explaining 63.39% of the variance of the initial predictors), and computations for Tajikistan — the first five principal components (explaining 65.38% of the variance of the initial predictors).

Then principal component dynamics are computed using the matrix of loadings on the principal components and the principal components computation algorithm presented above. Figures 2–5 present principal component movements for Armenia, Belarus, Kyrgyzstan, and Tajikistan, respectively, where the red dashed line is the threshold level, and the cross-hatched area is the stress (crisis) zone. If any point of a principal component falls within the crisis zone, a conclusion can be drawn that possible pressure exists, or that a stress (crisis) situation has occurred.

From Figures 2–5, one can see that the principal components identified for each country were able, collectively, to promptly signal stress (crisis) periods, while individual principal components could not produce a 100% predictive result.

Principal components' movements are used to compute composite indicators. To do that, we use principal components instead of the predictors selected for each economy (Appendix 3). They make it possible to compute composite indicators for the models described above (signal approach, logit/probit models, and the DMA).

Figure 2. Armenia: Principal Components' Movements in 2006/M1–2023/M6

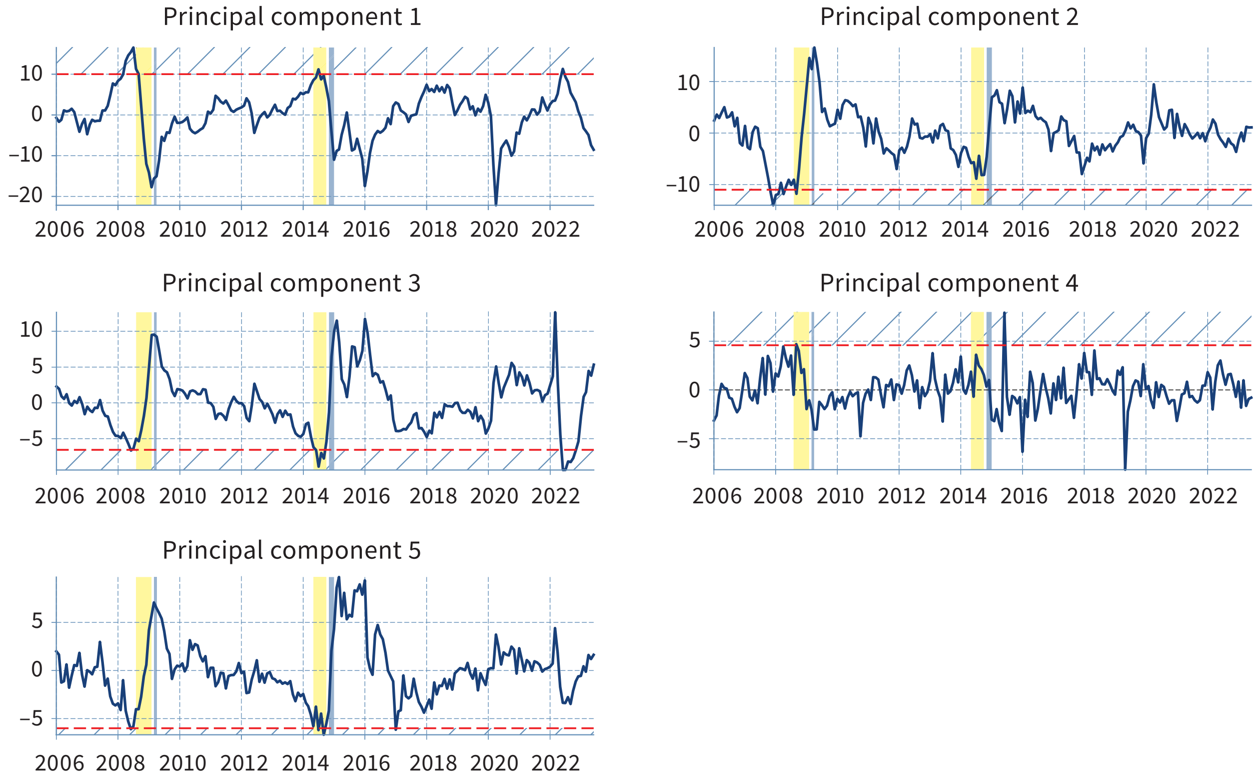


Figure 3. Belarus: Principal Components' Movements in 2006/M1–2023/M06

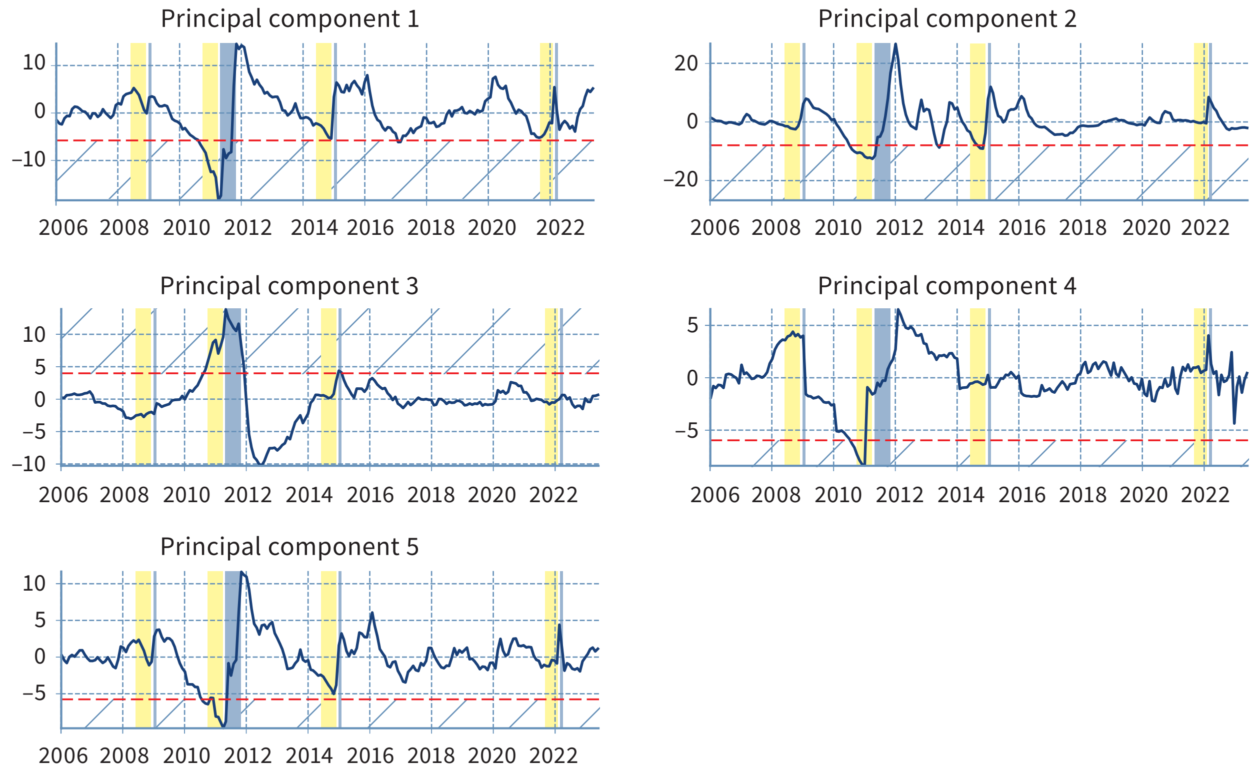


Figure 4. Kyrgyzstan: Principal Components' Movements in 2006/M1–2023/M6

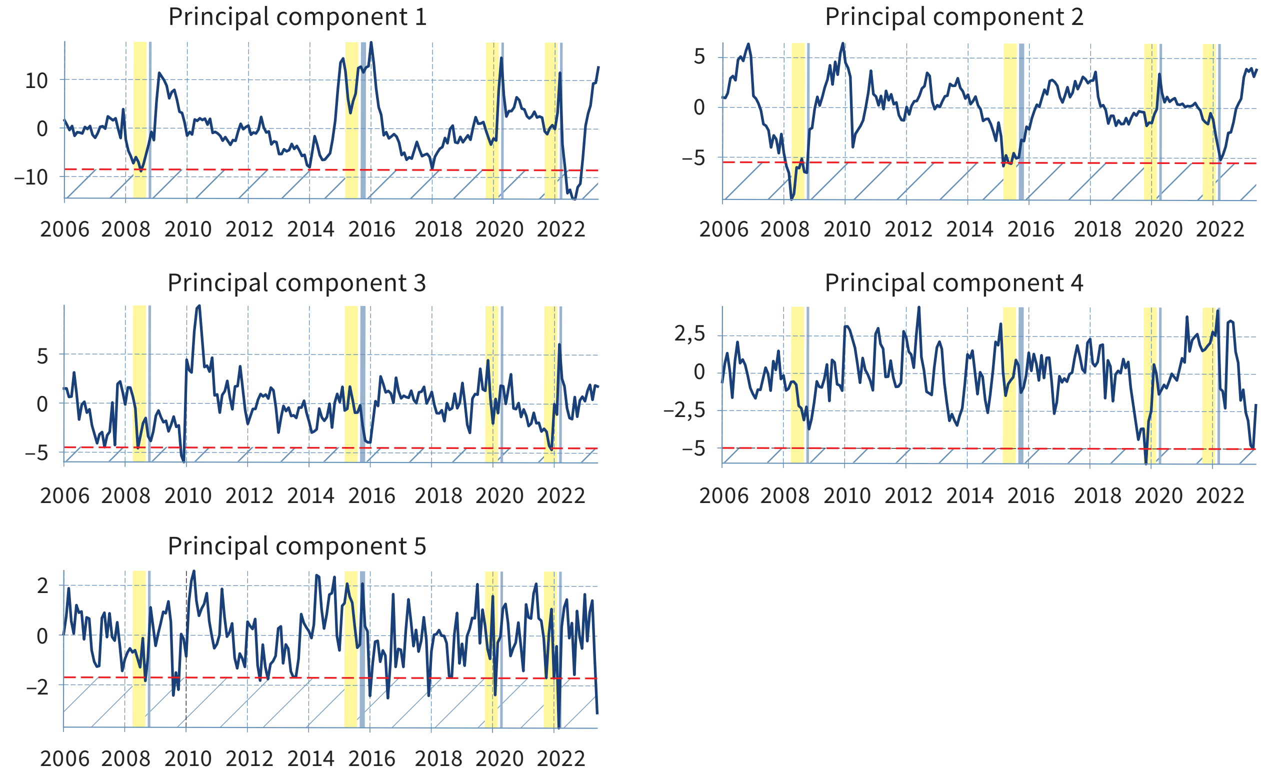
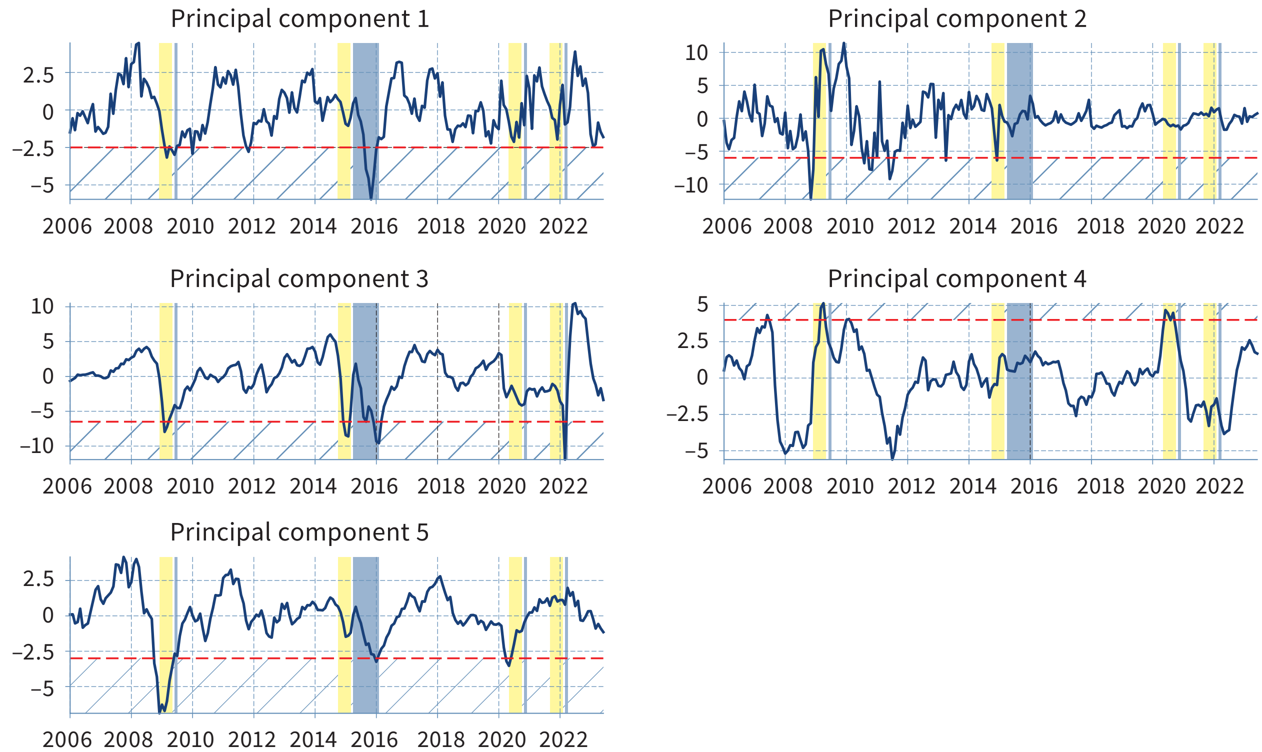


Figure 5. Tajikistan: Principal Components' Movements in 2006/M1–2023/M6



8. Selection and Testing of EWS Models: Empirical Results

This section presents the following results: (1) thresholds are determined for each of the models described in Section 3; (2) thresholds are used to analyse the sensitivity of the models under review to extremal values; (3) the selection procedure for forecast models is presented, and an account of a retrospective forecasting experiment.

It appears impossible to give an unambiguous answer regarding the occurrence of stress periods based only on the dynamics of each of the selected principal components (see Figures 2–5). One of the possible solutions is to construct and use a single composite indicator on the basis of several principal components.

Several variants of construction of composite indicators are presented below, as well as the thresholds computed on the basis of those indicators.

Signal approach. When the signal approach is used, an *NSR* efficiency indicator is selected for each principal component. The resultant *NSR* values are employed as weights to compute the composite indicator as a weighted arithmetic mean using Formula (6). Then the composite indicator can be used to compute the probability of a crisis during the time period $[t, t + h]$. It is suggested that the computation be made subject to Formula (7), which can be presented in the following form:

$$Pr\,(Crisis_{t,t+6}) = \frac{\Sigma M^*}{\Sigma M}, \tag{36}$$

where $Pr\,(Crisis_{t,t+6})$ is the probability of a crisis during the time interval $[t, t + 6]$; ΣM^* is the number of months when the composite indicator value falls within the interval $CI_l < CI_t < CI_u$, and a crisis occurs within the next six months (CI_l — lower boundary, CI_u — upper boundary), ΣM is the total number of months when the composite indicator value falls within the interval $CI_l < CI_t < CI_u$ (Kaminsky, 1998).

The selected percentiles, as well as probability values computed for the four countries using the signal approach, are presented in Tables 3–6.

Table 3. Armenia: Computation of Crisis Probability within the Interval $CI_l < CI_t < CI_u$

PERCENTILES	≤ 0.274	≤ 0.452	≤ 0.658
Percentile Values	0.25	0.6	1.0
M*	5	4	3
M	187	11	7
Probability	0.027	0.364	0.429
Threshold Level		**0.274**	

Table 4. Belarus: Computation of Crisis Probability within the Interval $CI_l < CI_t < CI_u$

PERCENTILES	≤ 0.2	≤ 0.8	≤ 1.0
Percentile Values	0.25	0.7	1.0
M*	18	5	1
M	191	6	3
Probability	0.094	0.833	0.333
Threshold Level		**0.2**	

Table 5. Kyrgyzstan: Computation of Crisis Probability within the Interval $CI_l < CI_t < CI_u$

PERCENTILES	≤ 0.106	≤ 0.282	≤ 0.388
Percentile Values	0.25	0.7	1.0
M*	21	2	1
M	189	12	3
Probability	0.111	0.167	0.333
Threshold Level			**0.282**

Table 6. Tajikistan: Computation of Crisis Probability within the Interval $CI_l < CI_t < CI_u$

PERCENTILES	≤ 0.22	≤ 0.44	≤ 0.937
Percentile Values	0.25	0.7	1.0
M*	22	5	3
M	194	7	3
Probability	0.113	0.714	1.0
Threshold Level		**0.22**	

The percentiles are selected on the basis of expert judgments, subject to specific values of the ranked composite indicator series. Selection of the percentiles is performed at the points characterised by significant indicator jumps. To verify the stability of the decomposition results, one can use equal intervals for the percentiles or, for example, compute the optimal number of intervals for a given ranked series. Specific values of the ranked series for a given percentile are shown in the "Percentile Values" line of Tables 3–6. For example, in Table 3, the relevant value for the percentile 0.25 is 0.274.

