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Forecasting growth in eastern Europe and central Asia

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Summary

Growth forecasts are at the heart of investment decisions and yet in emerging and developing markets they often receive limited support from quantitative models. This paper describes the main quantitative modelling techniques that have informed EBRD growth projections since 2009. The paper describes how bridge models use high-frequency data and the generalised dynamic factor model uses a vast body of cross-country data to nowcast growth. In addition, a Bayesian vector-autoregressive model is used to forecast growth under various scenarios. The paper includes a comparison between the forecasting performance of the model and that of economists, the latter working both at the EBRD and at other institutions.

Keywords: nowcasting, forecasting, models, eastern Europe

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The working paper series has been produced to stimulate debate on the economic transformation of central and eastern Europe and the CIS. Views presented are those of the authors and not necessarily of the EBRD.

1. Introduction

Growth forecasts are at the core of investors' and economic policy-makers' decisions. However, in emerging markets in the EBRD region, they have until recently received little support from quantitative modelling. This often reflected the limited availability of relevant and sufficiently long time series data. These are needed to reap the benefits of traditional forecast models used for advanced economies. Increasingly, however, models are being developed that address these data weaknesses. Some of these models incorporate judgment through Bayesian methods to anchor model estimates. Others address the shortness of the time dimension of datasets by expanding the cross-sectional dimension.

As the available economic time series lengthen, central banks are increasingly adding statistical methods to their forecasting tools. Autoregressive Integrated Moving Average (ARIMA) models were developed for EU Member States in Barhoumi et al (2008), Benkovskis (2008) or Krajowski (2009), but increasingly also for countries outside the European Union, including Albania (Mancellari, 2010), Ukraine (Petrik and Nikolaichyk, 2006) and Russia (Styrin, Zamulin and Krylova, 2010).

It is in the spirit of this literature that this paper develops a set of statistical models to forecast growth in the EBRD region. The main aim is to develop and test forecasting tools, rather than policy analysis tools, for as wide a range of countries as possible. These models, of course, are only one input into final EBRD forecasts. They are mainly designed to capture the impact of the external environment on growth in the region. Domestic economic and political developments are introduced through economists' judgment.

The other approach, which is gaining more and more attention from the central banks in the region, is the development of Forecasting and Policy Analysis System (FPAS) models which in principle can be applied with minimal local data input.

FPAS models have by now been developed for most countries in the EBRD region to support monetary policy analysis and decision-making. These include all the EU member countries but more recently also Serbia (Mirko Đukić, Jelena Momčilović i Ljubica Trajčev, 2010); Albania (Kota and Dushku, 2010); Montenegro (Franjo, Žan, Veselin, 2006); Armenia (Mkrтчyan, Dabla-Norris and Stapanyan, 2009); Ukraine (Petrik and Nikoleyчuk, 2006); Tajikistan, Belarus, Mongolia and Uzbekistan (OGRResearch, 2009); Russia (Benediktow, Fjærtoft and Løfsnæs, 2009); and FYR Macedonia (De Haan, Naumovska and Peeters, 2001).

The FPAS models' strength (minimal need for data input) can also be their weakness: FPAS models typically require the calibration of many parameters. In countries with limited data availability, many of these parameters need to be established by judgement. This may be convenient but risks erroneous parameter choices. By not incorporating high frequency data, FPAS models can also miss structural breaks. Lastly, FPAS models do not allow statistical inference and thus do not provide information on possible error bands around forecasts. FPAS models, therefore, are at times poor instruments for forecasting purposes (for example, Edge and Gurkaynak, 2011) although they remain very useful for scenario analysis.

The outline of the paper is as follows. We begin by introducing the two statistical filters that are used for nowcasting¹ and very short-term forecasting: ARIMA-based bridge models and

¹ Nowcasting techniques are used to monitor the state of the economy in real time. Historically, nowcasting techniques have been based on simplified heuristic approaches. A paper by Giannone, Reichlin and Small (2008) has shown that the process of nowcasting can be formalised in a statistical model which produces predictions without the need for informal judgement. The model exploits information from a large quantity of data series at different frequencies and with different lags. The idea is that signals about the direction of change in GDP can be extracted from this large and heterogeneous set of information sources (for example, jobless

the Generalised Dynamic Factors Model (GDFM). Then we discuss a Bayesian vector-autoregressive (VAR) model developed to underpin scenario analysis. Lastly, we conduct a “horse race” between the three types of models and economist forecasts at the EBRD and IMF.

figures, industrial orders, the trade balance, and so on) before GDP itself is published. In nowcasting, these data are used to compute sequences of current quarter GDP estimates in relation to the real time flow of data releases.

2. Nowcasts and short-term forecasts: ARIMA and GDFM

Real GDP growth data releases often lag by almost two quarters. Higher-frequency data – such as industrial production, retail sales or exports – can help “nowcast” real GDP growth of the current or the most recent quarter. We employ two models:

- country-specific ARIMA models which “bridge” the gap from monthly high-frequency data to quarterly real GDP growth
- a Generalised Dynamic Factors Model (GDFM) which uses the estimated lag structure of a large cross-country quarterly dataset to project growth.

Each of these two models has advantages and disadvantages. ARIMA bridge models can incorporate higher-frequency rather than quarterly data. However, they are country-specific and therefore have wide error bands when applied to the short-term time series prevalent in EBRD countries. The GDFM makes up for the shortage of data in the time dimension by including a vast collection of data in the cross-sectional dimension – under the assumption that many of the series are not only correlated with real GDP growth but also lead real GDP growth and, hence, can help predict growth. However, since the GDFM requires a complete matrix of data, it averages out the most recent high-frequency information and may therefore miss turning points.

2.1 Country-specific ARIMA models

Bridge models are a widely used method to forecast quarterly GDP from daily, weekly or monthly data (see, for example, Baffigi, Golinelli and Parigi, 2004). The models thus create a “bridge” between high-frequency and quarterly data. Quantitative and qualitative monthly indicators are chosen that are correlated with GDP growth and then they are forecast by an ARIMA² process. These are then used to project quarterly real GDP growth out-of-sample based on an OLS equation of quarterly real GDP growth using quarterly averages of monthly indicators.

Specifically, the process has two steps. First, we select the set of monthly indicators that are published on a timely basis and could plausibly correlate with real GDP growth in any given country. An autoregressive moving average (ARIMA) model is estimated to project any monthly indicator which does not cover the entire quarter. The lag length of the ARIMA is chosen to minimise the root mean squared error (RMSE).³ Our monthly indicators are industrial production indices from national statistical offices and Eurostat for countries in the EBRD region, the eurozone and Germany and daily information on the VIX index⁴ from Bloomberg as a proxy for financial market conditions.