To compute the number of observations in the interval $CI_l < CI_t < CI_u$, it is necessary to create intervals based on specific percentile values. For example, the first interval will be [0–0.274], the second interval (0.274–0.452], etc. For line *M**, we need to find composite indicator values which simultaneously fall within that interval, and a crisis occurs within the next 6 months (for example, for the interval [0–0.274] *M** = 5). Line *M* lists all composite indicator values for the interval $CI_l < CI_t < CI_u$ (for the interval [0–0.274], the total number of values falling within that interval is 187). Finally, we divide *M** by *M* to determine the probability of a crisis (for example, for the first interval, the probability value is 0.027). The computed probability value shows that, if the composite indicator value falls within the interval [0–0.274], the probability that a crisis will occur within the next 6 months is 0.027. Similarly, from Table 3, one can see that when the percentile value falls within the interval (0.274–0.452], the probability of a crisis increases from 0.027 to 0.364. Based on the foregoing, we conclude that the threshold is 0.274. Thresholds for the other countries are found in the same way.

Binary choice models. Continuous values of the principal components were selected as the predictors in such models (to ensure comparability with the results produced by the signal approach). In other words, in logit/probit models, the dependent variable is binary, while the predictors are continuous values of the principal components. The principal components can enter the logit/probit models with lags (from 1 to 6). The selection of that number of lags is explained by the six-month width of the signal window.

Logit/probit models are used to estimate the appropriate probabilities. Next, we compute, for the probabilities so obtained, the *NSR* efficiency indicator which will be the optimal threshold for the occurrence of crisis periods under the relevant models.

To preserve comparability, we included in the logit/probit models the same principal components as in the signal approach model. The main difference is that such principal components enter the logit/probit models with lags. The results of model estimation for the countries under review are shown in Appendix 7. The signs of the estimated parameters coincide with our expectations.

The impact of the estimated parameters on the dependent variable in binary models is explained by the so-called *marginal effect.* For example, from Appendix 7, we see that in the logit model for Armenia the coefficient for PC1(-3) is equal to 0.354. Then the marginal effect for the logit model can be computed using the following formula:

$$\text{marginal effect} = \Lambda(x'\beta)(1 - \Lambda(x'\beta))\beta_j. \tag{37}$$

For our data, $\Lambda(x'\beta)(1 - \Lambda(x'\beta)) = 0.0166$. Consequently, the marginal effect on the indicator is $PC1(-3) = 0.354 \times 0.0166 = 0.00588$.

The resultant coefficient is interpreted as follows: if the third lag of the first principal component increases by one conventional unit, the probability of stress (a crisis) increases by 0.00588. The other estimated parameters are explained in a similar way.

Dynamic model averaging. Below is an explanation of preliminary preparations and realisation of the DMA method. As noted in the previous section, five principal components were identified for each country based on the selected potential predictors. Taking into consideration that the principal components were included in the logit/probit models with lags, the number of lags for each country varied from 1 up to and including 4 to ensure comparability under the DMA model. The specifications presented in Appendix 7 represent one of several possible specific specifications for the DMA method. For example, if five principal components are included with lags from 1 to 4, the total number of predictors in the DMA model will be equal to 20. Consequently, the total number of specifications that need to be estimated is (2^{20}). The model also includes a constant which is used in all possible specifications.

Before estimating each of the possible specifications, it is necessary to select values for the two forgetting factors λ and α, and a value for the parameter k. As regards the parameter k, it should be noted that in many papers it is equal to 0.95, while the values of the forgetting factors λ and α vary from 0.90 to 0.99 with a step of 0.01 (Catania and Nonejad, 2018). In this paper, $\lambda = 0.99$ and $\alpha = 0.9$ (Koop and Korobilis, 2012). The initial weight values are equal for each of the possible specifications, as each of them is *a priori* equally important.

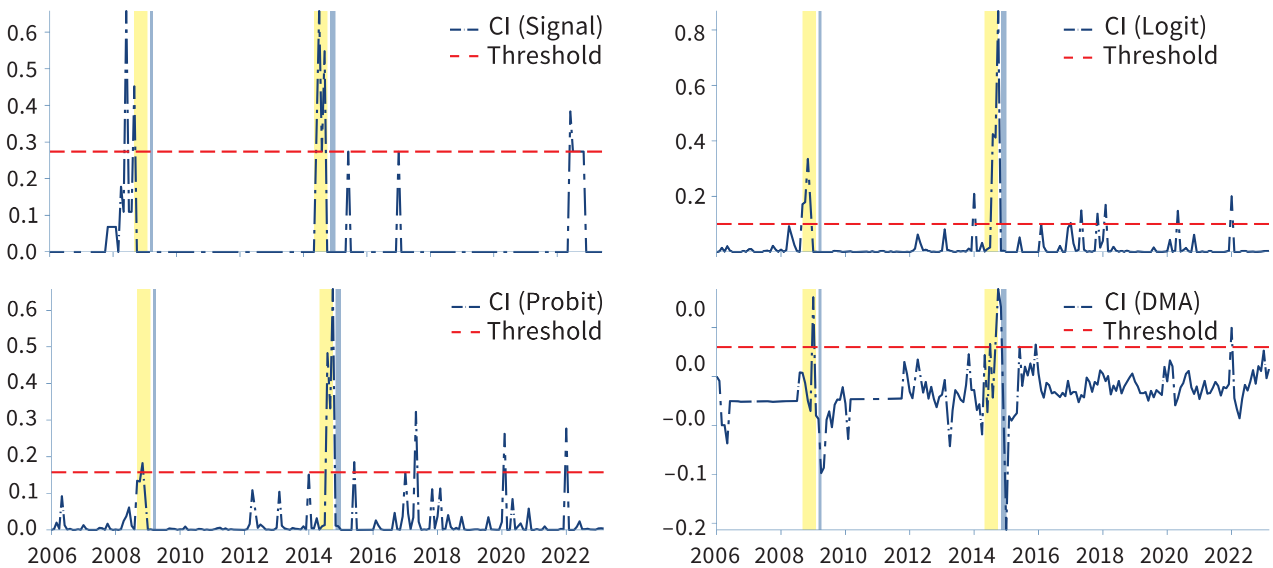
After the initial values are fixed, the parameter estimation process begins (see Section 3) — i.e., we compute the probability density for each combination and for a specific time period, showing the extent of approximation of the dependent variable *empi* achieved by the relevant specifications. A comparison of the actual and DMA-estimated *empi* dynamics is presented in Appendix 8.

As noted in Section 3, the application of the DMA makes it possible to consider all possible model specifications, and thereby resolve the problem of uncertainty related to the selection of model specifications. In that connection, there arises the question of what percentage of total variance is explained by model selection uncertainty.

To answer this question, we can refer to Catania and Nonejad (2018), who provide formulae for calculating the variance of actual observations, the variance attributable to uncertainty of coefficients, and the variance attributable to uncertainty of model specifications. According to our computations, for Armenian data the share of variance attributable to model specifications in total variance is 15.32%. A similar picture can be observed for the other countries. Therefore, uncertainty associated with the choice of specifications accounts for a relatively large share of total variance and, consequently, its inclusion may have a significant impact on the dependent variable forecast.

The composite indicators of stress in the exchange markets of Armenia, Belarus, Kyrgyzstan, and Tajikistan that were computed using all of the models described above, as well as the relevant threshold levels, are presented in Figures 6–9. It should be noted that the thresholds for each composite indicator were found on the basis of the optimal *NSR* estimation.

Figure 6. Armenia: Composite Indicator Movements in 2006/M1–2023/M6



Note: Here and below: CI = composite indicator.

Figure 7. Belarus: Composite Indicator Movements in 2006/M1–2023/M6

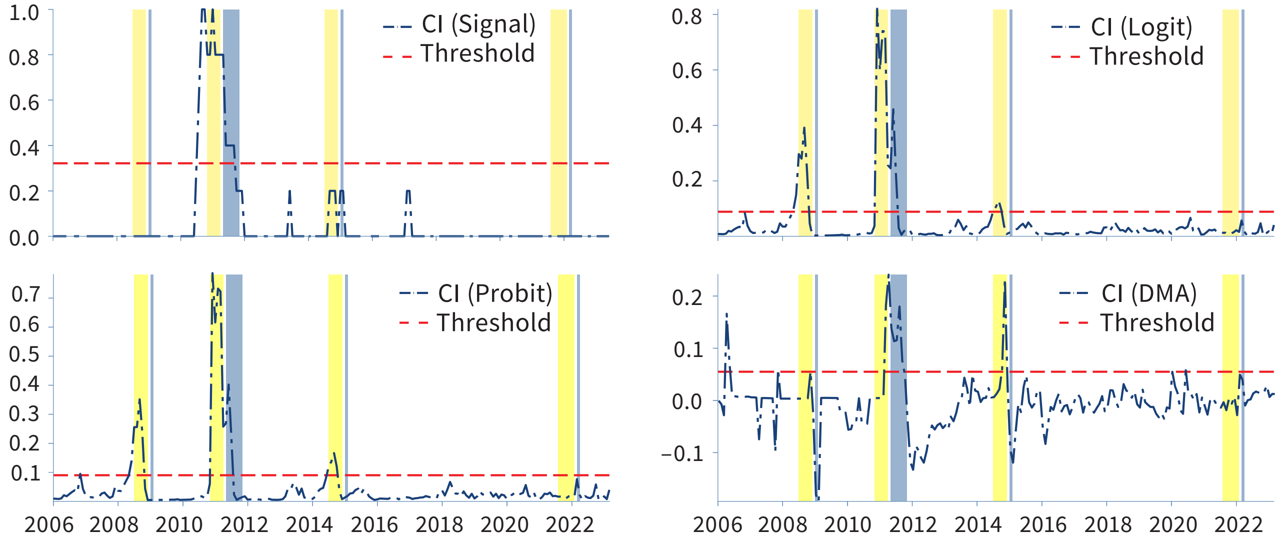


Figure 8. Kyrgyzstan: Composite Indicator Movements in 2006/M1–2023/M6

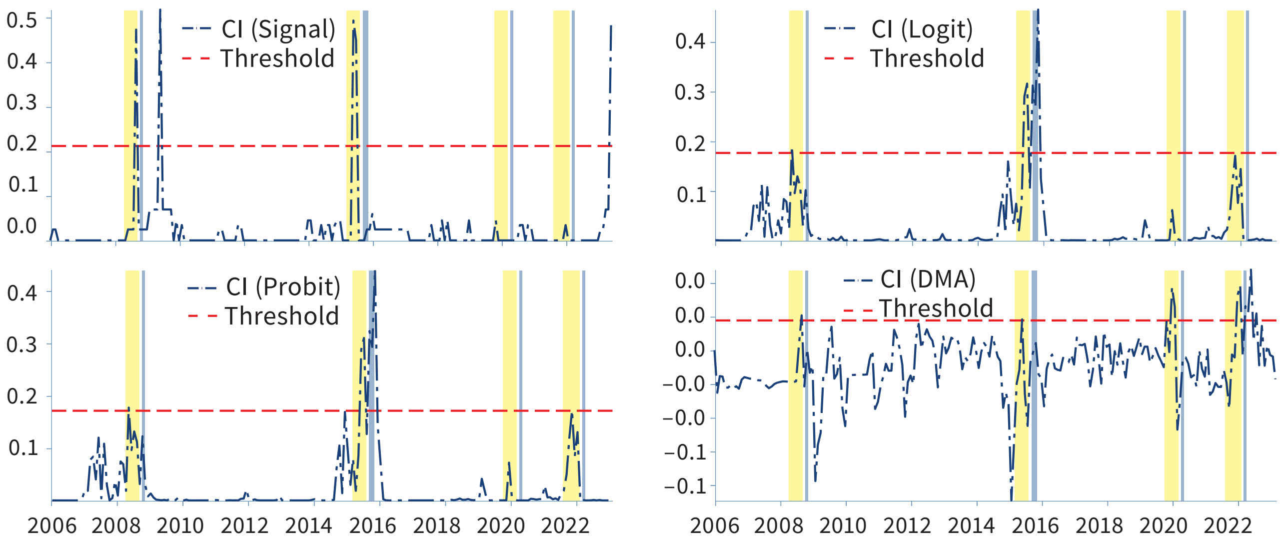
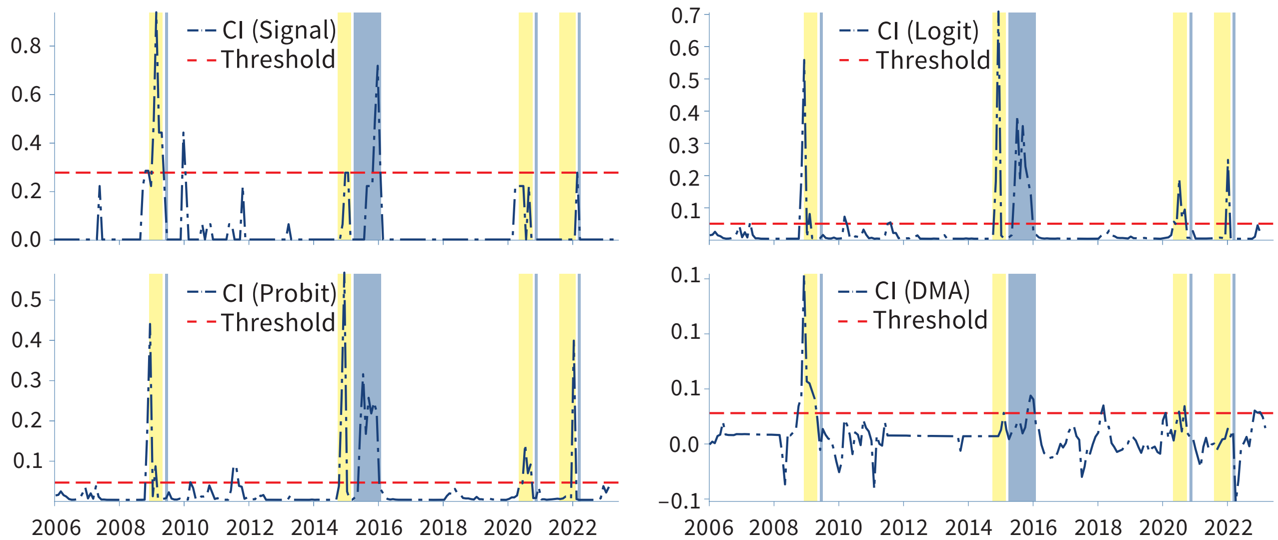


Figure 9. Tajikistan: Composite Indicator Movements in 2006/M1–2023/M6



Analysis of sensitivity to extremal values. This step is required for a comparison of the predictive properties of the models used. For that, we compute confidence intervals for principal component changes using the bootstrap method explained below.

At the first stage, each principal component is modelled as an AR(2) process:

$$y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + u_t, \tag{38}$$

where φ_0, φ_1, φ_2 are unknown parameters that can be consistently estimated by using the least squares method.

At the second stage, we compute $\hat{y}_t = \hat{\varphi}_0 + \hat{\varphi}_1 y_{t-1} + \hat{\varphi}_2 y_{t-2}$ and the residuals $\hat{u}_t = y_t - \hat{y}_t$. The resultant residuals are scaled as follows:

$$\bar{u}_t = \frac{\hat{u}_t}{\sqrt{1-h_t}} - \frac{1}{N}\Sigma_{S=1}^{N}\frac{\hat{u}_S}{\sqrt{1-h_S}}, \tag{39}$$

where $h_t = X_t (X'X)^{-1} X'_t$.

At the third stage, we perform resampling with return for $\bar{u}_t$. This yields new $\bar{u}_t^*$ values which, when added to $\hat{y}_t$, produce new values for the dependent variable (principal component) $y_t^* = \hat{y}_t + \bar{u}_t^*$. Using y_t^*, we estimate an AR(2) model to determine $\hat{y}_t^*$ (Johnston and DiNardo, 1997).

Following the *bootstrap* algorithm described above, computation iterations are repeated multiple times (in this case, 1,000 times). This makes it possible to compute 5% and 95% *bootstrap* confidence intervals. The intervals for the selected principal components determined using the *bootstrap* method, with a breakdown by countries and relevant selected principal components, are shown in Appendix 9.

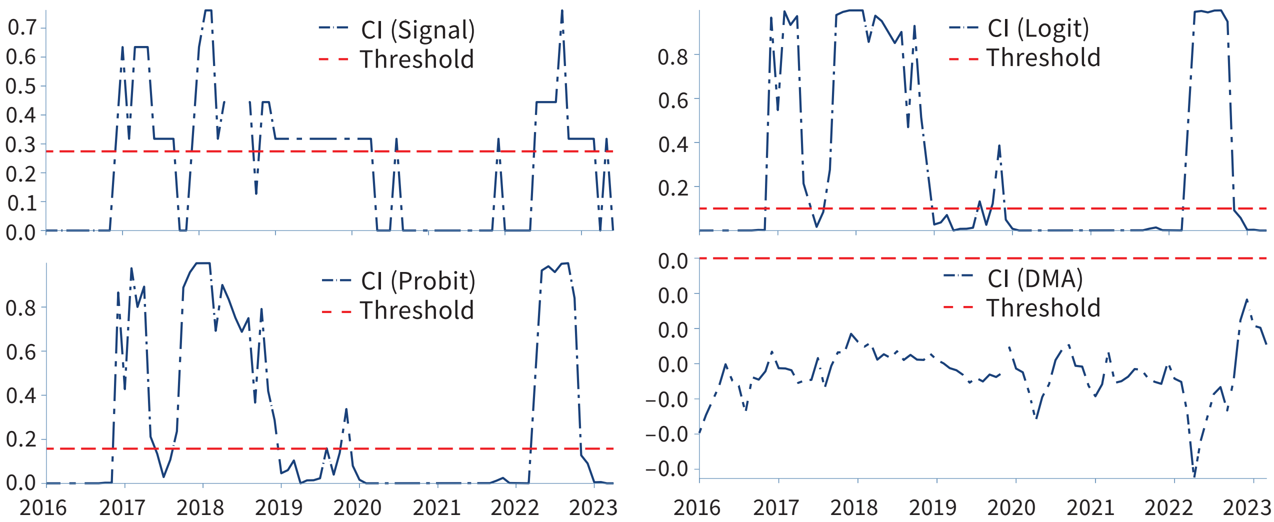
From the charts in Appendix 9, one can see that the actual dynamics of the principal components mostly fluctuate within the intervals, which testifies to good approximation under the *bootstrap* method. The confidence intervals determined using the *bootstrap* method can be used to draw conclusions as to the predictive properties of the models. This is done in accordance with the procedure described below.

Instead of the actual principal component values, interval values (extremal values) are inserted in the model, and then model behaviour in those points is examined. In our case, only a portion of the sample is used, namely, extremal values for 2016/M1–2023/M6. As we insert extremal values in the test subsample (2016/M1–2023/M6 data), we compute the new composite indicator values. Then the composite indicator values are compared with the threshold values (see Figures 10–13).

In Figures 10–13, one can clearly see that the signal approach generates the most false signals compared to the other models. The logit/probit models and the DMA/DMS methods generate relatively few false signals, so their use in the EWSs is justified.

Selection of predictive models. The purpose of this step is to find qualitative tools for the short-term forecast and identification of stress (crisis) periods.

Figure 10. Armenia: Model Behaviour in Extremal Points



Note: Here and below: CI = composite indicator.

Figure 11. Belarus: Model Behaviour in Extremal Points

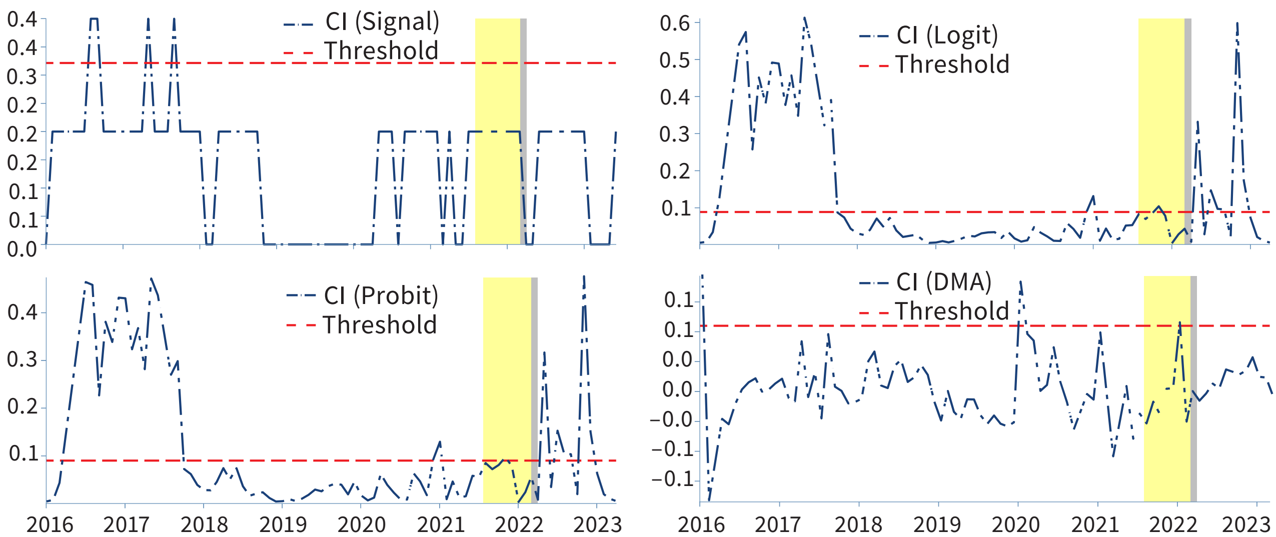


Figure 12. Kyrgyzstan: Model Behaviour in Extremal Points

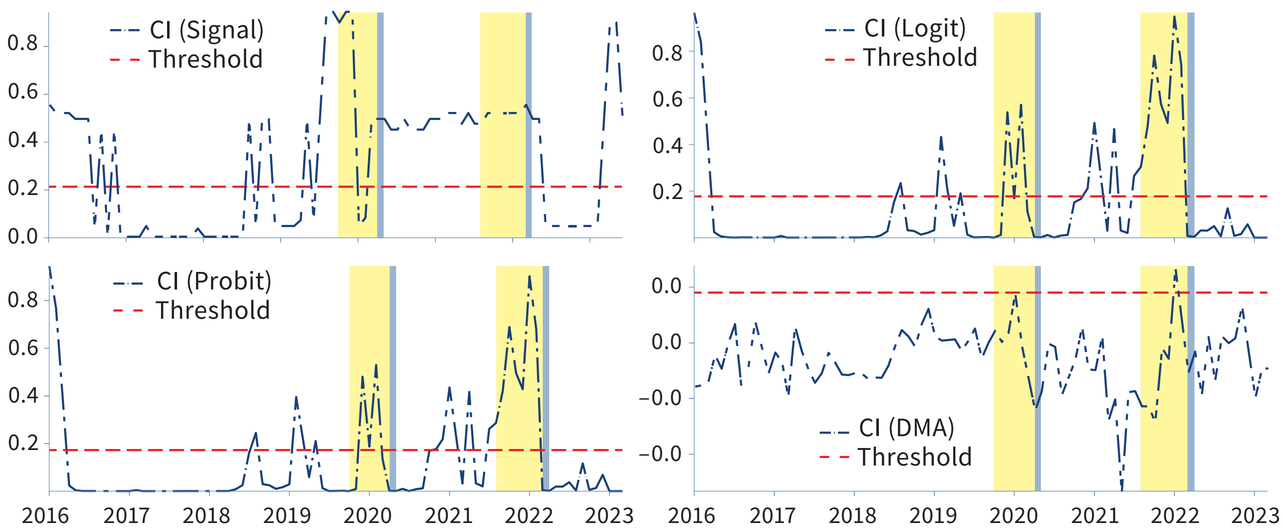
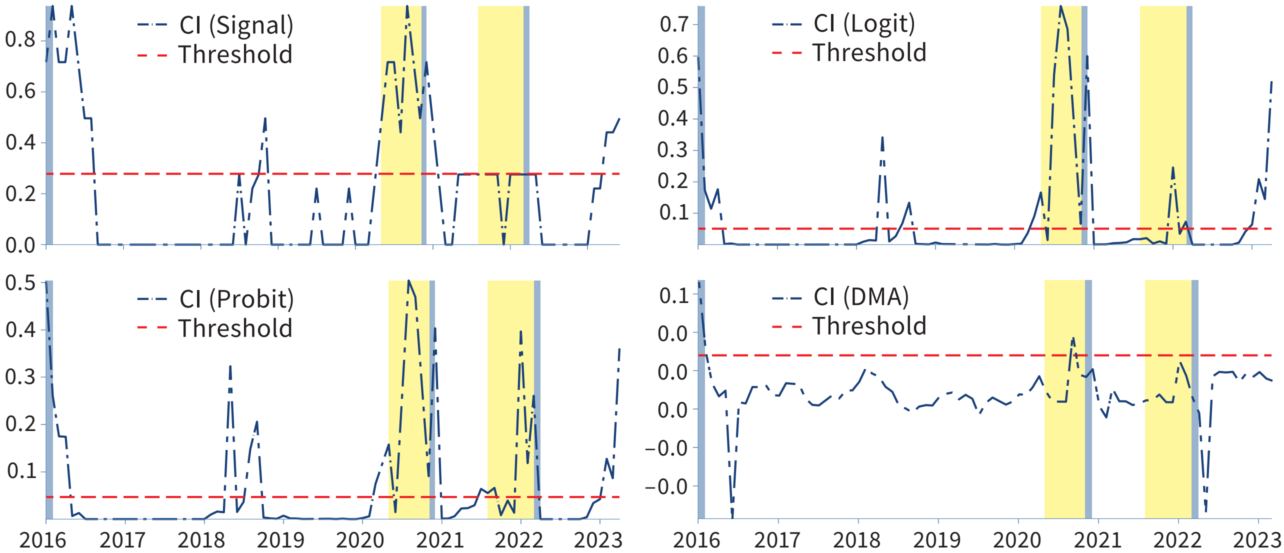


Figure 13. Tajikistan: Model Behaviour in Extremal Points



To do that, it is necessary, as a first step, to decide which methods should be used to forecast the selected principal components. The choice is made from among conventional time series forecast models: AR, VAR, and BVAR. To select the most suitable model for each country, we performed retrospective analyses of forecasts using the recursive and moving regression experiment schemes (Figure 14).

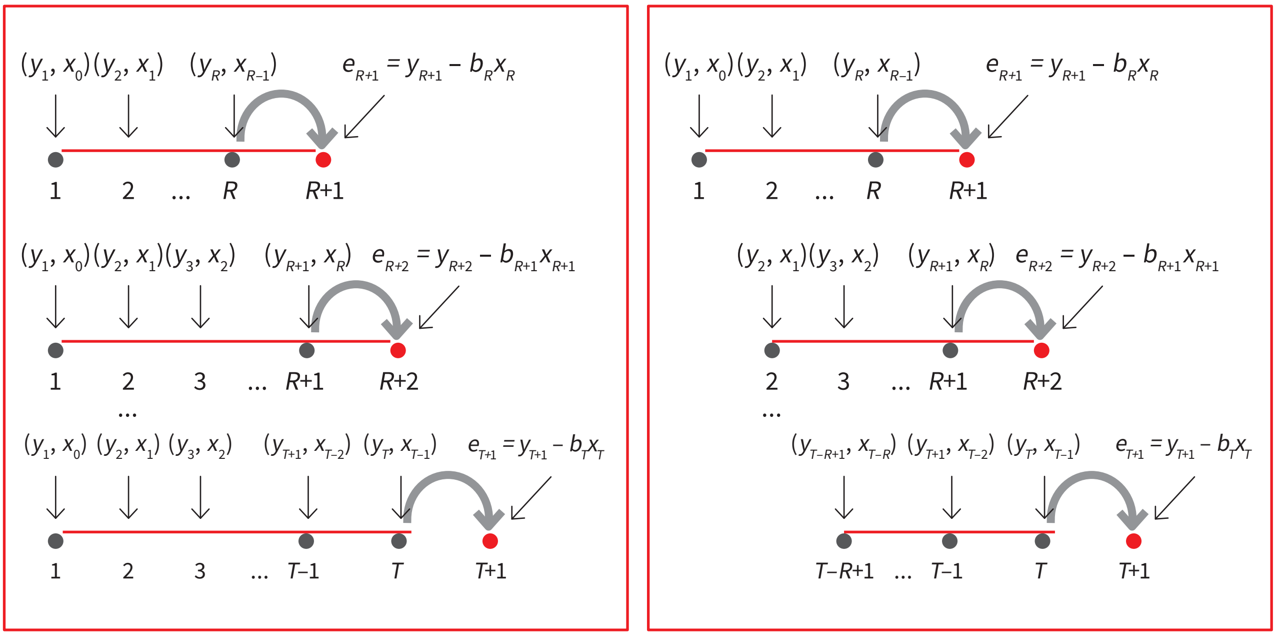
The recursive scheme envisages the following steps. Model estimation is performed on the actual data — for example, for the period 2006/M1–2016/M7. Then the estimated model is used to forecast one step ahead (2016/M8). Next the length of the sample is increased by one more observation (and we receive the period 2006/M1–2016/M8), the model is re-estimated, and a forecast is made for one more time step ahead (2016/M9). In this manner, we perform successive iterations until 2023/M3, where the last forecast is made for the period 2023/M6.

The moving scheme is not principally different from the recursive scheme. Its main difference is that the length of time series is preserved — i.e., we estimate the model for the period 2006/M1–2016/M7, and then make a forecast for the next period (2016/M8). Then the sample is moved by one observation (we take the interval 2006/M2–2016/M8), the model is re-estimated, and a forecast is made for one month ahead. Such successive iterations are performed until a forecast is made for the last time period (2023/M6).

The number of lags successively used for the AR, VAR, and BVAR predictive models was 1, 2, and 3. Selection of the above number of lags is explained as follows: first, the principal components are rather volatile, and second, inclusion in the model of a larger number of lags may result in an over-identification of the model, which may affect the forecast accuracy. The results of the experiments using the recursive and moving schemes for all four countries are presented in Appendix 10.

Figure 14. Recursive and Moving Regression Algorithm

Recursive Scheme | **Moving Scheme**



Source: Rossi (2014).

According to the estimation results (see Appendix 10), the minimal value of the RMSFE indicator (by country) is achieved in the following cases:

- for Armenia: when the BVAR model is used (with 1 or 2 lags). Therefore, the BVAR model should be used to forecast the principal components.
- for Belarus: when the AR model is used. Therefore, it suggested that the AR model should be used to forecast the principal components.
- for Kyrgyzstan: when the VAR or BVAR model is used (with 1 or 2 lags). Inasmuch as both models have the same predictive power, we suggest that one of them should be used, namely, the BVAR model.
- for Tajikistan: when the AR model is used. It suggested that the AR model should be used to forecast the principal components.

It is important to note that such retrospective analyses should be performed on a regular basis, switching from one model to another if the RMSFE value changes.

The AR and BVAR models make it possible to produce accurate forecasts; however, to generate forecast distribution intervals, the Gibbs sampling algorithm should be used with those models. The algorithm where the AR model is used concurrently with Gibbs sampling is described in detail in Blake and Mumtaz (2017).

Therefore, an experiment where a retrospective forecast was generated for each economy under review was made before attempting a prospective forecast, where the AR and BVAR models are employed concurrently with Gibbs sampling. The main purpose of such a retrospective forecast is to check how the AR and BVAR models work on the actual data when used together with Gibbs sampling. The results of the experiment are presented in Appendix 11, where the charts show that in most cases the actual values of the principal components lie within the projected intervals. Therefore, if the algorithm where the AR/BVAR models are used with Gibbs sampling accurately forecasts the actual dynamics of the principal components on historical data, it is expedient to use the same method to forecast the principal components for the next 12 months. If extremal projected values of the principal components are inserted in the relevant models (signal approach, logit/probit models, the DMA), it is possible to produce the forecast of composite indicator dynamics. Then conclusions can be formulated regarding the probability of stress (a crisis) in the exchange market by comparing the values of the composite indicator and the threshold.

Conclusion

In this paper, we present the methodology and step-by-step algorithm for the development of tools that can be used to identify imbalances (crises) and stress situations in the economy. Taking into consideration the course of economic development in the countries under review and the economic upheavals that took place in Armenia, Belarus, Kyrgyzstan, and Tajikistan from January 2006 until the present time, the main emphasis was on tools for prompt detection of mounting pressure in the exchange market.

We generally used the best EWS development practices, from collection and primary processing of data and choice of data analysis methods for identification and selection of potential predictors of stress (crisis) phenomena, to development and selection of predictive models. In the course of our work on building the EWS, we used conventional approaches and data analysis methods, including the signal approach, or the leading indicators model, and the logit/probit models. To account for the uncertainty factor, we also resolved to include the DMA method in the list of tools used for analysis.

Based on the actual data for the four countries under review, and the findings of comparative analysis of predictive properties of the models under analysis, we demonstrated that the DMA reduces the number of false signals, and ensures a more robust response to predictor extremal values. Therefore, the DMA method, with its uncertainty accounting capability, is the preferred method for the development of EWS models that can be used to identify stresses (crises) in the exchange market. However, despite the evident advantages of the DMA method, it is suggested that the EWS toolset be complemented with the leading indicator models and the logit/probit models, which may offer not only an alternative estimation, but also additional information on the buildup of imbalances in the economy. That will make it possible to advance more robust arguments in the course of substantiation of the forecast and development of appropriate recommendations.

Development of the EWS implies constant analysis and search for additional variables which may be included in the list of predictors of emergence of stress situations in the financial market (in addition to, or as replacements for, some of the previously identified predictors). Furthermore, in the future the EWS model apparatus can be supplemented with new tools, such as machine learning algorithms.

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Appendix 1

Currency and Banking Crisis Definitions (Criteria)

Currency Crisis

Kaminsky and Reinhart (1999)	"Currency crisis" is defined as a situation where an assault on the exchange market leads to a steep devaluation of the domestic currency and/or a massive drop in international reserves. To measure the strength of the currency crisis, the authors propose to use the *exchange market pressure index*, which is computed as the average weighted monthly change in the exchange rate and the gross international reserves. A crisis is deemed to have occurred if the index diverges from its average value for a particular country by three standard deviations.
Laeven and Valencia (2008, 2013, 2018)	"Currency crisis" is defined as a situation where nominal depreciation of the domestic currency against the US dollar is at least 30%, and there is at least a 10% depreciation compared to the year before.
Reinhart and Rogoff (2011)	"Currency crisis" is defined as excessive devaluation of the exchange rate where annual devaluation against the US dollar or another currency peg (GBP, FRF, DM, EUR) exceeds the threshold of 15%.
Frankel and Rose (1996)	"Currency crisis" is defined as a 25% nominal annual devaluation of the domestic currency, provided that it also exceeds the average devaluation rate recorded over the last five years by 10%.
Cruz-Rodriguez (2011)	"Currency crisis" is defined as a 6%+ nominal quarterly devaluation of the domestic currency, provided that it also exceeds the devaluation rate recorded the year before by at least 10%.