² An autoregressive integrated moving average (ARIMA) regression models a series as a function of its own lags and lags in its error terms. It is a popular short-term forecasting tool.

³ RMSE is the square root of the average squared distance of a data point from the fitted value based on the model line. In other words it is a measure of the differences between values predicted by a model or an estimator

and the values actually observed from the data. $RMSE = \sqrt{\frac{1}{n} \sum_{j=1}^n (y_j - \hat{y}_j)^2}$, where y denotes a continuous

variable, j denotes time and n stands for a number of periods in the time series.

⁴ VIX is the Chicago Board Options Exchange Market Volatility Index, a measure of the implied volatility of S&P 500 index options. It represents one measure of the market’s expectation of stock market volatility over the next 30-day period. The VIX is quoted in percentage points and translates, roughly, to the expected movement in the S&P 500 index over the next 30-day period, which is then annualised. The VIX Index was developed by Professor Robert E. Whaley in 1993 and is a registered trademark of the CBOE.

Second, the quarterly average of all monthly indicators are used as independent variables in an OLS regression for quarterly real GDP growth – our equation to bridge the gap from monthly to quarterly data. Again, we select the exact equation specification – variable inclusion and lag length – to minimise the mean squared error (RMSE) of the regression equation.⁵ We use seasonally adjusted quarterly real GDP growth as released by national statistical offices or else adjusted in an X12 procedure.⁶

The following can be summarised as follows:

$$y_t^Q = \alpha_i + \sum_{i=1}^3 \sum_{s=0}^{q_i} \beta_{is} x_{i,t-s}^Q + \varepsilon_{i,t}^Q \quad (1)$$

where quarterly GDP growth is y_t^Q and the variables $x_{i,t}^Q$ are the quarterly averages of domestic and global monthly industrial production and the VIX, evaluated in the last month of each quarter. The GDP growth forecast y_{t+h}^Q is the fitted value of the equation using the quarterly aggregates for $x_{i,t+h}^Q$ that were partly generated in the first step by ARIMA models based on monthly information $x_{i,t}$.

We develop ARIMA models for 17 out of the 29 countries in the EBRD region, covering all 10 EU members (excluding the Czech Republic), Armenia, FYR Macedonia, Kazakhstan, Russia, Serbia, Turkey and Ukraine. The time series start in 2001, except for Serbia where data are only available from 2002.

2.2 Cross-country Generalised Dynamic Factor Model

Since the ARIMA models are sensitive to the time horizon used, we also employ the Generalized Dynamic Factor Model (GDFM), developed by Forni, Hallin, Lippi and Reichlin (2000, 2001, 2002) and Forni and Lippi (2000), to base our growth forecasts on a large cross-section of data. The GDFM is premised on the assumption that a vast cross-sectional dataset contains many series that lead growth and are therefore powerful predictors of growth. The model extracts a small number of common factors – as in any principal components model – and estimates the co-movement of these few common factors with each series in the dataset.

For each variable j in our dataset, the data series x_{jt} , where $j = 1 \dots 4692$ in our case, can be decomposed as the sum of two stationary, mutually orthogonal and unobservable components: the “common component” χ_{jt} and the “idiosyncratic component” ξ_{jt} . As in any standard principal components analysis, the common component χ_{jt} is driven by a small number q of common “factors” u_{ht} , where $h = 1, 2, 3$ in our case. These three common factors are the same for the whole dataset but they affect each of the 4,692 series in different ways: with different lags s and different coefficients (“loadings”) b_{hjs} for each of the three factors h

⁵ Given the short time series in our data, we restrict the lag length to two lags.

⁶ X12 procedure is an adaptation of the US Bureau of the Census X-12-ARIMA Seasonal Adjustment programme, which seasonally adjusts monthly or quarterly time series.

and lags s . For our dataset, we allow three lags s . The “idiosyncratic component” ξ_{jt} is driven by variable specific shocks, with mean zero.

$$x_{jt} = \chi_{jt} + \xi_{jt} = \sum_{h=1}^2 \sum_{s=0}^3 b_{hjs} u_{hjt-s} + \xi_{jt} \quad (2)$$

The GDFM developed in Forni, Hallin, Lippi and Reichlin (2002) estimates the relevant covariances by means of frequency-domain techniques. The u 's are estimated as the first $r = q(s + 1)$ largest “generalised principal components” of the x 's, defined as the contemporaneous linear combinations of the x 's with the smallest idiosyncratic-common variance ratio. As the number of tables and time periods go to infinity, this estimate is consistent.

Forni, Hallin, Lippi and Reichlin (2005) show that the GDFM produces more accurate forecasts (for example, for inflation) than standard univariate autoregressive models at horizons up to six months after which the GDFM's superiority becomes less clear. Stavrev (2006) compares the GDFM's forecast performance against an even wider range of models and indicators and again finds that the GDFM outperforms its competitors over the horizon to 24 months.

Our 4,692 data series include quarter-on-quarter seasonally adjusted growth rates for real GDP; industrial production; survey indices on the degree to which domestic and export order books are full; and real exports in countries in the EBRD region, the euro area and the US. We also include quarterly averages of money market, loan and deposit interest rates; stock market returns; the VIX and EMBI; and data on loan and bond issuance for the EBRD region, the eurozone and the US.

Using data starting from the second quarter of 2001, the GDFM allows us to forecast growth for all 10 EU Member States in the EBRD region (excluding the Czech Republic), the Caucasus, Belarus, Ukraine, Moldova, Turkey, Russia and Central Asia (except Turkmenistan).

Because of the GDFM's strong forecast performance at short horizons, we also use it for short-term EBRD *inflation* forecasts which are beyond the scope of this paper.

3. Medium-term forecasts: Bayesian VAR

3.1 The rationale

The previous two sections described short-term filters that produce efficient nowcasts and forecasts one or two quarters out. Beyond this horizon, we would expect forecasts to depend increasingly on expected developments in the external environment.

Most of the EBRD region is deeply integrated into the world economy. Many countries both at the periphery of the European Union as well as in Central Asia are small, open economies with close trade and investment links to larger neighbouring countries. In addition, especially in Central Europe, the Baltics and south-eastern Europe, many countries have financial systems that are dominated by western European banks. Lastly, the EBRD region includes several commodity-producing countries (Russia, Azerbaijan, Kazakhstan, but also Mongolia and Armenia) whose economies follow the movements of global commodity markets. How do global economic developments transmit to these various groups of economies? And, consequently, conditional on expected external developments, what is growth likely to be?