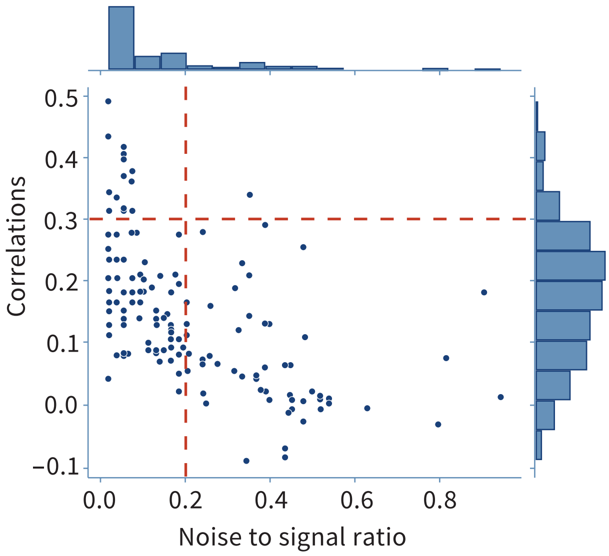
Banking Crisis

Kaminsky and Reinhart (1999)	Banking crises are defined by two types of events: (1) bank runs leading to closure, merger, or takeover by the government sector of one or more financial institutions; and (2) if there is no bank run, there is a closure, merger, takeover, or bailout of a critically important financial institution (or group of financial institutions) that triggers a series of similar events for other financial institutions.
Demirguc-Kunt and Detragiache (1998, 2005)	For financial stress to qualify as a full-scale banking crisis, one of the following conditions must be satisfied: (1) ratio of non-performing assets to total assets of the banking system exceeds 10%; (2) banking system support costs exceed 2% of GDP; (3) banking problems lead to nationalisation of more than 10% of the banking sector; (4) there is a massive withdrawal of bank deposits, to which the government responds by imposing deposit withdrawal limits or announcing bank holidays.
Laeven and Valencia (2008, 2013, 2018)	A banking crisis is deemed to be of systemic nature, if the following two conditions are satisfied: (1) significant bank runs, losses in the banking system, and/or bank liquidations; and (2) significant government policy interventions in response to significant losses in the banking sector. The first year when both conditions are satisfied is described as the year of commencement of the banking crisis. Government policy interventions in the banking sector are deemed significant, if at least three of the following six measures are used: (1) massive liquidity support; (2) bank restructuring costs; (3) significant bank nationalisations; (4) significant bank guarantees; (5) significant asset purchases; and (6) deposit freeze or bank holidays.
Reinhart and Rogoff (2008a, 2011)	Definition of the "banking crisis" is similar to that given by Kaminsky and Reinhart (1999).

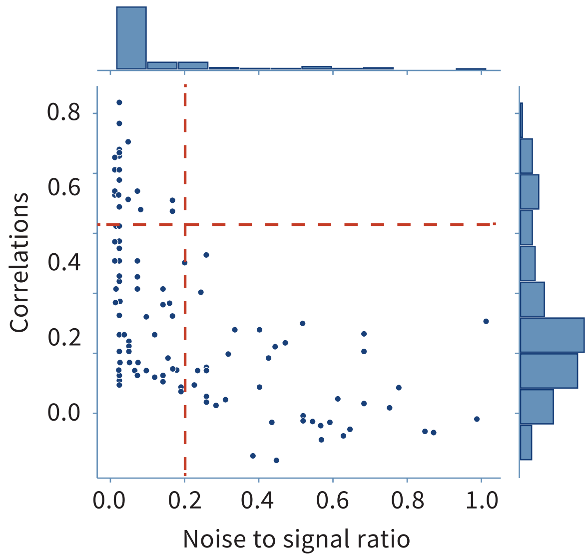
Appendix 2

Distribution of *NSR* Values and Coefficients of Correlation between Stress Periods and Lagging Signal Values

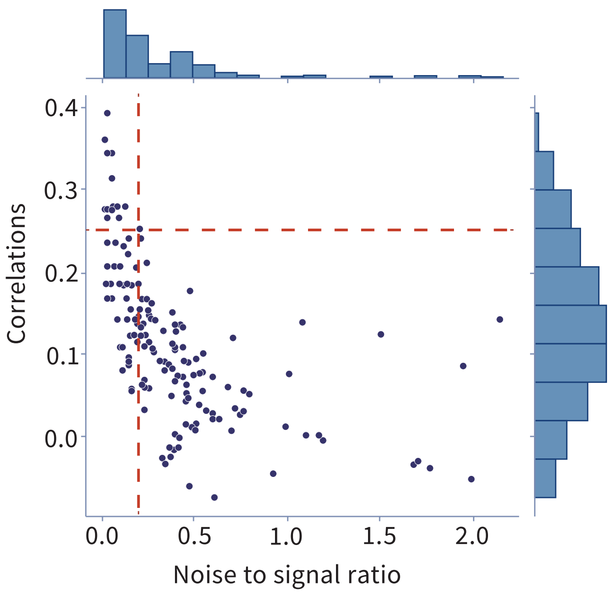
Armenia



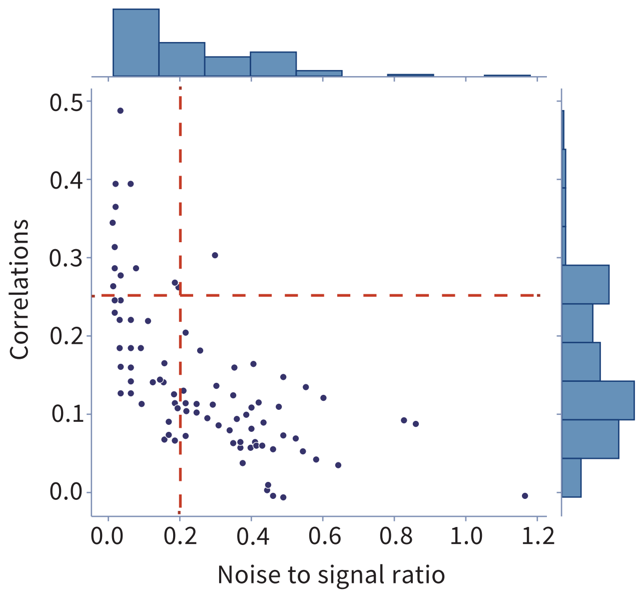
Belarus



Kyrgyzstan



Tajikistan



Appendix 3

Selected Potential Predictors of Stress (Crisis) in the Exchange Markets of Armenia, Belarus, Kyrgyzstan, and Tajikistan

Armenia: Potential Predictors

	Indicator	Abbreviated Form
1	Cash remittances to individual recipients from the Russian Federation through Armenian banks, USD	I1
2	Average exchange rate for the period, RUB/USD	I2
3	RUB nominal effective exchange rate index	I3
4	RUB real effective exchange rate index	I4
5	Demand deposits (domestic currency), AMD	I5
6	Monetary aggregate M2, USD equivalent	I6
7	Total resident deposits in commercial banks (EoP), AMD	I7
8	Resident demand deposits in commercial banks (domestic currency, EoP), AMD	I8
9	Corporate demand deposits in commercial banks (domestic currency, EoP), AMD	I9
10	Commercial bank loans to the trade sector (foreign currency, EoP), AMD	I10
11	Average deposit interest rate (maturity: <1 year; domestic currency), %	I11
12	Average deposit interest rate (maturity: 91–180 days; domestic currency), %	I12
13	Average deposit interest rate (maturity: 181–365 days; domestic currency), %	I13
14	Commodity price indices (2016 = 100), including fuel and non-fuel price indices	I14
15	Fuel (energy) price index (2005 = 100), including crude oil, natural gas, and coal price indices	I15
16	Dated Brent crude oil price, USD/bbl	I16
17	Dubai Fateh crude oil price, USD/bbl	I17
18	WTI crude oil price, USD/bbl	I18
19	Imports: plant-based food products, USD	I19
20	Imports: ready-to-eat food products, USD	I20
21	Imports: timber and timber products, USD	I21
22	Imports: articles of stone, plaster, and cement, USD	I22
23	Imports: machinery, equipment, and mechanisms, USD	I23

Belarus: Potential Predictors

	Indicator	Abbreviated Form
1	Wholesale trade, BYN	I1
2	Retail trade, BYN	I2
3	Term deposits of individuals (monthly average), BYN	I3
4	Transferable deposits of legal entities (monthly average), BYN	I4
5	Term deposits of individuals (monthly average), BYN	I5
6	Deposits of individuals (domestic currency, monthly average), BYN	I6
7	Total deposits of individuals (foreign currency, monthly average), BYN	I7
8	Deposits of legal entities (foreign currency, monthly average), BYN	I8
9	Deposits (domestic and foreign currency, monthly average), BYN	I9
10	Deposits of individuals (domestic and foreign currency, monthly average), BYN	I10
11	Ratio of cash in circulation to the GDP, %	I11
12	Deposits, state-owned commercial entities (foreign currency), BYN	I12
13	Private sector indebtedness under short-term loans (domestic currency), BYN	I13
14	Ratio of bank loans to the GDP, %	I14
15	Ratio of private sector bank loans to the GDP, %	I15
16	Change in ratio of private sector bank loans to the GDP over 2 years, p.p.	I16
17	Nominal interbank loans interest rate, %	I17
18	Interbank loans interest rate, % p.a., average per moving year	I18
19	Average nominal interest rate on new deposits of legal entities (domestic currency), %	I19
20	Average nominal interest rate on term deposits of legal entities (domestic currency), %	I20
21	Average nominal interest rate on new term deposits of individuals (domestic currency), %	I21
22	Average nominal interest rate on new term deposits of individuals (foreign currency), %	I22
23	Average nominal interest rate on new loans, excluding interbank loans (domestic currency), %	I23

Kyrgyzstan: Potential Predictors

	Indicator	Abbreviated Form
1	Average exchange rate for the period, RUB/USD	I1
2	RUB nominal effective exchange rate index	I2
3	RUB real effective exchange rate index	I3
4	Inflow of cash, individual remittances, USD	I4
5	Inflow of cash, individual remittances from the Russian Federation, USD	I5
6	Total demand deposits of individuals, KGS	I6
7	Total demand deposits (foreign currency), KGS	I7
8	Total corporate deposits (maturity: <1 month) (foreign currency), KGS	I8
9	Total deposits of individuals (maturity: 1–3 months) (foreign currency), KGS	I9
10	Total deposits of individuals (maturity: 6–12 months) (domestic currency), KGS	I10
11	Total corporate deposits (maturity: 6–12 months) (foreign currency), KGS	I11
12	Ratio of total commercial bank loans (foreign currency) (KGS), to seasonally adjusted GDP	I12
13	Ratio of total commercial bank loans (domestic and foreign currency) to total deposits	I13
14	Total commercial bank loans (foreign currency), KGS	I14
15	Total short-term commercial bank loans (domestic currency), KGS	I15
16	Total commercial bank loans (foreign currency, maturity: 1–3 months), KGS	I16
17	Average-weighted interest rate on commercial bank deposits (EoP), %	I17
18	Average-weighted interest rate on deposits of individuals (maturity: 1–3 months), %	I18
19	Average-weighted interest rate on deposits of individuals (maturity: 6–12 months), %	I19
20	Average-weighted interest rate on corporate demand deposits, %	I20
21	Average-weighted interest rate on corporate deposits (maturity: 1–3 months), %	I21
22	Average-weighted interest rate on commercial bank loans (domestic currency; maturity: <1 month), %	I22
23	Natural gas price, USD/MBTU	I23
24	Russian natural gas price in the global market, USD/MBTU	I24

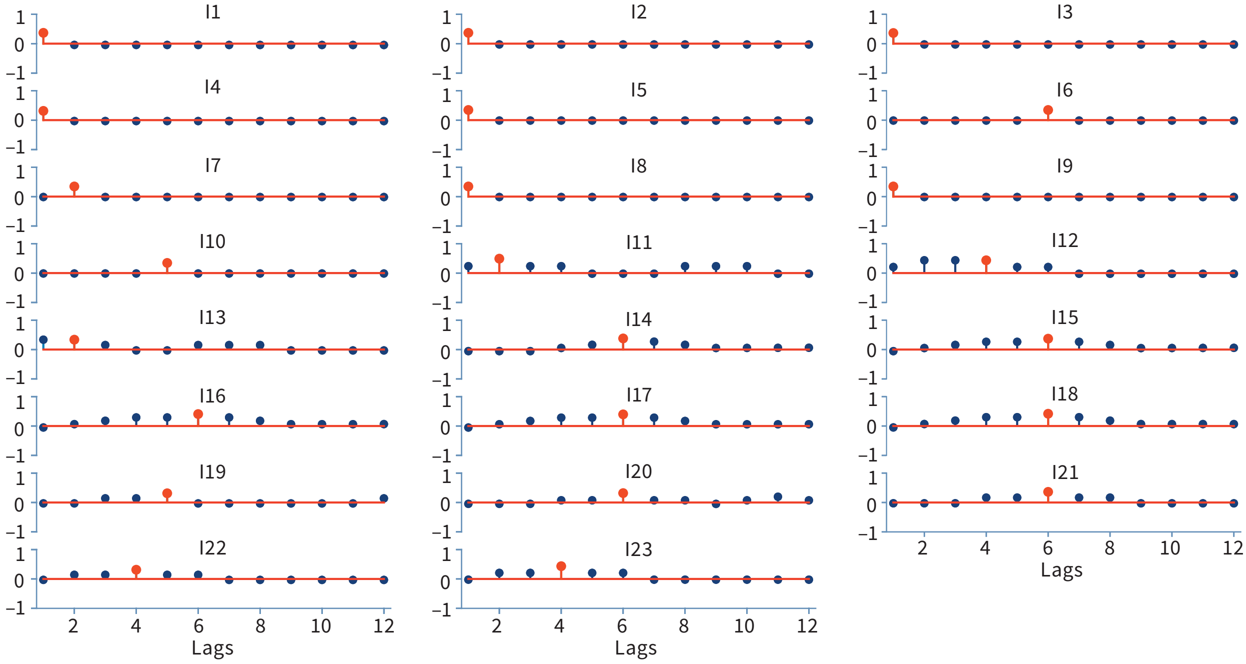
Tajikistan: Potential Predictors

	Indicator	Abbreviated Form
1	Total exports, USD	I1
2	Consumer price index, %	I2
3	Gasoline price index, %	I3
4	Corporate deposits (domestic currency), TJS	I4
5	Corporate demand deposits (domestic currency), TJS	I5
6	Corporate deposits (maturity: 3–6 months; domestic currency), TJS	I6
7	Other corporate deposits (domestic currency), TJS	I7
8	Total corporate demand deposits (foreign currency), TJS	I8
9	Individual deposits (maturity: 1–3 months; foreign currency), TJS	I9
10	Total credit exposure of the banking system (EoP), TJS	I10
11	Average-weighted interest rates on all deposits (foreign currency), %	I11
12	Average-weighted interest rates on savings deposits (foreign currency), %	I12
13	Average-weighted interest rates on all loans (foreign currency), %	I13
14	Average-weighted interest rates on term loans (foreign currency), %	I14
15	Average exchange rate for the period, RUB/USD	I15
16	RUB nominal effective exchange rate index	I16
17	RUB real effective exchange rate index	I17
18	Gold price, USD/ozt	I18
19	Zinc price, USD/MT	I19
20	Lead price, USD/MT	I20
21	Agricultural raw materials price index (2005 = 100), including timber, cotton, wool, rubber, and leather price indices	I21
22	Compensation of employees (primary income, BoP current account), USD	I22
23	Average exchange rate for the period, KZT/USD	I23
24	Ratio of domestic loans to the GDP	I24

Appendix 4

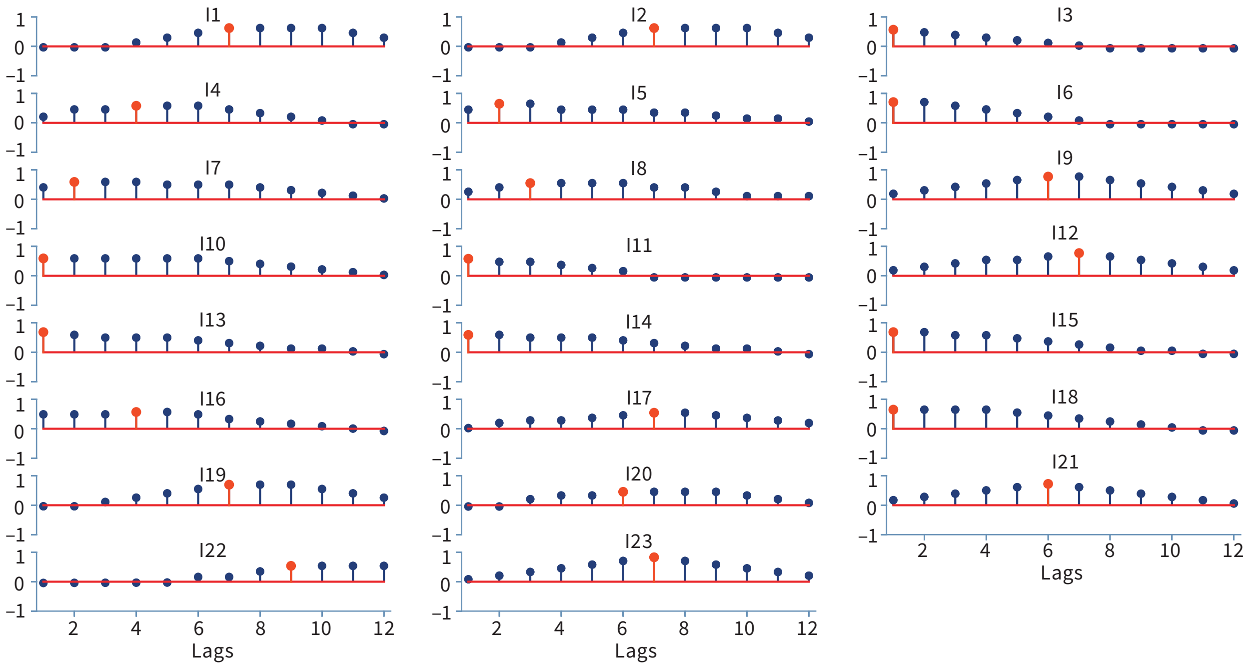
Cross-Correlational Dependencies between Signals and Actual Stress Periods