Estimating and forecasting econometrically this dependence on global trends is difficult: many countries in the region only gained independence around 1990 and have since then been buffeted by crises. For EBRD countries, econometric time series are therefore short, typically less than 20 years. Econometric estimates therefore tend to have large error bands and produce volatile forecasts. Vector-autoregressive models, in particular, tend to forecast poorly in such small samples because a large number of parameters – to which the forecasts converge – needs to be estimated based on few data points. To ensure the forecasts are sensible, we therefore need to anchor them with judgemental information from outside the model dataset.

To this purpose, we apply the Bayesian vector-autoregressive model (BVAR) described in Osterholm and Zettelmeyer (2007). Their approach, in turn based on Villani (2005), allows us to use additional information from outside our limited dataset to place “informative priors” on steady-state values. Thus, model forecasts will converge towards levels that we consider “plausible”. Villani (2005) argues that this improves out-of-sample forecast performance.

3.2 The model and its estimation

As in Osterholm and Zettelmeyer (2007), our regression model is

$$\mathbf{G}(L)(\mathbf{x}_t - \boldsymbol{\psi}) = \boldsymbol{\eta}_t \quad (3)$$

where $\mathbf{G}(L)$ is a lag polynomial of order p , \mathbf{x}_t is an $n \times 1$ vector of stationary macroeconomic variables, $\boldsymbol{\psi}$ is the $n \times 1$ vector of steady-state values of \mathbf{x}_t , $\boldsymbol{\eta}_t$ is an $n \times 1$ vector of i.i.d error terms with mean zero and variance $\boldsymbol{\Sigma}$.⁷ As in any Bayesian estimation, the likelihood

⁷ $E(\boldsymbol{\eta}_t) = 0$, $E(\boldsymbol{\eta}_t \boldsymbol{\eta}_t') = \boldsymbol{\Sigma}$.

function combines the priors with the data. Villani (2005) derives the conditional posterior distribution.⁸

The vector \mathbf{x}_t , of course, includes the main variable of interest – quarter-on-quarter real GDP growth, seasonally adjusted. In addition, the vector \mathbf{x}_t includes the macroeconomic variables we want to condition our model growth forecast on. These are variables that describe the external environment, capturing the potential of spillovers through trade, migration and financial channels: “world” growth, terms-of-trade shocks and ease of access to external finance.

- “World” growth is defined as export-weighted average quarter-on-quarter real GDP growth in EU-15 countries, Russia and the US. Export weights are average shares in total exports for 2000-07. Country-specific projections for the eurozone are available from the IMF’s most recent *World Economic Outlook (WEO)* on a semi-annual basis in May and October. Outside the full WEO cycle, we use only aggregate eurozone growth.
- Terms-of-trade shocks are proxied by the net export-weighted average of quarter-on-quarter changes in the Urals oil price, wheat, gold, copper, aluminium and cotton prices. Trade weights are shares of net exports for net commodity exporters and net imports for net commodity importers during 2000-07. Projections for the oil price are from the latest WEO and projections for all other commodity prices are futures prices as reported in Bloomberg.
- Ease of access to external finance is measured by two measures: global investor risk aversion – proxied by the VIX⁹ – and abundance of global liquidity – proxied by the three-month interbank market rate in the US (for projections for Russia, the Caucasus, Central Asia) or in the eurozone (for projections for EU members).

We estimate the model for five country aggregates (Table 1). Aggregates (instead of individual countries) serve to smooth some of the country-specific shocks to real GDP growth and, hence, improve forecast accuracy on average. The aggregates were chosen based on openness to trade and financial flows – and therefore also countries’ vulnerability to external shocks – their main export markets and products and exposure to regional financial markets.

- The most advanced group of countries, which we call “NM7”, is the group of seven eastern European countries which joined the European Union in 2004: the Baltic countries, Poland, Hungary, Slovenia and the Slovak Republic.¹⁰ With the exception of Poland, these countries are small, open economies, and all of them are primarily oriented towards the EU market. Banking systems are well-developed and in most countries predominantly foreign-owned.
- Our second group of countries, the EU countries of the Balkans, Romania, Bulgaria and Croatia, the “Balkans”, are similar to their northern neighbours in their exposure

⁸ The numerical evaluation uses a Gibbs sampler with 10,000 draws.

⁹ As a robustness check, we replaced the VIX with the high-yield spread (with a steady-state value around 620bps, the average since the beginning of 1997) but the results were virtually the same. We also added the EMBI Europe (for estimates for EU members, with a steady-state value around 590bps, the average since the beginning of 1997) or EMBI Russia (for Central Asian and non-EU member country estimates, with a steady-state value around 820bps, the average since the beginning of 1997) as a measure of region-specific access to finance but both EMBIs were insignificant and results for the other variables remained unchanged.

¹⁰ The Czech Republic, which graduated from EBRD operations in 2008, is excluded.

to western Europe but are somewhat poorer, less export-oriented with a heavier reliance on commodity exports, more dependent on FDI and remittances, and less financially developed. The reason for not including these three countries in the group of all EU entrants is their exposure to Greece and Italy. Greece's and Italy's growth paths over the past three years have decoupled from those of other large EU-15 countries, and so has the growth performance of this second group of EBRD countries.

- We combine Ukraine, Belarus, Moldova and the Caucasus into a group of eastern European countries, "EEC". These countries are also open and mostly small economies (except for Ukraine), but they are significantly more oriented towards Russia (in exports, FDI and migration), rely on commodities for about half their exports, and are less financially developed than their EU neighbours with little foreign bank ownership.
- Central Asia, "CA", includes the mainly commodity-producing economies Kazakhstan, the Kyrgyz Republic, Tajikistan, Uzbekistan and Mongolia. They are predominantly commodity exporters and/or reliant on remittance flows with little foreign investment outside the commodity sectors (despite some investment from China). The state still accounts for a substantial share of banking systems.
- We have also combined Russia and Kazakhstan into a separate group, "RUSKAZ", based on the important role of oil and gas for their economies. Their financial systems are predominantly domestically owned. A substantial share of capital inflows into these two economies tend to be channelled through offshore financial centres.
- Lastly, we combine all groups into an EBRD aggregate.