Armenia

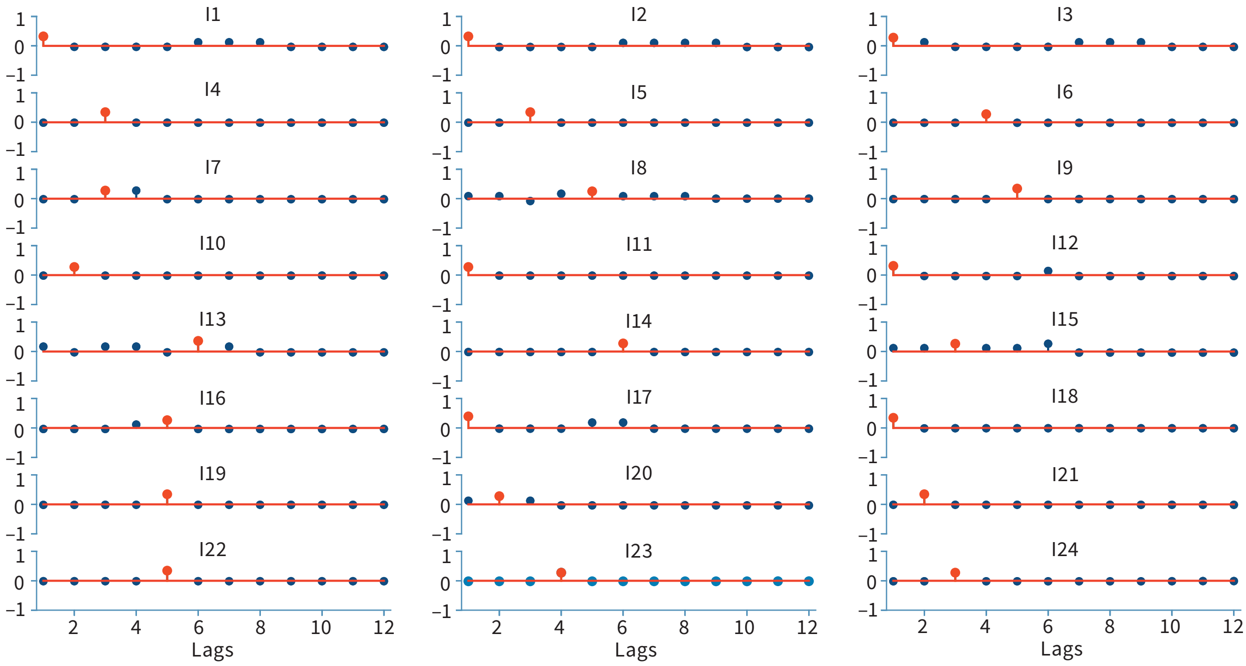


Note: Here and below, the lag with the highest correlation between the signal and stress periods is marked in red.

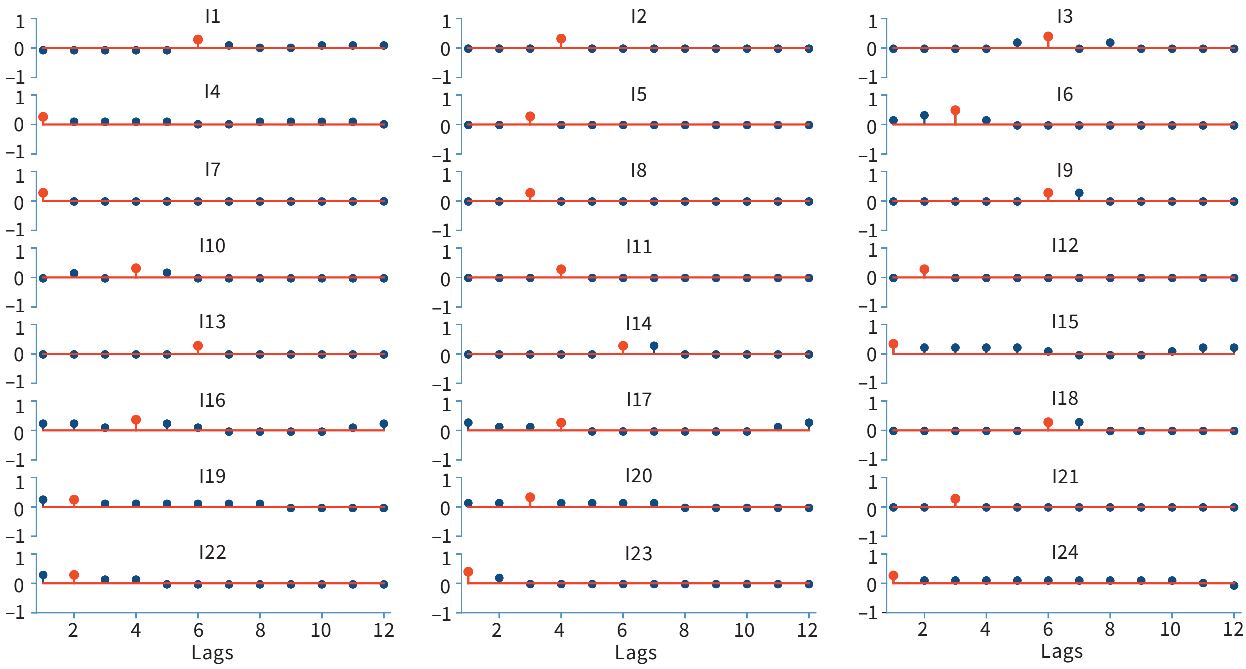
Belarus



Kyrgyzstan



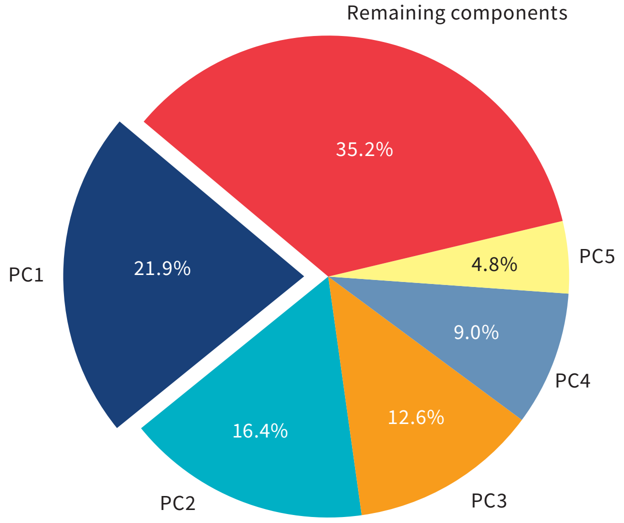
Tajikistan



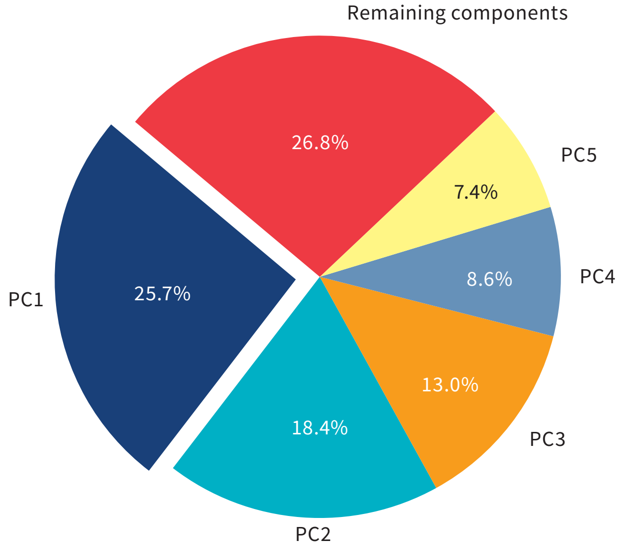
Appendix 5

Shares of Variance of Highlighted Principal Components in Total Variance of Initial Indicators

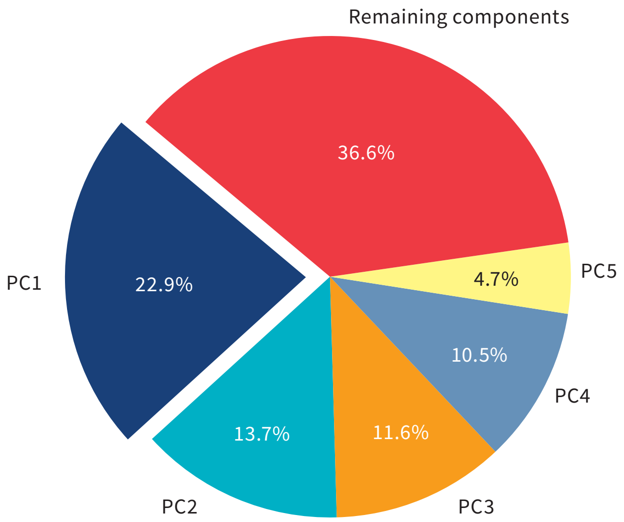
Armenia



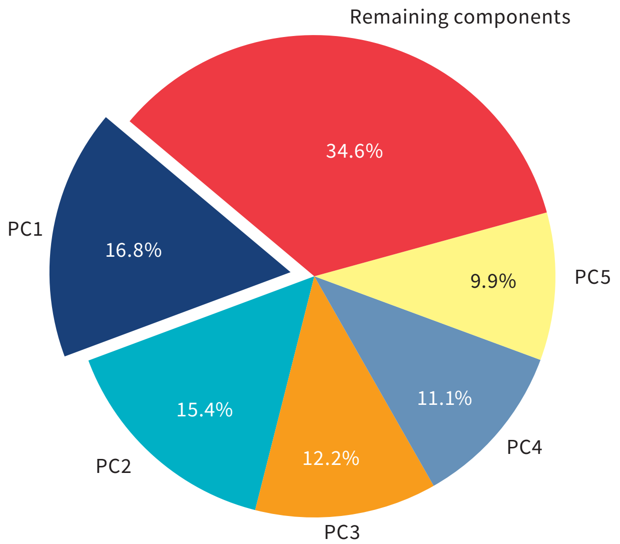
Belarus



Kyrgyzstan



Tajikistan

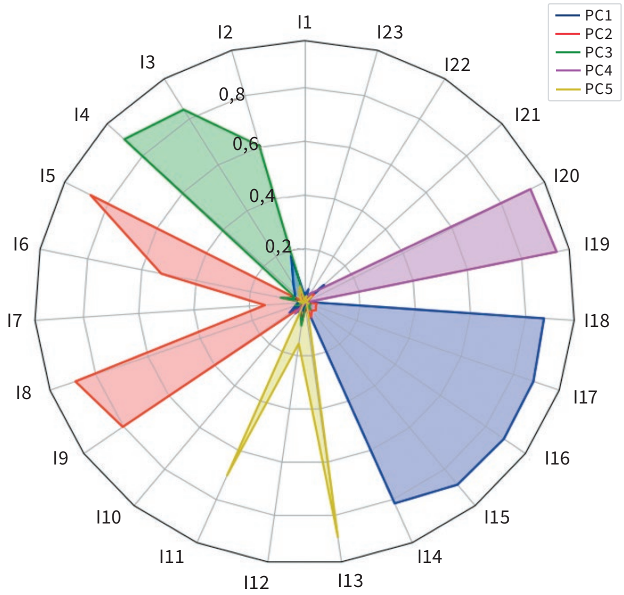


Note: Here, “PC” stands for “principal component”, while the figure following the letters “PC” indicates the number of the highlighted principal component. For example, for Armenia “PC1” is the first principal component which explains 21.9% of total variance of all selected predictors.

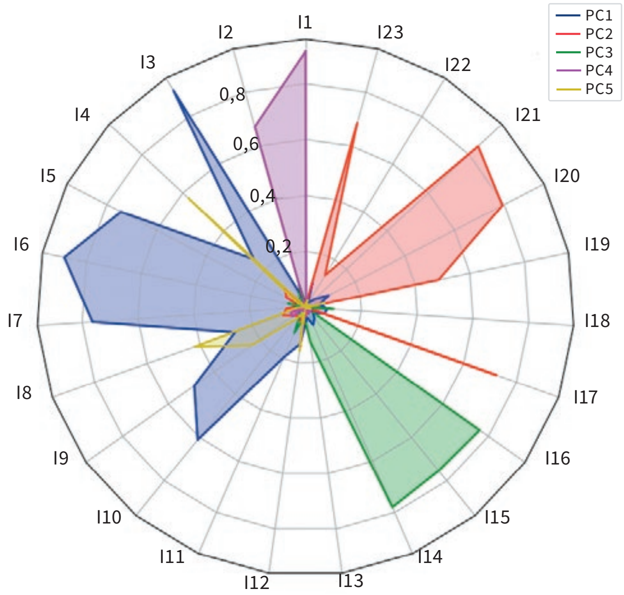
Appendix 6

Structure of Highlighted Principal Components

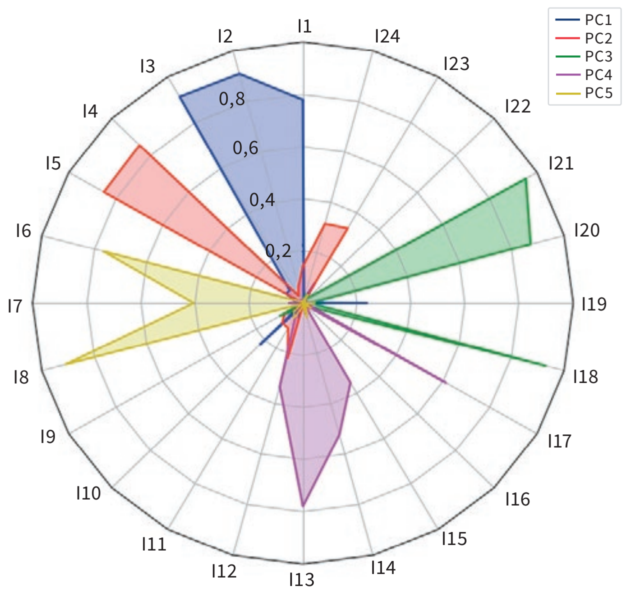
Armenia



Belarus



Kyrgyzstan



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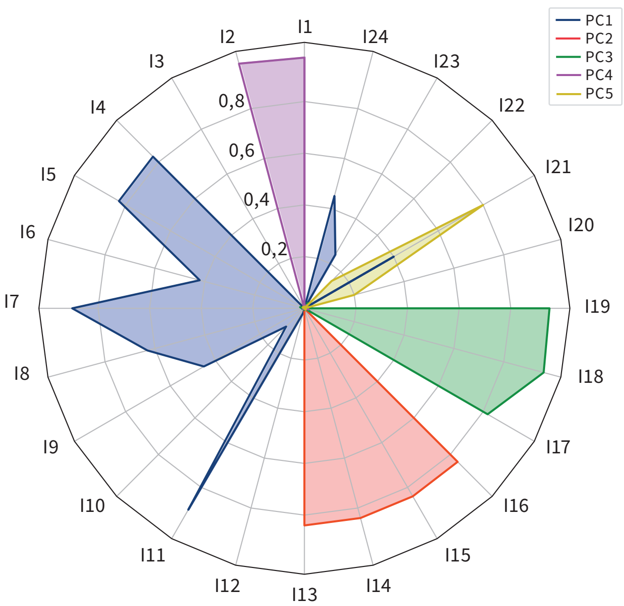


Note: Here, the charts show the shares of predictors in the variance of principal components. For example, for the first principal component for Armenia (highlighted in blue), the largest share in total variance is recorded for the predictors P14, P15, P16, P17, and P18, which are related to global price indicators. The other principal components can be explained in a similar way.

Appendix 7

Estimation Outcomes for Logit/Probit Models

Armenia

	Logit
PC1(-3)	0.354**
	(0.133)
PC2(-1)	-0.320**
	(0.165)
PC3(-2)	-0.221
	(0.309)
PC4(-2)	0.630**
	(0.331)
PC5(-2)	-1.207**
	(0.520)
Const.	-6.690***
	(1.623)
Number of obs.	204
LR chi2(5)	20.00
Prob > chi2	0.0013
Pseudo R2	0.4258

	Probit
PC1(-3)	0.147**
	(0.057)
PC2(-1)	-0.122**
	(0.073)
PC3(-2)	-0.100
	(0.139)
PC4(-2)	0.262**
	(0.157)
PC5(-2)	-0.486**
	(0.217)
Const.	-3.035***
	(0.547)
Number of obs.	204
LR chi2(5)	18.25
Prob > chi2	0.0027
Pseudo R2	0.3885

*, **, and *** indicate statistical significance at the level of 10%, 5%, and 1%, respectively. Standard deviations are shown in parentheses.

Belarus

	Logit
PC1(-3)	-0.266*
	(0.167)
PC2(-3)	-0.167
	(0.160)
PC3(-2)	0.423***
	(0.161)
PC4(-1)	-0.681***
	(0.259)
PC5(-1)	-0.420**
	(0.194)
Const.	-4.222***
	(0.640)
Number of obs.	207
LR chi2(5)	26.52
Prob > chi2	0.0001
Pseudo R2	0.3582

	Probit
PC1(-3)	-0.117
	(0.077)
PC2(-3)	-0.070
	(0.071)
PC3(-2)	0.199
	(0.076)
PC4(-1)	-0.331***
	(0.119)
PC5(-1)	-0.235**
	(0.103)
Const.	-2.207***
	(0.261)
Number of obs.	207
LR chi2(5)	26.88
Prob > chi2	0.0001
Pseudo R2	0.363

*, **, and *** indicate statistical significance at the level of 10%, 5%, and 1%, respectively. Standard deviations are shown in parentheses.