Table 1: Selected economic indicators for forecast groups

Region	NM8	Balkans	EEC	CA	RUSKAZ
Exports, average 2000-07, % of GDP	48	39	52	40	37
Structure					
Within region	9	3	4	6	4
EU-15	36	46	18	23	31
Russia	3	1	20	18	...
NAFTA	3	4	4	4	5
Developing Asia	1	2	7	15	9
Advanced Asia Pacific	1	1	1	1	3
MENA	1	4	10	6	3
Commodities	9	19	46	54	68
FDI in reporting economy, average 2002-07, % of GDP					
1/	4	7	6	2	3
Structure					
Within region	3	0	5	2	0
EU-15	78	56	39	29	39
Russia	0	0	5	7	0
NAFTA	0	0	1	2	0
Developing Asia	0	1	1	4	0
Banking system assets, average 2002-07, % of GDP	67	54	39	38	45
Structure					
Foreign-owned	72	73	22	13	11
State-owned	17	17	15	55	...
Remittances, average 2005-07, % of GDP	3	7	5	5	0

Source: CEIC and National authorities.

Note: NM8 stands for eight new EU Member States (Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovak Republic and Slovenia); Balkans include Bulgaria, Croatia, Romania; EEC includes Armenia, Azerbaijan, Belarus, Georgia, Moldova and Ukraine; CA stands for Central Asian countries (Tajikistan, Kyrgyz Republic, Kazakhstan, Mongolia and Uzbekistan); and RUSKAZ stands for Russia and Kazakhstan.

1/ Data only available for EU countries, Kazakhstan, Russia, Ukraine, Georgia, Armenia and Tajikistan.

Next, we define the priors for the distributions in equation (1).¹¹ We place a non-informative prior on the variance Σ , but informative priors (based on normal distributions) on the lag

¹¹ The following priors are used: for Σ $p(\Sigma) \propto |\Sigma|^{-(n+1)/2}$, for $\text{vec}(\mathbf{G})$ $\text{vec}(\mathbf{G}) \approx N_{pn^2}(\boldsymbol{\theta}_{\mathbf{G}}, \boldsymbol{\Omega}_{\mathbf{G}})$ where $\mathbf{G} = (\mathbf{G}_1 \dots \mathbf{G}_p)'$, and for $\boldsymbol{\psi} \approx N_n(\boldsymbol{\theta}_{\boldsymbol{\psi}}, \boldsymbol{\Omega}_{\boldsymbol{\psi}})$.

structure $\mathbf{G}(L)$ and the steady-state values $\boldsymbol{\psi}$, as in Osterholm and Zettelmeyer (2007). “Minnesota” priors (Lettermann, 1989), that is, zero means, were imposed on all lags of US and world growth as well as commodity price growth, assuming that these variables in levels approximately follow a random walk with drift (see Appendix Table 1). For the financial variables, which are included in the model in levels and hence cannot be assigned a Minnesota prior, we instead assume a coefficient of 0.9 on the first lag. World growth, commodity prices and US financial variables were treated as block exogenous with respect to EBRD regional variables.¹²

Table 2 shows the assumptions we made on the steady values in the vector $\boldsymbol{\psi}$.

- Steady-state growth in EBRD region aggregates was set in line with cross-country regression studies for central Europe and the Baltic states (Schadler et al, 2004), eastern Europe and the Caucasus (DB Research, 2005), Russia and Kazakhstan (Beck et al, 2007), or with medium-term (2016) forecasts from the IMF’s *World Economic Outlook* April 2011 (for Central Asia and for the Balkans).¹³
- World growth was defined as the export-weighted average of medium-term (2016) growth projections for the EU-15, Russia and the US from the IMF’s *World Economic Outlook* April 2011.
- As in Osterholm and Zettelmeyer (2007), we assumed that commodity price growth was about 1 per cent, in line with the assumption of a random walk with a small drift component in commodity price levels.
- As in Taylor (1993) and Clarida, Gali and Gertler (1998), we centred the prior for the US LIBOR and the EURIBOR to an inflation target of 2 per cent and an equilibrium real interest rate of about 2 per cent.
- Without any strong prior for steady state values for the VIX, we assumed that the steady state was these variables’ average since the publication of these series.¹⁴

Table 2: Assumed central steady state values

	EBRD region	NM7	BALK	EEC	CA	RUSKAZ
Regional GDP growth, per cent	3.7	4	2	3.7	6.5	4.2
World GDP growth, per cent	2	2	1.8	2.8	2.7	2
Commodity price growth, per cent	1					
VIX, basis points	20					

¹² Arguably, world commodity prices could respond contemporaneously to growth in the EBRD region but not vice versa because prices adjust faster than economic activity. The region, however, is a relatively small player in global commodity markets. For example, Russian oil output accounted for only about 11 per cent of global oil output in 2007 (EIA 2010). Our results did not change when we allowed commodity price growth to be contemporaneously affected by EBRD region growth but not vice versa.

¹³ DB Research (2005) estimates potential growth for Ukraine. Since Ukraine is the largest economy in the group EEC (about two-thirds bigger than the aggregate US dollar GDP for Armenia, Azerbaijan, Georgia and Moldova in 2010), the estimate is assumed to proxy potential growth for the group as a whole. Beck et al. (2007) estimate potential growth for Russia. Again, since the Russian economy is more than 10 times the size of the Kazakh one, we use the estimate as a proxy for the group as a whole.

¹⁴ For the VIX and the high-yield spread, this included an additional year of data to the sample period, for the EMBIs this included an additional quarter of data to the sample period.

Table 3 shows the close overlap of the posterior and prior distributions of the estimated steady state values of the variables. The forecast error variance decomposition indicates that the external factors included in the model explain between two-thirds (in the new EU members) and three-quarters (in Russia and Kazakhstan) of the forecast error variance of regional GDP growth at the four-quarter horizon (Table 4). In the relatively closed and financially underdeveloped economies of Central Asia, external factors explain about two-fifths of the forecast error variance. For our other country groups, the importance of external variables in our model is significantly higher than in Osterholm and Zettelmeyer (2007), partly because of our decision to rank domestic growth last in the Cholesky decomposition.¹⁵ Our choice of Cholesky ordering – all exogenous variables being ranked before the domestic variable – means that the role of external factors is probably overestimated because all covariances with the domestic variable are attributed to the external variables. The bulk of the explanatory power of external variables derives from world growth (partly also because world growth is the first-ranked variable in our Cholesky ordering), but the VIX is also an important contributor, especially for the new EU members.

Table 3: Prior and posterior distributions

	EBRD region	NM7	BALK	EEC	CA	RUSKAZ
World GDP growth (prior)	(1.5, 2.5)	(1.5, 2.5)	(1.5, 2.5)	(1.5, 2.5)	(1.5, 2.5)	(1.5, 2.5)
(posterior)	(1.5, 2.3)	(1.6, 2.3)	(1.3, 2.1)	(1.5, 2.5)	(1.4, 2.3)	(1.4, 2.3)
World interest rates (prior)	(1, 7)	(1, 7)	(1, 7)	(1, 7)	(1, 7)	(1, 7)
(posterior)	(1.6, 4.7)	(2.2, 4.3)	(1.7, 4)	(1.6, 4.7)	(1.6, 4.7)	(1.6, 4.7)
VIX (prior)	(18, 26)	(18, 26)	(18, 26)	(18, 26)	(18, 26)	(18, 26)
(posterior)	(18.4, 23.3)	(18.4, 23.6)	(18.2, 24.4)	(19.9, 25.4)	(18.2, 24.6)	(18.2, 24.6)
EBRD region GDP growth (prior)	(3.5, 4.5)	(3.5, 4.5)	(3.5, 4.5)	(3.5, 4.5)	(3.5, 4.5)	(3.5, 4.5)
(posterior)	(3.6, 4.5)	(3.5, 4.4)	(1.3, 3.3)	(3.6, 4.6)	(3.7, 5.1)	(3.7, 5.1)
Commodity prices growth (prior)	(-4, 5)	(-4, 5)	(-4, 5)	(-4, 5)	(-4, 5)	(-4, 5)
(posterior)	(-4.3, 1.3)	(-4.9, 2.3)	(-5.1, 1.6)	(-3, 1.2)	(-2.2, 6.5)	(-2.2, 6.5)

Note: Probability intervals refer to a normal distribution.

The impulse response functions estimated by the model generate some rules of thumb (Table 4), but also highlight some quirks of the model and the sample.

A 1 per cent increase in world GDP growth raises growth in the EBRD region more than proportionately (1.5 per cent in non-Balkan new EU Member States to 5.5 per cent in Russia and Kazakhstan). For all subregions, the effect peaks around four quarters and then ebbs off. The estimated magnitude of the effect is well above that estimated for other emerging market regions. For example, Osterholm and Zettelmeyer (2007) find a 1:1 effect of world growth on Latin American growth and argue that even this effect is probably overestimated. In an almost identical Bayesian VAR model, Utlaut and van Roye (2010) find that real GDP growth in Emerging Asia excluding China responds almost 1:1 to a 1 per cent increase in world GDP growth and growth in China responds by about half as much. In a more parsimonious VAR model, Borin et al. (2011) find no significant effect of world GDP growth on real GDP growth in Russia and Brazil or in Emerging Asia including China at the four-quarter horizon (but a small effect at the one or two-quarter horizon). Our very high estimate of the impulse response of domestic growth to global growth likely reflects a combination of

¹⁵ For the Cholesky variance decomposition, we assume an ordering of world GDP growth, world interest rates, the VIX, terms of trade growth and regional GDP growth.

a particularly strong sensitivity to global developments in a very globally integrated region – whether through commodity markets, financial or trade links – and an overestimate due to the Cholesky ordering.¹⁶ Our high estimates are also subject to substantial uncertainty with relatively wide 90th percentile confidence bands.

A 10 basis points increase in the VIX, our measure of investor risk aversion, reduces growth in the EBRD region by anywhere between 0.9 and 1.7 percentage points, more in the eastern reaches of the EBRD region than in the parts closer to the European Union. This compares with an estimate by Osterholm and Zettelmeyer (2007) of about 0.1 for Latin America and an estimate by Utlaut and van Roye (2010) of about 0.9 for Emerging Asia. The difference in estimates between East and West among our group of countries may reflect the kind of integration of each subregion into the global financial system: in the new EU members, domestic banking systems are mostly foreign-owned. These subsidiary networks have historically been the main conduit for capital inflows into these countries. In contrast, large Ukrainian and Russian corporates and banks have accessed global financial markets directly, often through syndicated loans. De Haas and Van Horen (2011) show that during the global financial crisis syndicated lending supported by subsidiary networks was more stable than other syndicated lending. This may help explain why worsening investor sentiment has more severe effects on the real economies of countries without subsidiary networks in the eastern reaches of the EBRD region than of those with such networks in new EU members. In the financially underdeveloped economies of Central Asia, investor sentiment as proxied by the VIX has no measurable impact on growth.

Improvements in the commodity terms-of-trade only have a significant short-term impact in the heavily commodity-exporting economies of Russia and Central Asia. A 10 per cent improvement in the commodity terms of trade raises GDP growth in Russia and Kazakhstan by some 1.25 per cent – about twice as much as that estimated for Latin America by Osterholm and Zettelmeyer (2007) – and in Central Asia by almost 2 per cent over the following year. In the new EU Member States, improvements in the commodity terms-of-trade generate growth effects of about half this size which take about twice as long to materialise.

World interest rates, and the three-month EURIBOR in particular, only impact growth in the new EU members and with a substantially longer lag than world growth. A 1 per cent increase in the EURIBOR can reduce growth in the new EU Member States by as much as 1.66 per cent – 2 per cent and takes about two years to wear off. Presumably, this strong impact captures the close integration of EU members’ banking system with the western European banking system.

Table 4: Cumulative response of real GDP growth over following four quarters

	EBRD region	NM7	Balkans	EEC	CA	RUSKAZ
1% world GDP growth increase	3.11*	1.51*	4.2*	4.31*	2.18*	5.65*
1 percentage point increase in world interest rates	0.23	-0.76*	-2.1*	0.32	0.57	-0.04
10 basis points increase in VIX	-0.9*	-0.8*	-0.9*	-1.7*	-0.6	-1.5*
10% terms of trade improvement	0.25	0.14	-0.26	-2.98	1.86*	1.27*

* Coefficient estimate significant at 20% level.

¹⁶ By ordering world growth as the first variable in the Cholesky decomposition of the VAR system, covariances with other variables are attributed to world growth (Hamilton, 1994).

3.3 Projecting growth conditional on external developments

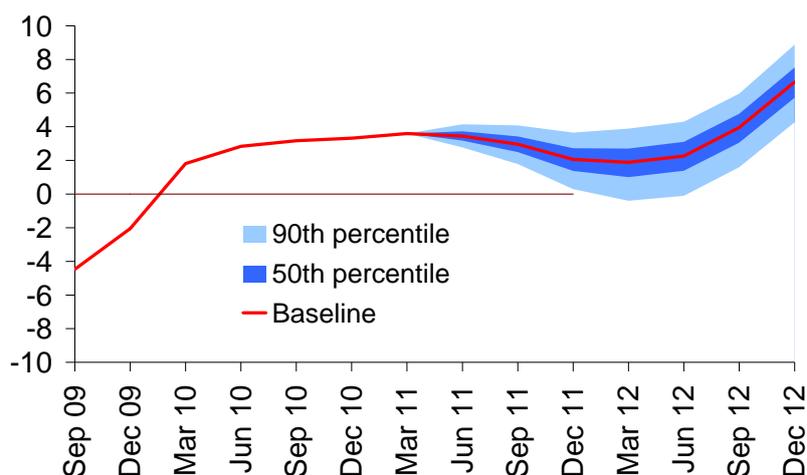
Based on the posterior distributions of the coefficient estimates, we can construct forecasts for growth. In contrast to the GDFM and ARIMA models, the BayesVAR allows us to *condition* the forecasts on actual or projected external developments. Below, in our “horse race”, we exploit this property of the BayesVAR for assessing past forecast performance based on *actual* external developments. Here, we outline what growth in 2011 and 2012 might look like under a plausible baseline scenario and an adverse scenario for *projected* external developments.