Kyrgyzstan

	Logit		Probit
PC1(-1)	-0.174**	**PC1(-1)**	-0.094
	(0.091)		(0.050)
PC2(-2)	-0.617**	**PC2(-2)**	-0.301
	(0.282)		(0.147)
PC3(-3)	-0.587**	**PC3(-3)**	-0.296
	(0.314)		(0.163)
PC4(-2)	-0.279	**PC4(-2)**	-0.127
	(0.315)		(0.164)
PC5(-4)	-0.532	**PC5(-4)**	-0.272
	(0.600)		(0.306)
Const.	-6.325***	**Const.**	-3.307
	(1.672)		(0.857)
Number of obs.	206	Number of obs.	206
LR chi2(5)	16.2	LR chi2(5)	16.93
Prob > chi2	0.0063	Prob > chi2	0.0046
Pseudo R2	0.3443	Pseudo R2	0.3597

*, **, and *** indicate statistical significance at the level of 10%, 5%, and 1%, respectively. Standard deviations are shown in parentheses.

Tajikistan

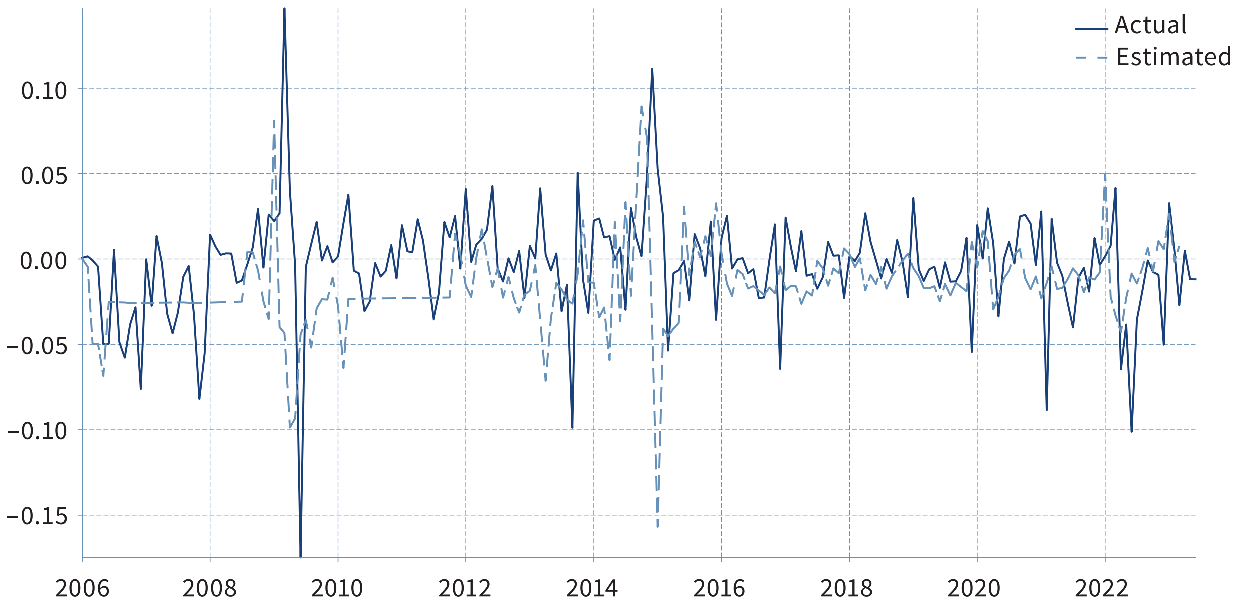
	Logit		Probit
PC1(-2)	-0.736**	**PC1(-2)**	-0.252
	(0.407)		(0.178)
PC2(-4)	-0.434**	**PC2(-4)**	-0.159**
	(0.226)		(0.091)
PC3(-2)	-0.451**	**PC3(-2)**	-0.221**
	(0.185)		(0.089)
PC4(-3)	0.532	**PC4(-3)**	0.150
	(0.388)		(0.152)
PC5(-3)	-0.476	**PC5(-3)**	-0.173
	(0.399)		(0.183)
Const.	-6.610***	**Const.**	-2.982***
	(1.683)		(0.555)
Number of obs.	206	Number of obs.	206
LR chi2(5)	20.83	LR chi2(5)	19.6
Prob > chi2	0.0009	Prob > chi2	0.0015
Pseudo R2	0.4427	Pseudo R2	0.4164

*, **, and *** indicate statistical significance at the level of 10%, 5%, and 1%, respectively. Standard deviations are shown in parentheses.

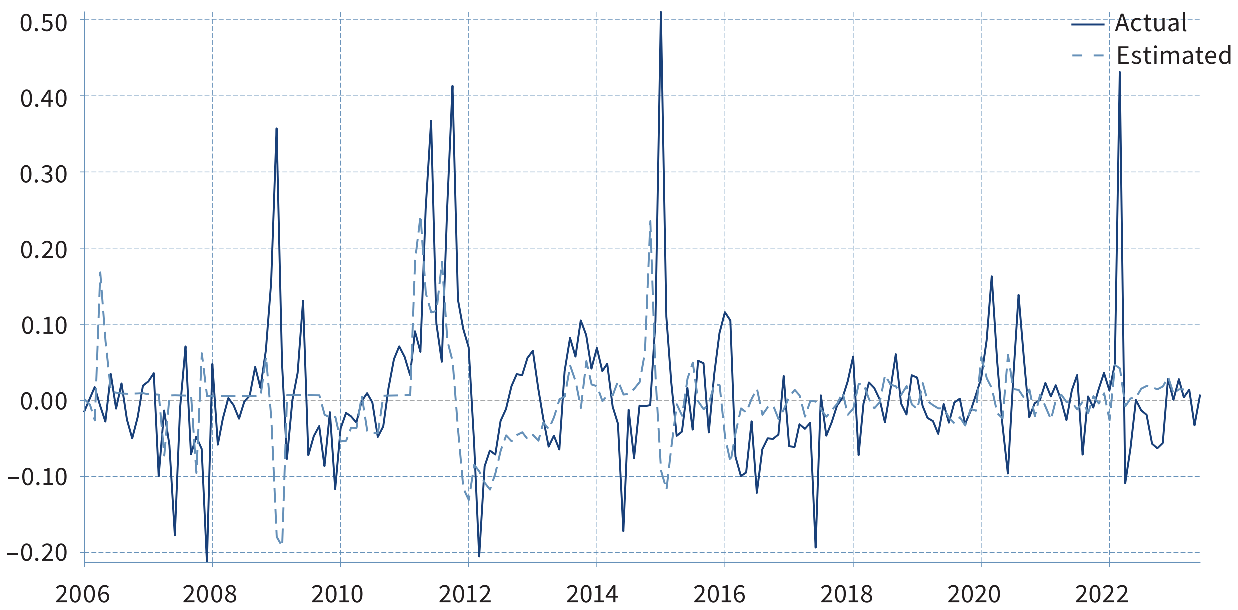
Appendix 8

Actual and DMA-Estimated Dynamics of the Exchange Market Pressure Index (*empi*)

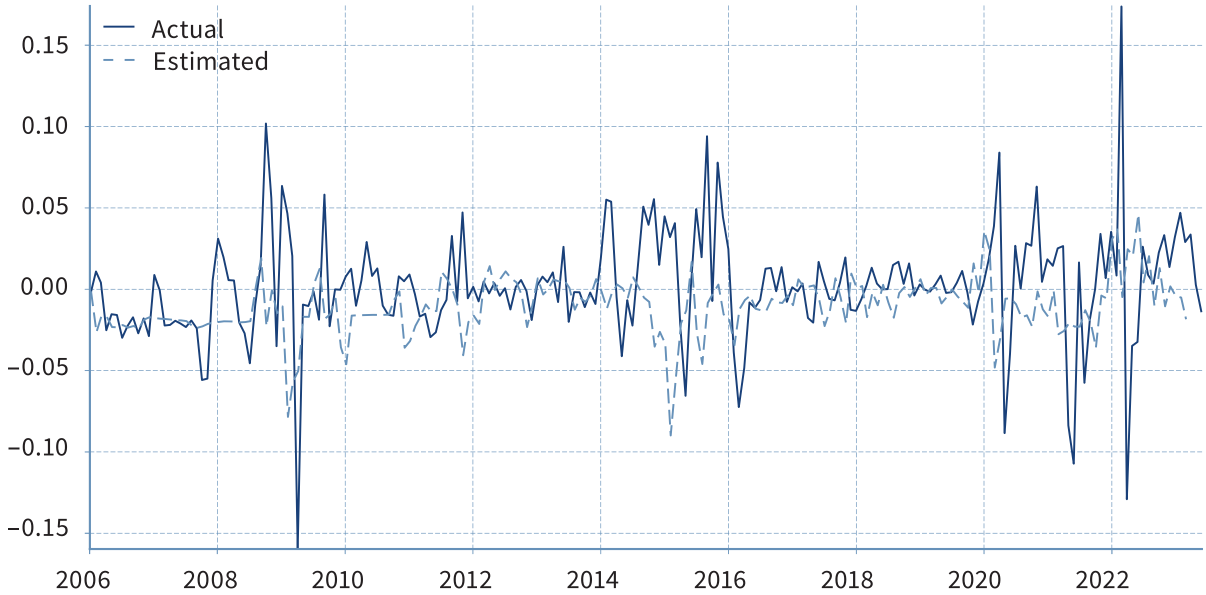
Armenia



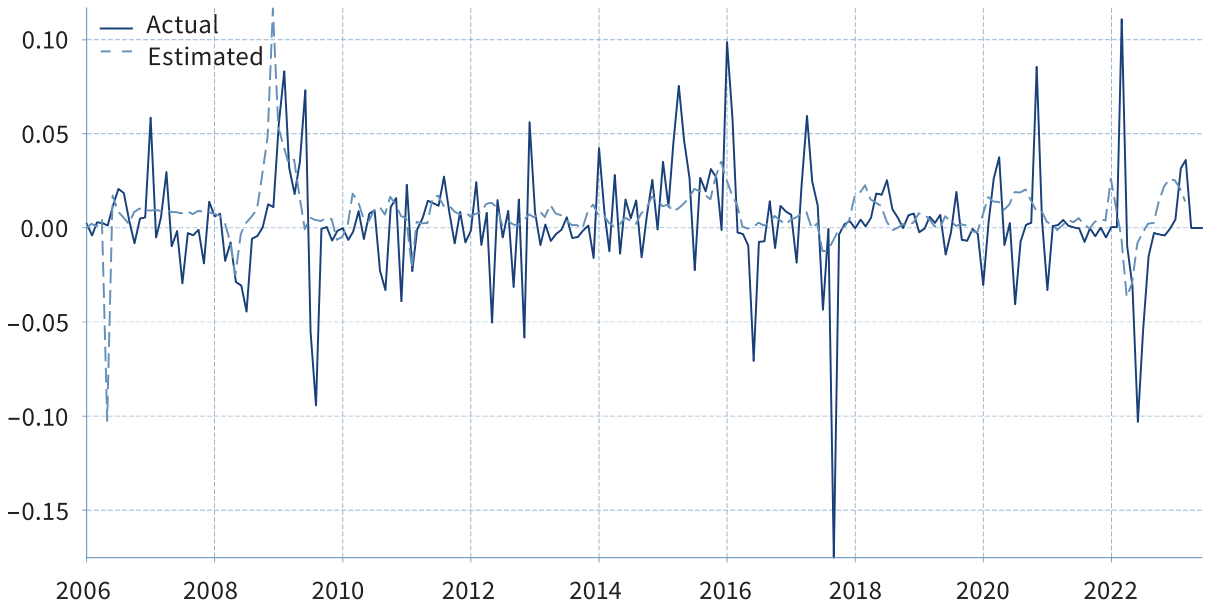
Belarus



Kyrgyzstan



Tajikistan

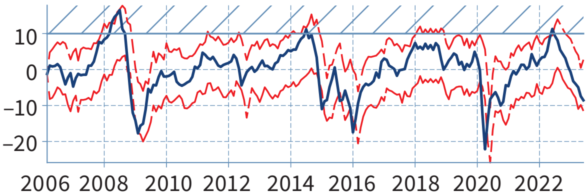


Appendix 9

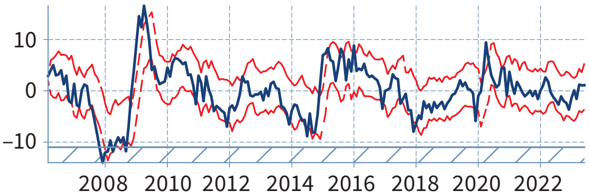
Bootstrap-Estimated Principal Component Intervals