Our baseline scenario assumes that financial markets remain calm; that eurozone, Russian, and US growth proceeds are as assumed in the IMF’s World Economic Outlook April 2011; and that commodity prices will materialise at their future’s prices at end-July 2011 as reported by Bloomberg.

The adverse scenario is one of financial sector turmoil in Europe that goes beyond the immediate stress in sovereign debt markets in the IMF programme countries of Greece, Ireland and Portugal. The assumption is that financial markets will be disrupted sufficiently to lead to a credit crunch in the eurozone which, in turn, will sharply slow eurozone growth to 0.5 per cent in 2011 and zero in 2012 while it will dampen US growth by less than 1 per cent and only in 2012. Such a growth slow-down and protracted weakness in advanced countries would trigger a drop in the oil price to around US\$ 70 per barrel in the fourth quarter of 2011 for the next six quarters and would increase investor risk aversion sufficiently to raise the VIX to 50bps. Such a severe downside scenario, of course, has only a small probability of materialising. We assume that the probability is about 20 per cent.

We combine these two scenarios into a fan chart.¹⁷ Each scenario is associated with its own forecast and predictive density. As shown in Osterholm (2009), a weighted-average linear combination of the two fan charts for the two scenarios provides a combined forecast and the forecast error around it while taking into account judgement about scenario probabilities. The fan chart below illustrates the downside risks, especially in the first half of 2012 that such a downside scenario generates.

Chart 1: GDP growth projection for EBRD region, 2011-2012 fan chart



¹⁷ The fan chart shows the observed past and projected growth rate data as well as the probability distribution around the projected future growth rate. The probability distribution is based on coefficient estimates and model error terms. As predictions become increasingly uncertain, the further into the future one goes, the wider the probability distribution becomes, thus creating a "fan" shape.

4. The horse race: comparison of forecast performance

We next compare the out-of-sample forecasting performance of the BayesVAR, GDFM and ARIMA models with the semi-annual published and judgement-based EBRD staff forecasts and IMF WEO forecasts over the four years of 2007-10. We compare spring and autumn forecast rounds for the current and the next year. Hence, we compare out-of-sample model projections based on data to December for the following year with EBRD staff forecasts in Interim Transition Reports typically published in May and Regional Economic Prospects published in May as well as forecasts of the IMF World Economic Outlooks published every April/May. We compare out-of-sample model projections based on data to June for the full current year and the next year with EBRD staff forecasts in *Transition Reports* published every October/November as well as forecasts of the IMF World Economic Outlooks published every September/October.

The horserace is “unfair” in several respects.

- EBRD forecasts are typically published at least a month after IMF WEO forecasts, in autumn sometimes even two months later. This difference usually means that one more GDP growth flash estimate is available to be incorporated into published forecasts at the last minute.
- The BayesVAR “knows” the future. The BayesVAR projections are *conditional* on the actually realised paths of external variables as they later become known. In this respect the BayesVAR has an advantage over the other models as well as economist forecasts at the EBRD and the IMF. We would therefore expect the conditional BayesVAR projections to be more accurate than either economist forecasts or other model projections, especially over longer horizons. To neutralise this advantage, we also include unconditional BayesVAR projections.
- The GDFM incorporates a vast amount of information, more than any other model and probably any economist can take into account. Compared with *unconditional* projections of the BayesVAR and with the contemporaneous projection of the IMF’s WEO, we expect the GDFM to be more accurate at the shortest of horizons when most economic variables are still largely determined by the momentum of past developments. At longer horizons, we may well expect even the unconditional BayesVAR projection to be more accurate than the GDFM, as long as the informed priors pose reasonable constraints on estimates.
- ARIMA models are parsimonious but sensitive to the length of the time series. We therefore expect reasonably strong forecast performance for countries with well-developed databases and long time series. As soon as time series shorten, for example, for eastern Europe, the Caucasus, Central Asia and even Russia, ARIMA estimates should be inaccurate.

Table 5 confirms these priors. The RMSE of the BVAR conditional on actual external developments is the smallest except at very short horizons. ARIMA models outperform the GDFM only when relatively long time series data exist, for example, in the new EU Member States and the Balkans. EBRD economist forecasts have lower RMSE than unconditional models in countries with poor data quality but not necessarily in countries with well-established data. Given the small sample size, none of the differences in the RMSEs are, of course, statistically significant.

Table 5: Comparison of RMSE of projections

Region	Method of projections					
	ARIMA model	BVAR cond.	BVAR uncond.	GDFM	EBRD economists	IMF WEO
EBRD region						
October previous year	9.05	1.85	4.11	4.77	3.78	4.92
April same year	9.2	0.96	1.05	2.11	0.87	1.13
October same year	10.16	0.55	0.75	0.94	0.87	0.9
New EU Member States, excluding Balkans						
October previous year	0.89	2.01	2.58	3.02	2.54	3.3
April same year	0.32	1.16	1.13	1.59	0.85	0.97
October same year	0.08	0.36	0.36	0.49	0.52	0.77
New EU Member States in Balkans						
October previous year	1.41	4.05	5.13	5.07	4.16	5.13
April same year	0.18	1.91	1.52	3.41	1.28	1.45
October same year	0.12	0.79	0.89	0.59	0.39	0.63
Ukraine, Moldova and Caucasus						
October previous year	18.97	4.66	6.09	7.19	6.62	7.84
April same year	18.73	4.04	5.87	2.75	2.66	4.5
October same year	20.3	0.39	1.36	1.85	2.57	3.93
Central Asia						
October previous year	27.19	1.93	3.24	4.12	3.8	4.33
April same year	27.44	2.93	4.24	2.88	2.16	2.42
October same year	30.38	1.15	1.53	2.72	1.29	1.57
Russia and Kazakhstan						
October previous year	2.25	2.47	5.37	6.9	5.3	6.97
April same year	0.46	2.74	2.1	2.44	1.12	1.64
October same year	0.18	0.73	1.33	1.63	1.42	1.29

Note: In this table we compare the forecasting performance of the ARIMA, mean-adjusted BVAR (conditional and unconditional), GDFM models, the EBRD economists' official forecasts and the IMF's WEO forecasts with actual GDP growth in the different regions *ex post* over the four years of 2007-10. We focus the comparison on forecasts of annual growth rates (derived from the model's quarterly forecasts) over a two-year horizon. The model's out-of sample forecasts are compared with the latest available GDP growth data. We compute root mean squared errors for each of the forecasts which are shown in the table. For example, for the EBRD region as a whole the conditional mean-adjusted BVAR models perform better for all three time periods.

The crisis allows a particularly interesting snapshot of forecast performance (Table 6). Who picked up faster that a global economic disruption was under way: the models or the economists?

- The worst forecasts were undoubtedly those of the GDFM 18 months in advance. This is a well-known property of the GDFM: its forecast accuracy is strong for a quarter or two. Once the shock of Lehman Brothers' bankruptcy had found its way into the data, the model performed better than the economists at the six-month horizon, that is, in 2009.
- Economist forecasts at the EBRD and the IMF were fairly close (except in the EEC where IMF economists "saw the crisis coming" in autumn 2007) but underestimated the slow-down in 2008, especially in Central Asia. In autumn 2008, economists at

- What was the reason for the poor performance of economist and model forecasts – a lack of foresight about the magnitude of the global financial crisis or a poor understanding of its transmission into regional growth? The BayesVAR helps answer this question since the projections are conditional on the full depth of the global crisis as it eventually materialised. It is therefore no surprise that for the region as a whole the BayesVAR under-projected the growth slow-down less than other models and economists and, on average across regions and over the forecast period 2008-09, the BayesVAR showed the lowest forecast errors. However, the BayesVAR projections distributed the impact of the global crisis differently over time and across regions from how it eventually evolved. Hence, the *average* absolute forecast error of the BayesVAR was therefore much closer to (although still less than) that of other models and economists.
- The BayesVAR was the only forecast that had in mid-2008 projected negative growth in 2009 for the Balkans, the EEC, Russia and Kazakhstan, and the EBRD region as a whole. Other models and economist forecasts projected a rapid rebound and positive growth in 2009 based on data available to June 2008, just before the bankruptcy of Lehman Brothers.
- For the Balkans, the BayesVAR projected early on a deep recession in 2008 and a sharp upswing in 2009. Both the depth of the 2008 recession and the strength of the 2009 upswing were overestimated. In a milder form, this was also the case for the NM7 where particularly the strength of the 2009 upswing was overestimated.
- For Central Asia, the EEC, and to a lesser extent Russia and Kazakhstan, the BayesVAR projected a milder impact in 2008 but a slower recovery in 2009 than eventually materialised.
- The ARIMA models projected extraordinarily well, especially the lack of a recovery in 2009. Based on mid-2008 data, ARIMA models had already projected a deep and protracted recession. This may reflect the fact that ARIMA model forecasts tend to perpetuate the most recent developments; by June 2008, a slow-down in industrial production had already begun to set in and financial market jitters had already started. It just so happened that the Great Recession led to a protracted period of slow growth. Rogoff and Reinhart (2010) argue that this is common in the aftermath of financial crises but not for more normal business cycle swings. If the recession of winter 2008-09 had been more of a “normal” recession, the ARIMA models would probably have missed the V-shaped recovery that is typical of normal business cycles.

Table 6: Forecast error in 2008 and 2009

Region	Model	2008 in Oct '07	2008 in Apr '08	2008 in Oct '08	2009 in Oct '08	2009 in Apr '09	2009 in Oct '09	Average
EBRD	ARIMA	-2.5	0.1	0.1	-0.5	0.4	0.4	-0.3
EBRD	BVAR cond	0	-1	-0.2	-2.3	-0.8	-0.8	-0.8
EBRD	BVAR uncond.	-0.7	-1.6	-0.9	-8.2	0.7	-0.9	-1.9
EBRD	Economists	-1.9	-1.3	-1.3	-7.5	-0.2	0.6	-1.9
EBRD	GDFM	-1.7	-1.9	-1.9	-10.1	-4.6	0	-3.4
EBRD	IMF WEO	-1.4	-1.1	-1.3	-8.6	-0.8	0.4	-2.1
NM7	ARIMA	-1.7	0.1	0.1	-0.6	0	0	-0.4
NM7	BVAR cond	0.5	-1.7	-0.5	-3.3	-1.7	0.3	-1.1
NM7	BVAR uncond.	-0.6	-2.1	-0.8	-4.7	-1.7	0	-1.6
NM7	Economists	-1.7	-1	-0.6	-4	0.5	0.4	-1.1
NM7	GDFM	-1.1	-1.6	-0.8	-6.1	-3.3	-0.4	-2.2
NM7	IMF WEO	-1.6	-1	-0.9	-5.3	0.4	0.7	-1.3
Balkans	ARIMA	-1.8	0.1	0.1	-1.4	0.1	0.1	-0.5
Balkans	BVAR cond	7.3	2.7	-0.6	-3.6	-1	0.3	0.9
Balkans	BVAR uncond.	1.9	1.2	-1.5	-10.5	-2.5	0.2	-1.9
Balkans	Economists	-0.9	0	-0.6	-9.5	-2.8	0.3	-2.3
Balkans	GDFM	-0.3	-0.3	-1.4	-11.9	-7.9	-0.8	-3.8
Balkans	IMF WEO	-0.5	0	-1	-10.3	-2.8	0.4	-2.4
EEC	ARIMA	-3.7	1.4	1.4	7.2	7.9	7.9	3.7
EEC	BVAR cond	-3.3	-2.1	-0.2	6.5	6.2	-0.5	1.1
EEC	BVAR uncond.	-6.1	-4.8	-3.2	-12.5	10.5	-0.3	-2.7
EEC	Economists	-6.3	-5	-4.7	-13	-2	0.9	-5
EEC	GDFM	-6	-5.3	-4.1	-16	-6.3	0.2	-6.2
EEC	IMF WEO	-1	-1.8	-3.9	-13.9	-3.1	-0.5	-4
CA	ARIMA	-3.7	0.4	0.4	0.5	0.8	0.8	-0.1
CA	BVAR cond	-5.2	-4	-2.2	-0.9	3.5	0.4	-1.4
CA	BVAR uncond.	-6.3	-4.6	-2.6	-5.9	6.7	0.8	-2
CA	Economists	-4.4	-1.3	-0.7	-3.2	3	2.1	-0.8
CA	GDFM	-6	-0.5	-2.7	-6.1	2.1	0.8	-2.1
CA	IMF WEO	-3.7	-1.4	-0.9	-4.1	2.7	2.8	-0.8
RUSKAZ	ARIMA	-3.9	-0.2	-0.2	-0.8	0.2	0.2	-0.8
RUSKAZ	BVAR cond	-1.2	-1.7	-1.5	-1.4	2.4	0	-0.6
RUSKAZ	BVAR uncond.	-1.3	-2.5	-2.6	-12	2.4	0.4	-2.6
RUSKAZ	Economists	-1.7	-1.7	-2	-11	0	0.9	-2.6
RUSKAZ	GDFM	-2.3	-2.2	-3.2	-14.4	-5.4	0.5	-4.5
RUSKAZ	IMF WEO	-1.6	-1.6	-1.7	-12.4	-1.3	0.1	-3.1