Armenia

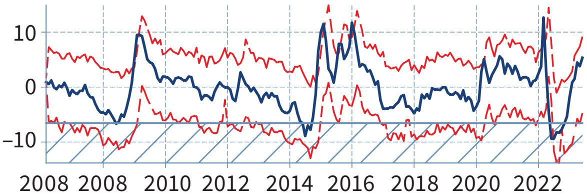
Principal component 1



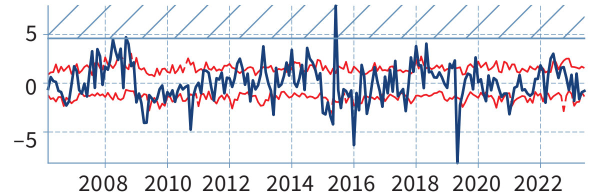
Principal component 2



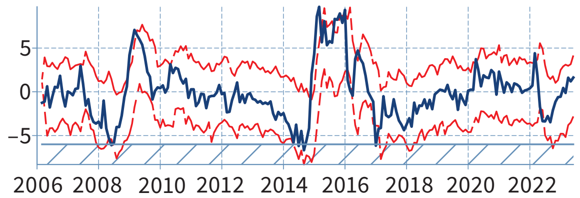
Principal component 3



Principal component 4

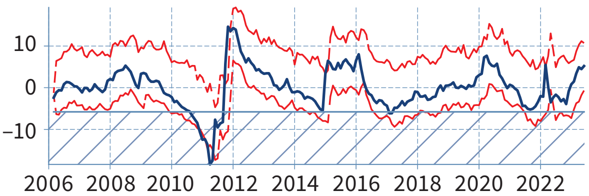


Principal component 5

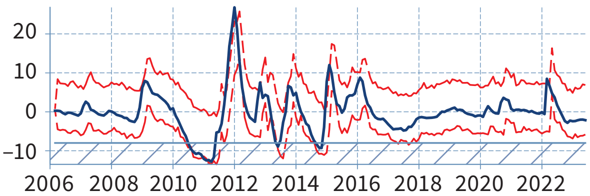


Belarus

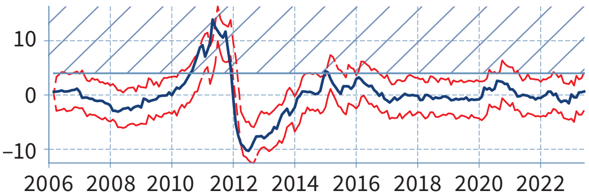
Principal component 1



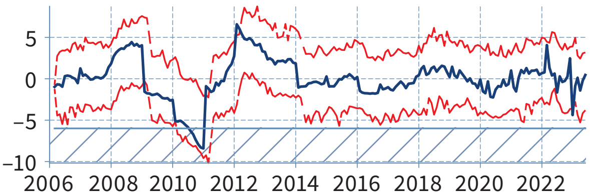
Principal component 2



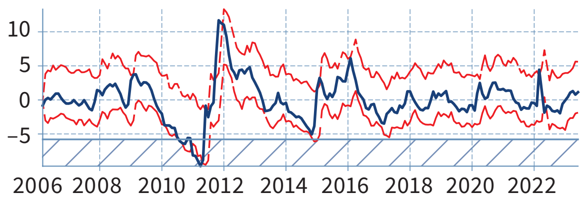
Principal component 3



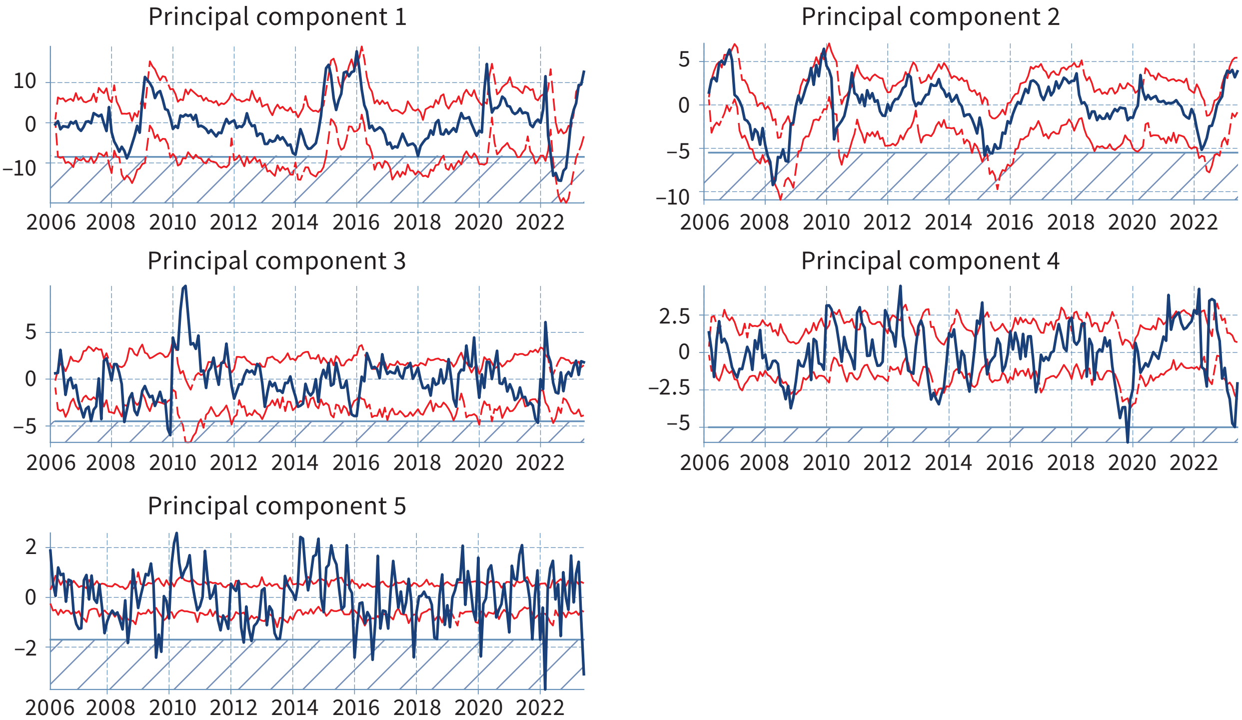
Principal component 4



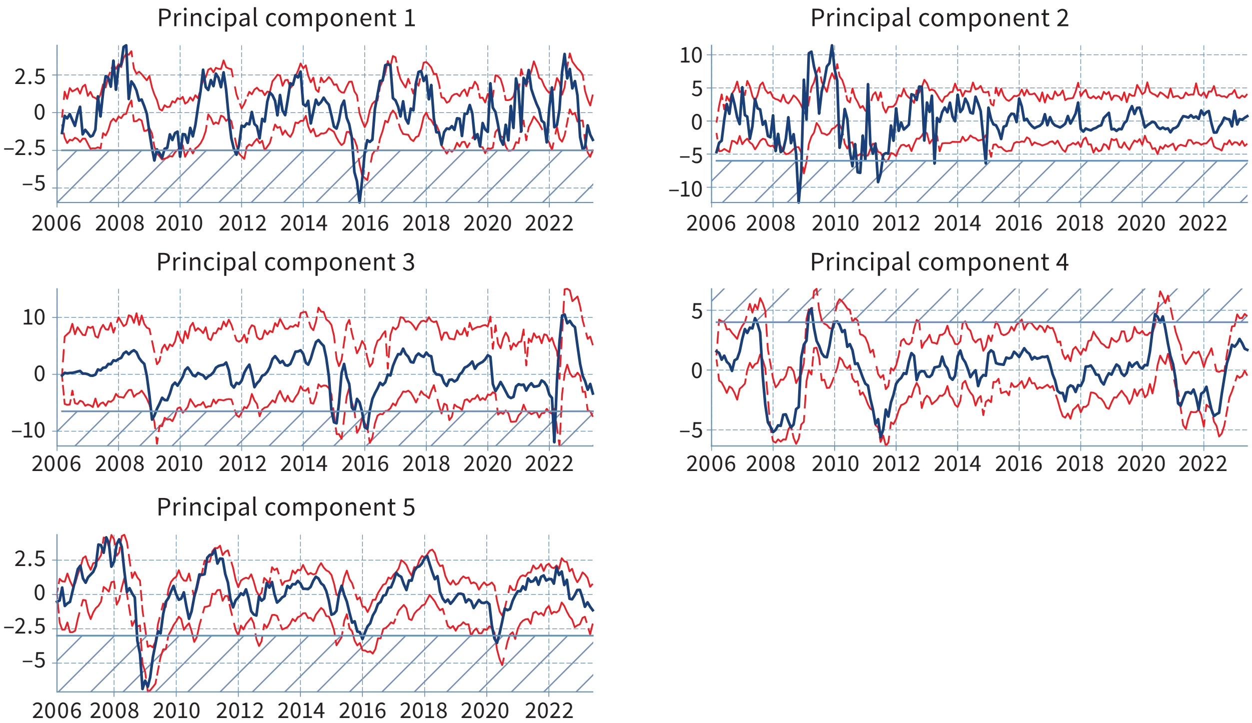
Principal component 5



Kyrgyzstan



Tajikistan



Appendix 10

Retrospective Analysis of Forecasts Using the Recursive and Moving Regression Experiment Schemes

Armenia

RMSFE Results[3] under Recursive Regression Scheme

		PC1	PC2	PC3	PC4	PC5
1 lag	AR	3.003	2.185	2.679	1.865	3.285
	VAR	3.015	2.151	2.678	1.878	2.844
	BVAR (w = 0.3, d = 1)	2.987	2.144	***1.693***	***1.421***	***1.857***
2 lags	AR	2.807	2.195	2.684	1.899	3.258
	VAR	2.844	***2.131***	2.792	1.907	2.953
	BVAR (w = 0.3, d = 1)	***2.765***	2.135	2.629	1.866	2.882
3 lags	AR	2.887	2.228	2.713	1.941	3.266
	VAR	3.078	2.513	2.943	2.086	3.098
	BVAR (w = 0.3, d = 1)	2.880	2.257	2.750	1.975	2.916

RMSFE Results under Moving Regression Scheme

		PC1	PC2	PC3	PC4	PC5
1 lag	AR	3.003	2.178	2.679	***1.868***	3.289
	VAR	3.043	2.217	2.758	1.979	2.877
	BVAR (w = 0.3, d = 1)	3.026	***2.157***	2.704	1.902	***2.871***
2 lags	AR	2.816	2.199	2.691	1.935	3.263
	VAR	2.854	2.255	2.956	2.088	3.043
	BVAR (w = 0.3, d = 1)	***2.788***	2.165	***2.690***	1.938	2.911
3 lags	AR	2.908	2.236	2.719	1.979	3.275
	VAR	3.139	2.648	3.082	2.308	3.261
	BVAR (w = 0.3, d = 1)	2.887	2.269	2.770	2.095	2.948

[3] Root Mean Square Forecast Error.

Belarus

RMSFE Results under Recursive Regression Scheme

		PC1	PC2	PC3	PC4	PC5
1 lag	AR	***1.979***	***1.499***	***1.388***	1.228	1.048
	VAR	2.157	1.631	1.429	1.242	1.160
	BVAR (w = 0.3, d = 1)	2.121	1.590	1.427	1.244	1.127
2 lags	AR	2.038	1.824	1.604	1.200	1.104
	VAR	2.251	1.961	1.556	1.260	1.345
	BVAR (w = 0.3, d = 1)	2.090	1.693	1.441	1.234	1.130
3 lags	AR	2.062	1.816	1.497	***1.198***	1.109
	VAR	2.502	2.196	1.556	1.217	1.474
	BVAR (w = 0.3, d = 1)	2.085	1.665	1.438	1.246	1.130

RMSFE Results under Moving Regression Scheme

		PC1	PC2	PC3	PC4	PC5
1 lag	AR	***2.005***	***1.482***	***1.382***	1.180	***1.043***
	VAR	2.154	1.679	1.463	1.133	1.119
	BVAR (w = 0.3, d = 1)	2.111	1.588	1.435	1.201	1.092
2 lags	AR	2.044	1.783	1.574	1.129	1.096
	VAR	2.160	1.991	1.522	1.199	1.299
	BVAR (w = 0.3, d = 1)	2.070	1.692	1.440	1.199	1.089
3 lags	AR	2.050	1.751	1.474	***1.088***	1.102
	VAR	2.431	2.247	1.519	1.141	1.438
	BVAR (w = 0.3, d = 1)	2.063	1.650	1.410	1.202	1.099

Kyrgyzstan

RMSFE Results under Recursive Regression Scheme

		PC1	PC2	PC3	PC4	PC5
1 lag	AR	2.968	3.570	0.842	1.456	0.833
	VAR	2.883	***3.467***	0.833	1.477	0.819
	BVAR (w = 0.3, d = 1)	2.859	3.481	0.803	1.468	0.816
2 lags	AR	2.741	3.768	0.752	1.454	0.822
	VAR	2.837	3.685	0.786	***1.436***	0.822
	BVAR (w = 0.3, d = 1)	***2.723***	3.558	***0.747***	1.456	***0.795***
3 lags	AR	2.785	3.818	0.758	1.450	0.817
	VAR	2.957	3.678	0.829	1.512	0.857
	BVAR (w = 0.3, d = 1)	2.804	3.566	0.791	1.489	0.825

RMSFE Results under Moving Regression Scheme

		PC1	PC2	PC3	PC4	PC5
1 lag	AR	2.983	3.576	0.839	***1.472***	0.833
	VAR	3.045	***3.415***	0.897	1.537	0.822
	BVAR (w = 0.3, d = 1)	2.984	3.430	0.825	1.491	0.820
2 lags	AR	2.802	3.769	***0.754***	1.484	0.822
	VAR	2.968	3.518	0.840	1.508	0.839
	BVAR (w = 0.3, d = 1)	2.829	3.432	0.789	1.498	***0.797***
3 lags	AR	***2.787***	3.823	0.773	1.481	0.816
	VAR	2.886	3.647	0.804	1.677	0.853
	BVAR (w = 0.3, d = 1)	2.855	3.485	0.834	1.581	0.814

Tajikistan

RMSFE Results under Recursive Regression Scheme

		PC1	PC2	PC3	PC4	PC5
1 lag	AR	***0.935***	***1.511***	***2.219***	1.553	0.827
	VAR	1.115	1.536	2.240	***1.512***	0.855
	BVAR (w = 0.3, d = 1)	1.061	1.517	2.234	1.522	***0.825***
2 lags	AR	***0.949***	***1.509***	2.204	1.555	***0.745***
	VAR	1.184	1.542	2.204	1.560	0.801
	BVAR (w = 0.3, d = 1)	1.066	1.513	***2.138***	***1.530***	0.791
3 lags	AR	***0.949***	***1.511***	2.258	1.559	***0.730***
	VAR	1.270	1.574	2.274	1.567	0.816
	BVAR (w = 0.3, d = 1)	1.091	1.514	***2.133***	***1.530***	0.792

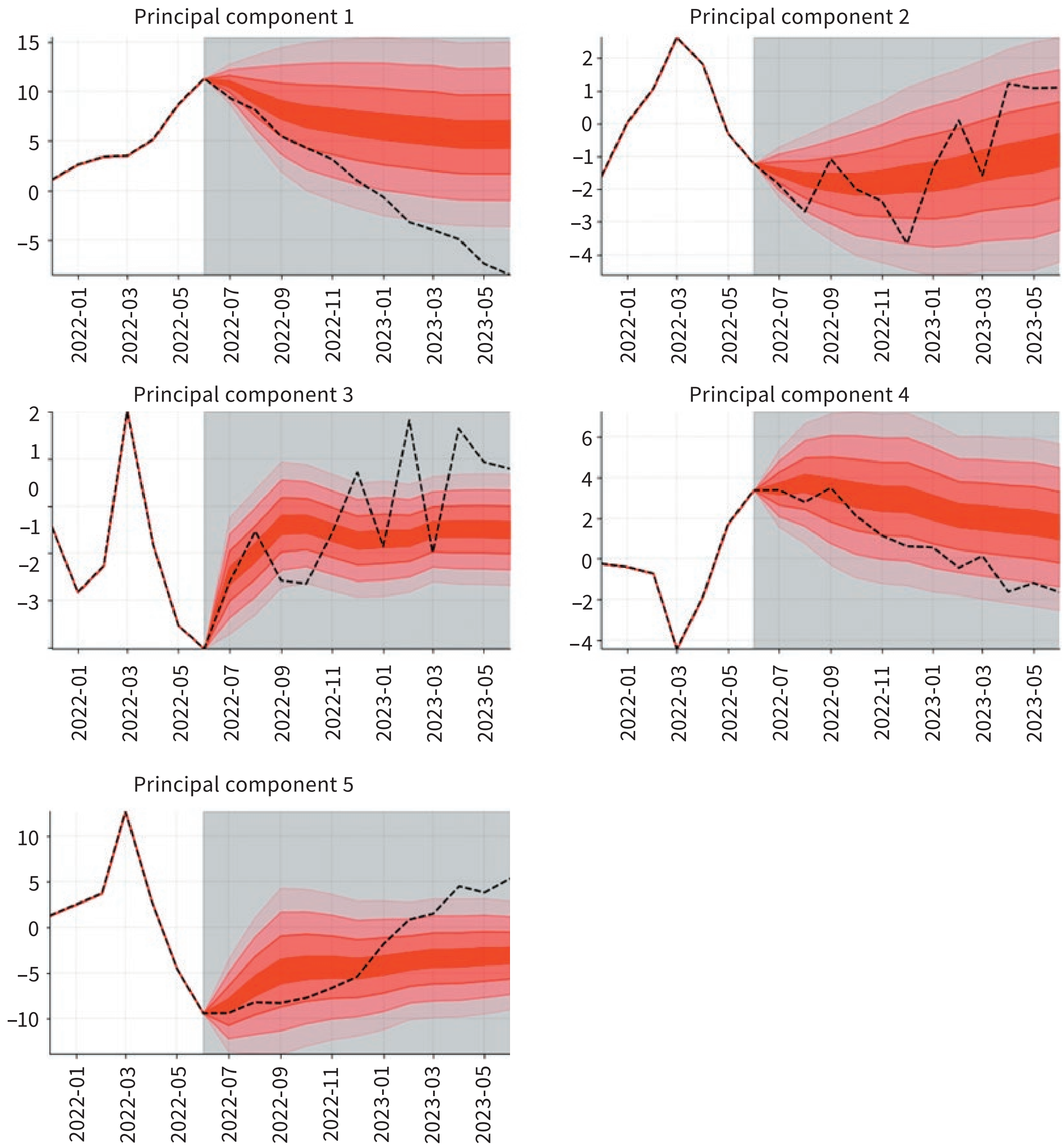
RMSFE Results under Moving Regression Scheme

		PC1	PC2	PC3	PC4	PC5
1 lag	AR	***0.935***	***1.508***	***2.222***	1.548	0.816
	VAR	1.193	1.545	2.246	***1.471***	0.848
	BVAR (w = 0.3, d = 1)	1.091	1.525	2.238	1.487	***0.809***
2 lags	AR	***0.949***	***1.498***	2.215	1.549	***0.737***
	VAR	1.313	1.546	2.233	1.530	0.796
	BVAR (w = 0.3, d = 1)	1.102	1.519	***2.149***	***1.489***	0.778
3 lags	AR	***0.950***	***1.503***	2.283	1.555	***0.729***
	VAR	1.451	1.597	2.322	1.560	0.817
	BVAR (w = 0.3, d = 1)	1.124	1.517	***2.147***	***1.491***	0.778

Appendix 11

Retrospective Forecast Generation Experiment Results: Use of AR and BVAR Models with Gibbs Sampling

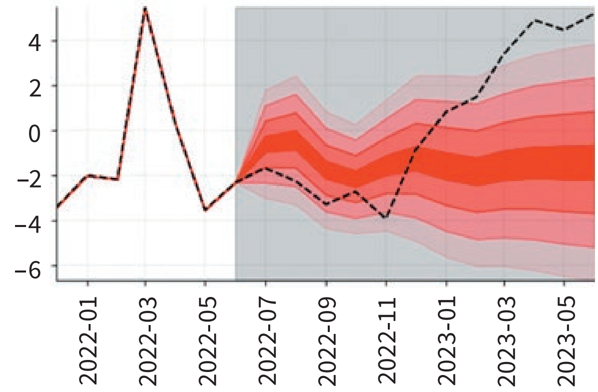
Armenia (BVAR model)



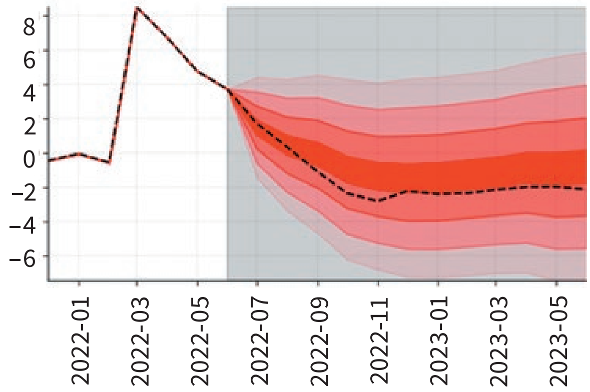
Note: Here and below, the red fan represents the intervals in which the forecast values may fall. The lighter the red band, the lower the probability that the forecast will fall into the given interval. The lower and upper boundaries of the intervals correspond to the 2.5% and 97.5% percentiles of standard normal distribution. The black dashed line shows the actual dynamics of the principal components.