5. Conclusion

As our horse race shows, the models outlined in this paper each have their strengths and weaknesses. Not surprisingly, none of them was able to project the turning point of the 2008 crisis. However, once the crisis had materialised, the Bayesian VAR model forecast particularly well over the medium term based on the rapid deterioration of the external environment. The GDFM, while it failed to predict the crisis, forecast particularly well over the short term.

In practice, of course, each of these model forecasts need to be calibrated by the judgement of economists. The models are heavily based on external factors. Economist judgement including non-quantitative information and domestic factors is an irreplaceable element of the full forecasting exercise.

Appendix

Table 1: Augmented Dickey Fuller Tests

Variable	Region	Test statistic	MacKinnon approximate p-value
Regional GDP	EBRD	-1	0.8
	NM7	-0.3	0.9
	Balkans	-2.7	0.1
	EEC	-0.6	0.9
	CA	0.1	1
	RUSKAZ	-1.2	0.7
Terms of trade	EBRD	-2	0.3
	NM7	-2.1	0.3
	Balkans	-1	0.8
	EEC	-1.2	0.7
	CA	0.6	1
	RUSKAZ	1.1	1
World GDP	EBRD	-2	0.3
	NM7	-1.7	0.4
	Balkans	-2.4	0.1
	EEC	-1.9	0.3
	CA	-1.9	0.3
	RUSKAZ	-2.1	0.2

Table 2: Forecast error variance decomposition of GDP growth at four-quarter horizon

	EBRD	NM7	Balkans	EEC	CA	RUSKAZ
World GDP growth	0.59	0.35	0.41	0.58	0.23	0.51
World interest rate	0.04	0.06	0.07	0.03	0.06	0.04
VIX	0.13	0.2	0.12	0.09	0.07	0.12
Terms of trade improvement	0.05	0.07	0.05	0.04	0.04	0.08
TOTAL	0.81	0.68	0.64	0.75	0.4	0.75

Table 3: Forecast error in 2008 and 2009

Region	Model	Err_Prev Oct '08	Err_Same Apr '08	Err_Same Oct '08	Err_Prev Oct '09	Err_Same Apr '09	Err_Same Oct '09	Avg.
EBRD	ARIMA	-2.5	0.1	0.1	-0.5	0.4	0.4	-0.3
	BVAR cond	0	-1	-0.2	-2.3	-0.8	-0.8	-0.8
	BVAR uncond.	-0.7	-1.6	-0.9	-8.2	0.7	-0.9	-1.9
	EBRD							
	Economists	-1.9	-1.3	-1.3	-7.5	-0.2	0.6	-1.9
	GDFM	-1.7	-1.9	-1.9	-10.1	-4.6	0	-3.4
	IMF WEO	-1.4	-1.1	-1.3	-8.6	-0.8	0.4	-2.1
NM7	ARIMA	-1.7	0.1	0.1	-0.6	0	0	-0.4
	BVAR cond	0.5	-1.7	-0.5	-3.3	-1.7	0.3	-1.1
	BVAR uncond.	-0.6	-2.1	-0.8	-4.7	-1.7	0	-1.6
	EBRD							
	Economists	-1.7	-1	-0.6	-4	0.5	0.4	-1.1
	GDFM	-1.1	-1.6	-0.8	-6.1	-3.3	-0.4	-2.2
	IMF WEO	-1.6	-1	-0.9	-5.3	0.4	0.7	-1.3
Balkans	ARIMA	-1.8	0.1	0.1	-1.4	0.1	0.1	-0.5
	BVAR cond	7.3	2.7	-0.6	-3.6	-1	0.3	0.9
	BVAR uncond.	1.9	1.2	-1.5	-10.5	-2.5	0.2	-1.9
	EBRD							
	Economists	-0.9	0	-0.6	-9.5	-2.8	0.3	-2.3
	GDFM	-0.3	-0.3	-1.4	-11.9	-7.9	-0.8	-3.8
	IMF WEO	-0.5	0	-1	-10.3	-2.8	0.4	-2.4
EEC	ARIMA	-3.7	1.4	1.4	7.2	7.9	7.9	3.7
	BVAR cond	-3.3	-2.1	-0.2	6.5	6.2	-0.5	1.1
	BVAR uncond.	-6.1	-4.8	-3.2	-12.5	10.5	-0.3	-2.7
	EBRD							
	Economists	-6.3	-5	-4.7	-13	-2	0.9	-5
	GDFM	-6	-5.3	-4.1	-16	-6.3	0.2	-6.2
	IMF WEO	-1	-1.8	-3.9	-13.9	-3.1	-0.5	-4
CA	ARIMA	-3.7	0.4	0.4	0.5	0.8	0.8	-0.1
	BVAR cond	-5.2	-4	-2.2	-0.9	3.5	0.4	-1.4
	BVAR uncond.	-6.3	-4.6	-2.6	-5.9	6.7	0.8	-2
	EBRD							
	Economists	-4.4	-1.3	-0.7	-3.2	3	2.1	-0.8
	GDFM	-6	-0.5	-2.7	-6.1	2.1	0.8	-2.1
	IMF WEO	-3.7	-1.4	-0.9	-4.1	2.7	2.8	-0.8
RUSKAZ	ARIMA	-3.9	-0.2	-0.2	-0.8	0.2	0.2	-0.8
	BVAR cond	-1.2	-1.7	-1.5	-1.4	2.4	0	-0.6
	BVAR uncond.	-1.3	-2.5	-2.6	-12	2.4	0.4	-2.6
	EBRD							
	Economists	-1.7	-1.7	-2	-11	0	0.9	-2.6
GDFM	-2.3	-2.2	-3.2	-14.4	-5.4	0.5	-4.5	
IMF WEO	-1.6	-1.6	-1.7	-12.4	-1.3	0.1	-3.1	

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