Belarus (AR Model)

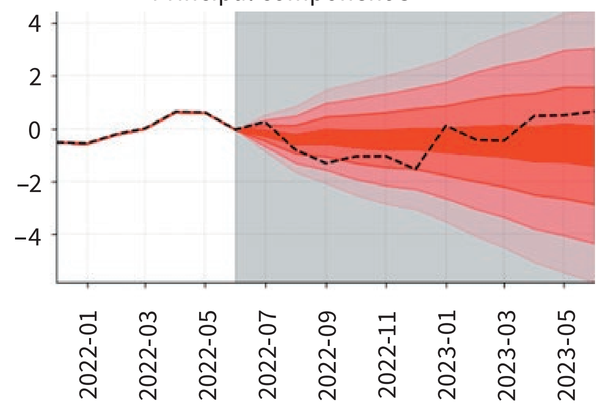
Principal component 1



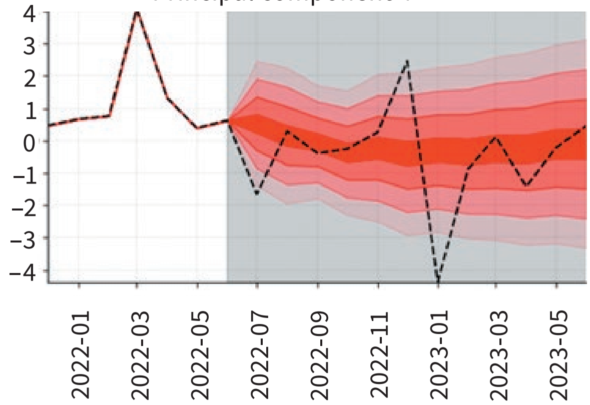
Principal component 2



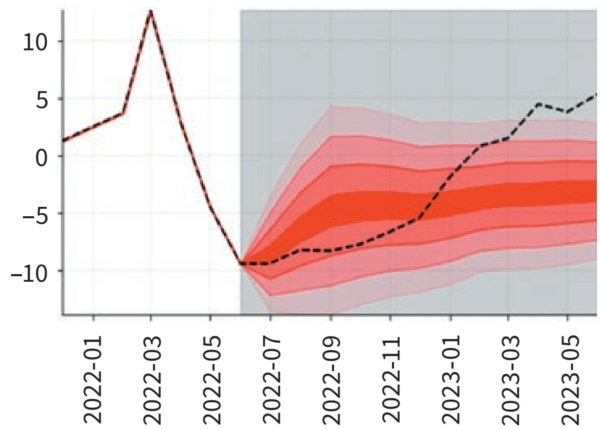
Principal component 3



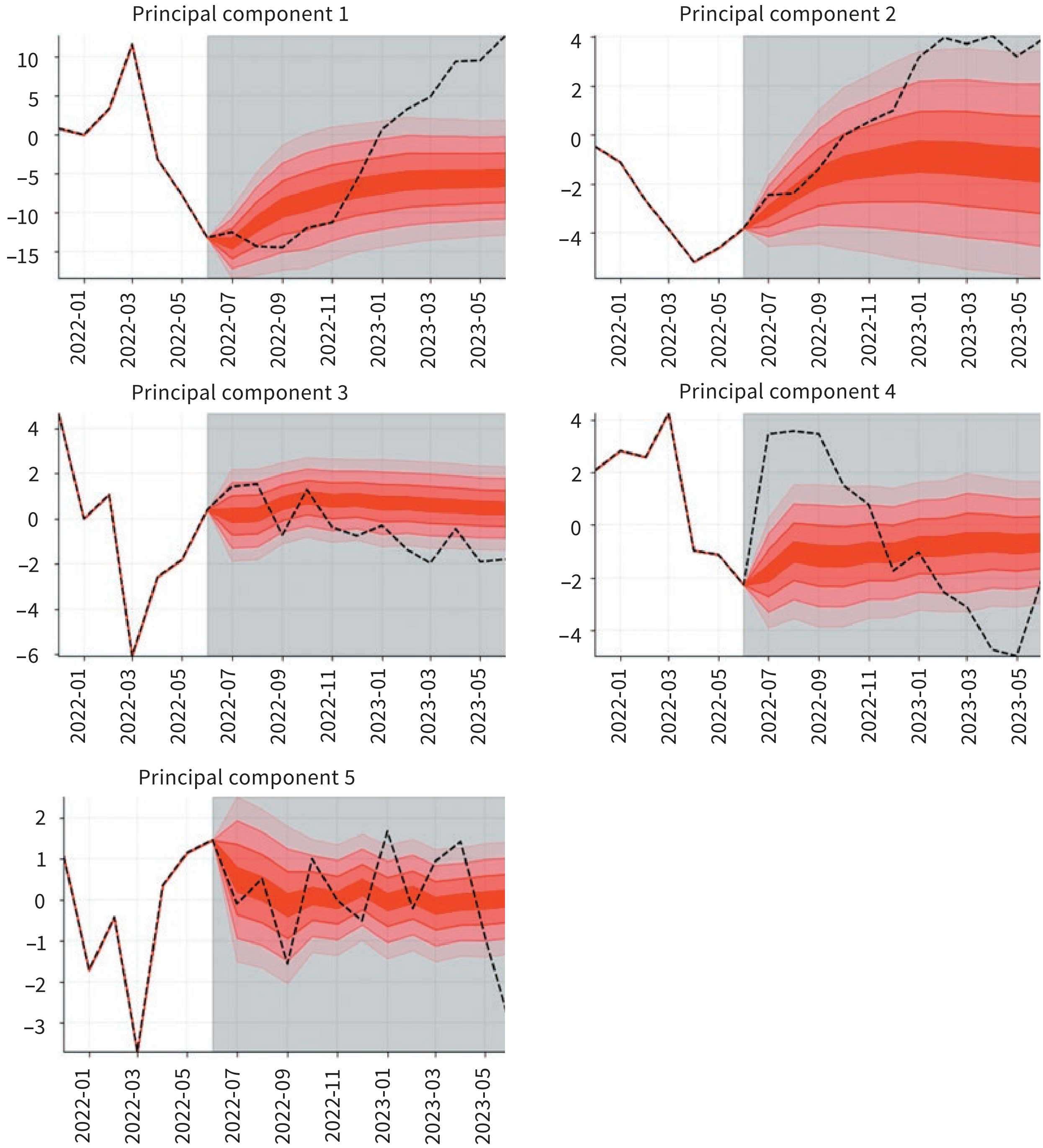
Principal component 4



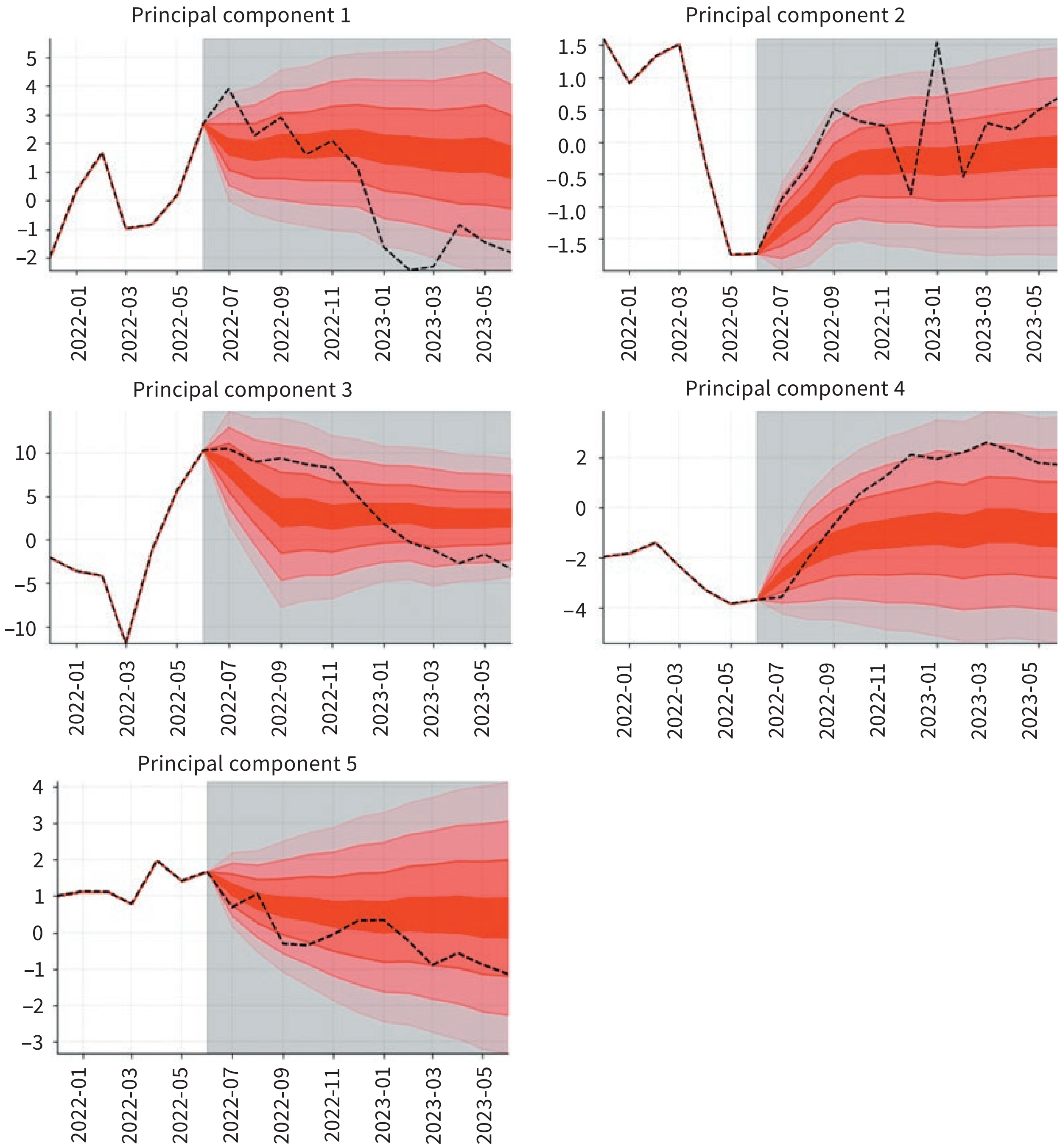
Principal component 5



Kyrgyzstan (BVAR model)



Tajikistan (AR Model)



Working paper WP/24/3
(RU/EN)

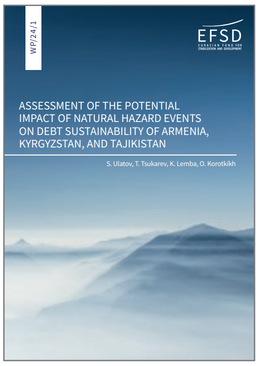
**Sovereign Financing in Eurasia:
H1 2024**

The Paper covers of sovereign financing operations in Eurasia for 1H 2024.

Working paper WP/24/2
(RU/EN)

**Sovereign financing in Eurasia:
trends and areas**

The Report focuses on the monitoring of sovereign financing in Eurasia, relying on a database maintained by the EFSD.



Working paper WP/24/1
(RU/EN)

Assessment of the Potential Impact of Natural Hazard Events on Debt Sustainability of Armenia, Kyrgyzstan, and Tajikistan

The paper presents an algorithm that can be used to assess the impact of natural hazards on macroeconomic indicators and debt sustainability of various countries.

Working paper WP/23/3
(RU/EN)

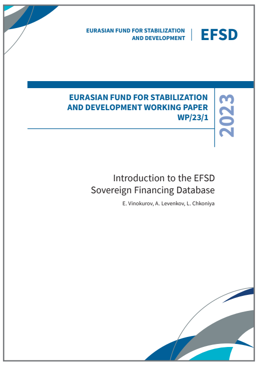
International Reserves as the core element of the GFSN for developing economies

The paper assesses factors affecting the decision of developing economies on the source of anti-crisis support. The study showed that international reserves are the most sought-after instrument among all the elements of the GFSN.

Working paper WP/23/2
(RU/EN)

**Sovereign Financing in Eurasia:
Water Sector and Hydropower
Generation**

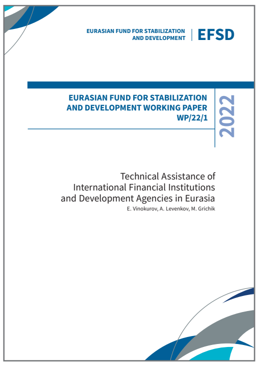
The purpose of this Working Paper is to analyse operations of IFIs, climate funds, and development agencies in the water and HPP sector between 2008 and H1 2023 in 11 countries of the Eurasian region.



Working Paper WP/23/1
(RU/EN)

Introduction to the EFSD Sovereign Financing Database.

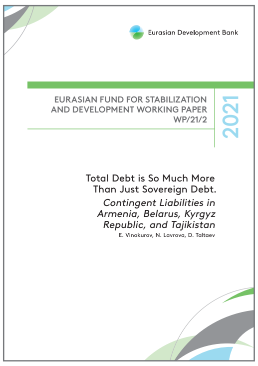
In this Working Paper the Sovereign Financing Database (SFD) Methodology is presented and also quantitative and qualitative analysis of sovereign financing operations in 11 countries of the region from 2008 to 2022 is carried out.



Working Paper WP/22/1
(RU/EN)

Technical Assistance of International Financial Institutions and Development Agencies in Eurasia.

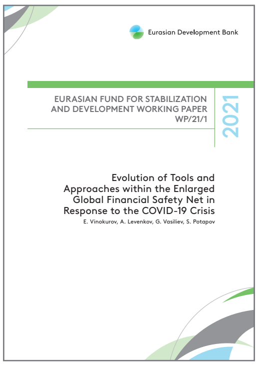
The purpose of this analytical document is to review technical assistance projects implemented by international financial institutions and development agencies in 2009–2021 in 11 Eurasian countries with a detailed thematic and institutional breakdown.



Working Paper WP/21/2
(RU/EN)

Total Debt Is So Much More Than Just Sovereign Debt. Contingent Liabilities in Armenia, Belarus, Kyrgyz Republic and Tajikistan

The study aims to contribute to understanding the potential risks and impacts of both explicit and implicit contingent liability shocks on government fiscal and debt positions in the EFSD recipient countries. Special attention is paid to the significance of state-owned enterprises and their role in countries' debt positions.

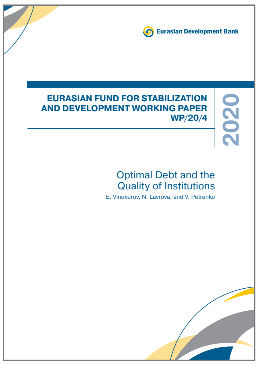


Working Paper WP/21/1

(RU/EN)

Evolution of Tools and Approaches within the Enlarged Global Financial Safety Net in Response to the COVID-19 Crisis

This working paper provides the analysis how the GFSN responded to pandemic on global level and on regional level (in the EFSD countries).

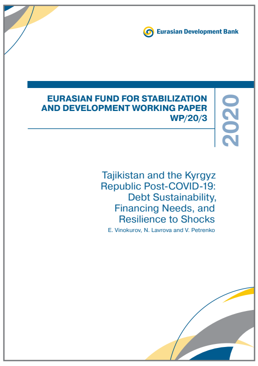


Working Paper WP/20/4

(RU/EN)

Optimal Debt and the Quality of Institutions

Amid the COVID-19 pandemic policymakers now face the dilemma of whether to stimulate infrastructure development by raising debt, which may reduce future flexibility, or to strengthen their fiscal positions.

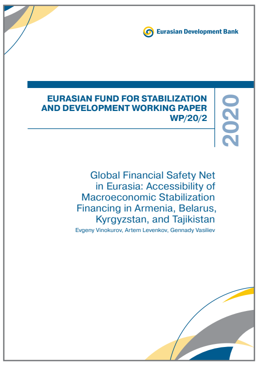


Working Paper WP/20/3

(RU/EN)

Tajikistan and the Kyrgyz Republic Post-COVID-19: Debt Sustainability, Financing Needs, and Resilience to Shocks

The COVID-19 outbreak has revealed the sensitivity of economies and their debt positions to a wide range of disruptions.

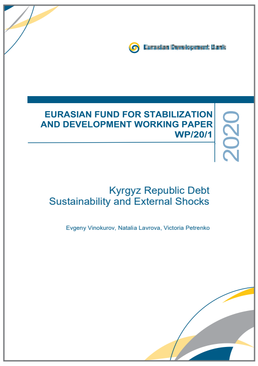


Working Paper WP/20/2

(RU/EN)

Global Financial Safety Net in Eurasia: Accessibility of Macroeconomic Stabilization Financing in Armenia, Belarus, Kyrgyzstan, and Tajikistan

The document estimates the availability of stabilization financing for Armenia, Belarus, the Kyrgyz Republic, and Tajikistan based on three approaches.



Working Paper WP/20/1

(RU/EN)

Kyrgyz Republic Debt Sustainability and External Shocks

The document examines the resilience of the Kyrgyz debt under three stress-scenarios: (1) a global recession, (2) a financial crisis, and (3) the combination of a global recession and a financial crisis.

Working Paper WP/19/2

(RU/EN)

Achieving Stabilization and Development Objectives in a Single Agenda: The Experience of the Eurasian Fund for Stabilization and Development

This working paper analyses the experience of the EFSD, which suggests that in the context of low-income countries, the RFA's stabilisation mandate may benefit from complementing it with developmental agenda.

Working Paper WP/19/1

(RU/EN)

The Eurasian Fund for Stabilization and Development: A Regional Financing Arrangement and Its Place in the Global Financial Safety Net

The objective of the first working paper is to bridge the gap in understanding the dynamics of EFSD development and its place in the Global Financial Safety Net (GFSN) and the region's financial architecture.

EFSD Early Warning System: Developing Tools
to Predict Currency Crises

Tsukarev T., Poghosyan K.

The **Eurasian Fund for Stabilization and Development (EFSD)** amounting to US$8.513 billion was established on June 9th, 2009 by the governments of the Republic of Armenia, the Republic of Belarus, the Republic of Kazakhstan, the Kyrgyz Republic, the Russian Federation, and the Republic of Tajikistan. The objectives of the EFSD are to assist its member countries in overcoming the consequences of the global financial crisis, ensure their economic and financial stability, and foster integration in the region. More information about the EFSD is available at: efsd.org/en/.

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